THREE ESSAYS ON CONFLICT AND CLIMATE EFFECTS IN COLOMBIA

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Declaration

I hereby declare that this thesis has not been, and will not be, submitted in whole or in part to another University for the award of any other degree. I affirm that all the material presented in this thesis is original work that I have undertaken with guidance and input from my supervisors. Any errors or omissions are my own.

Signature: ____________________________

Rafael Isidro Parra-Peña Somoza

1st May 2019

Summary

UNIVERSITY OF SUSSEX

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DEGREE OF DOCTOR OF PHILOSOPHY (PHD) IN ECONOMICS
THREE ESSAYS ON CONFLICT AND CLIMATE EFFECTS IN COLOMBIA

In Colombia, it is a common refrain that there is not a single family unaffected by the conflict that marked the country for over half a century. During 2016, with the peace agreement that ended 60 years of fighting with the FARC, the country entered into a post-conflict phase. This thesis provides empirical evidence to inform policies designed to foster rural development (especially in places where the livelihoods have been damaged by conflict), protect the environment, and promote sustainable growth in a context of increasing extreme global weather events. In particular, the work is comprised of three empirical essays examining respectively the impact of conflict on (i) agribusiness durations, (ii) deforestation, and (iii) selected crime outcomes.

The first essay provides an analysis on agribusiness contract durations, defined as the survival of contractual partnerships between smallholder producer organizations and their commercial buyers, and their relationship with specific manifestations of violence. There is evidence that the presence of violence increases the hazard rate of agribusiness contract commercial failure. In particular, the presence of terrorist events at the start year of the agribusiness contracts registers as the main determinant. In particular, when violent incidents vary over time, the subversive actions, mainly provoked by the guerrillas, emerge as a cause of commercial failure.

The second empirical essay offers evidence on the relationship between armed conflict and its environmental impact. There is evidence that the armed conflict is a force for forest protection and growth, though the effect is found to be small. Forest degradation often increases in post-conflict situations. These findings highlight a need for increased protection of Colombia's forests in the wake of the peace agreement.

The third empirical essay investigates the impact of the most recent extreme weather event in Colombia, "La Niña" (between 2010-2011 and named by the local media as the "winter wave") on theft rates in the municipalities affected. This essay demonstrates that the winter wave brought a decrease in theft from persons. This is perhaps attributable to the emergence of pro-social behaviour in the municipalities most affected. We also find an increase in theft from houses possibly linked to a 'survival mechanism'. In addition, we also reveal that the presence of conflict discourages theft perhaps due to the establishment of coercive institutions by illegal armed groups.

Acknowledgments

This thesis is more than an academic work; it represents a testimony of a chapter of a life journey.

First and foremost, I am very grateful to Professor Barry Reilly, my PhD supervisor, at the University of Sussex (US) at Brighton, UK. He is the reason why I have chosen US for my doctorate studies. Professor Barry's desire to help students is remarkable. Every meeting with him has been source of inspiration. His frequent reviews (too many!) on my drafts of the chapters included here represents a testimony of his research and teaching distinction.

I'm also grateful to Mr. Mark Lundy, leader of the Linking Farmers to Markets (LFM) team of the International Center for Tropical Agriculture (CIAT) in Cali, Colombia. When I was working for CIAT he managed to secured a grant from the Ford Foundation that eventually helped me to cover a couple of years of the Ph.D. tuition fees. In addition, during the first two years of my PhD studies Mark allowed me to be based at Brighton for long periods of time while keeping my job at CIAT in Cali, which facilitated my thesis supervision.

Given the lack of a scholarship that covered all of my expenses I managed to work full-time in other jobs back home in Colombia to support my doctoral studies. During times when I was without a job I was worried I couldn't finance the PhD. However, I overcame this set back and was able to secured other jobs. However, working full-time in other jobs and the Ph.D. at the same time has been not easy; indeed, it has required enormous personal sacrifice.

The efforts paid-off in 2016. Professor Reilly and I successfully published the third chapter of this thesis in a peer-review the book entitled "El desarrollo equitativo, competitivo y sostenible del sector agropecuario en Colombia" edited by Carlos Gustavo Cano, former Deputy Director of the Central Bank of Colombia, Ana Maria Iregui, Maria Teresa Ramirez and Ana Maria Tribin, researchers from the Research Unit of the Central Bank of Colombia. I also had the opportunity to present the forth chapter of this thesis at two international workshops organized by Households in Conflict Network (HiCN); one at the Munk School of Global Affairs at the University of Toronto (2015) and the other at the Food and Agriculture Organization (FAO) headquarters in Rome (2016). I'm beyond grateful for receiving useful comments from the workshops participants.

In July 2018, with Professor Reilly as well, we published the fifth chapter of this thesis in the "Economic Archives", the economic studies working paper series of the National Planning Department (No. 481).

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In my career as an economist, apart from CIAT, I also have worked for the Economic Commission for Latin America (ECLAC) of the United Nations, the International Finance Corporation (IFC)- the World Bank Group-, the National Planning Department, and Universidad de Los Andes. In those institutions, I had several great mentors and friends that contributed in my professional career. Special thanks go to Dr. Fernando Mesa Parra, currently Professor of Universidad Jorge Tadeo Lozano, Bogotá, and Dr. Juan Carlos Ramirez J., Director of ECLAC, Bogotá Office.

I wish that my late loving father Mr. Isidro Parra-Peña would be proud of his son today. My dad was truly my first role model. He was convinced that education promotes social mobility. Consequently, he taught me the timeless values of responsibility, modesty and kindness. Initially, Isidro had strong liberal and peasant backgrounds. He was from el Libano (Tolima department), a traditional coffee town in Colombia. When he was a boy he migrated to Bogotá looking for a better future due to the conflict between liberals (leftists) and conservators (rightest). Thus, Isidro managed to overcome many obstacles to obtain a formal education as an accountant. Later on, he won a scholarship to course a Master in Industrial Engineer from Universidad de Chile (Chile) that he found published in a Colombian newspaper, and in Chile, he won another scholarship to course an additional Master in Development Economics at Vanderbilt University (USA). Afterward, with his professional career consolidated he coursed postgraduate studies in Public Administration at Harvard University (USA). He became a public servant, a man of integrity. Isidro held high-level positions in the Colombian Government, and multilateral agencies like ECLAC, CAF-Development Bank in Latin America, and the UN.

My mother, Dora Mercedes Somoza, lawyer graduated, a woman from Santa Marta, Colombia, a city right in the middle of the Caribbean Region, acted as a heroine when my father was terminally ill and passed away in October 30th 2001. Thus, she managed to raise two youths by her own. My brother, Felipe Alejandro Parra-Peña Somoza, nowadays living in Buenos Aires, Argentina, and me. I must thank to my mother Dora and my brother Felipe Alejandro "*F.Alex*" for conveying me the profound power love and unity. Without that, my PhD journey would have not been possible.

Among other my family members, I'd like to mention the encouragement given by Fidelina Zapata (passing in November 28th 2015) - my most beloved "Fide", my Caribbean "Grandma - the best cook of coconut rice ever"-, and, my beautiful aunt, Margarita Somoza. I also cannot forget my cousin Mabel Somoza and her husband Guy Enion living in London. During the MA and PhD studies Mabel and Guy were always there, specially, to invite me to a theatre play, treasure hunt or dinner in London.

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Regarding my family heritage, like my father, I’m a proud direct descendant of General Isidro Parra, a liberal war hero, autodidactic intellectual, and founder of El Libano in 1849. During his life, General Isidro defended the right to freedom of expression and religion, promoted awareness of the human rights, founded a school and brought the coffee culture to this remote peasant village. General Isidro was assassinated due to political reasons on March 17, 1895.

That’s why usually the first-born children in my family are named “Isidro” –however, I was also named also Rafael, after my uncle, “Rafael Parra Peña”, a lawyer and judge who was also assassinated at El Libano due to political reasons. These political troubles have led me to choose my PhD thesis topic, broadly, agricultural and conflict economics.

During 2016 I was appointed as Executive Director of the Centre for Coffee, Regional and Business Studies (CRECE), which is the economic research unit of the Colombian Coffee Growers Federation in the field, located in Manizales, Colombia, a town in the Coffee triangle. I’d like to thank Dr. Jose Leibovich and Dr. Alfonso Angel, for giving me the opportunity to contribute with economic research changing the lives of the coffee farmers of Colombia.

During January 2018, I submitted the thesis, and I subsequently assumed a policymaker role as Director of the Directorate of Sustainable Rural Development of the National Planning Department (DNP, in Spanish) Government of Colombia, whose mission is to design, promote and assess rural and agricultural development policies in the country.

In July 30th 2018 I traveled to the UK and I passed the viva exam. I'm thankful with Andy Mckay and Frank Walsh, my Ph.D. internal and external examiners, respectively.

Early 2019, I've been involved in the construction of the National Development Plan 2018-2022, which include the main policy strategies, goals and planned investments, including the ones of the agricultural sector.

I feel grateful and humbled by the support and love I received during my studies.

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Abbreviations

AC	Agribusiness Contracts
AFT	Accelerate Failure Time duration models
AIC	Akaike Information Criterion
AUC	Autodefensas Unidas de Colombia (United Self-Defence Forces of Colombia Colombia)
BACRIM	Bandas Criminales Emergentes (Emergent Criminal Bands)
CB	Commercial Buyer
CEDE	Centro de Estudios Sobre Desarrollo Económico (Centre of Development Economics Studies)
CIAT	International Centre for Tropical Agriculture
CLOPAD	Comité Local para la Prevención y Atención de Desastres (Local Committee for Emergencies and Disasters Prevention and Attention)
CREPA	Comité Regional para la Prevención y Atención de Desastres (Regional Committee for Emergencies and Disasters Prevention and Attention)
DANE	National Administrative Department of Statistics
DIRAN	Colombian Antinarcotics Police (DIRAN)
DNP	Departamento Nacional de Planeación (National Planning Department)
ELN	Ejército de Liberación Nacional (National Liberation Army)
EWE	Extreme Weather Event
FAO	Food and Agriculture Organization
FARC	Fuerzas Armadas Revolucionarias de Colombia (The Revolutionary Armed Forces of Colombia)
FDI	Foreign Direct Investment
FE	Fixed Effects
GDP	Gross Domestic Product
IV	Instrumental Variable
M-19	Movimiento 19 de abril (April 19 Movement)
MADR	Ministerio de Agricultura y Desarrollo Rural (Colombian Ministry of Agriculture and Rural Development)
MAS	Muerte a Secuestradores (Death to Kidnappers).
MI	Modular Incentives
OGA	Organizaciones Gestoras Acompañantes (Regional Accompaniment Organization)
OLS	Ordinary Least Squares

PAAP	Proyecto de Apoyo a Alianzas Productivas (Productive Alliances Project)
PAs	Productive Alliances Smallholder
PH	Proportional Hazard
POs	Producer Organizations
RF	Revolving Fund
SIEDCO	Sistema de Información Estadístico, Delincuencial, Contravencional y Operativo (Information System of Delinquency Statistics of the National Police)
SIMCI	Integrated Monitoring System of Illicit Crops of the United Nations Office of Drugs and Crime
SNPA	Sistema Nacional de Atención y Prevención de Desastres (National System for Disaster Prevention and Attention)
SIMCO	Colombian Mining Information System
UAF	Unidades Agrícolas Familiares (Family Agricultural Units)
UNGRD	Unidad Nacional para la Gestión del Riesgo de Desastres (Colombian government National Unit for Disaster Risk Management)
SIMCI	Integrated Monitoring System of Illicit Crops of the United Nations Office of Drugs and Crime

1. Introduction

It is a common refrain in Colombia that there is not a single family unaffected by the conflict. The human toll of the conflict is immense. Between 1958 and 2012, the armed conflict claimed the lives of around a quarter of a million people, with civilians accounting for an average of eight out of every 10 of these fatalities. There were 25,007 forced disappearances (1985-2012) and around 27,023 persons kidnapped.[1]

Several academic studies within the conflict literature have used quantitative approaches to compute the high economic and social costs the country has paid during this violent conflict (Rubio 1995; Parra, 1998; Echeverry et al. 2001; Querubin, 2003; Vargas, 2003; Cárdenas, 2007; and Villa et al. 2013). For example, according to Villa et al. (2013), using panel data at the departmental level between 1988-2009, the average departmental GDP took around 18.5 years to double. In the absence of the armed conflict, it would have taken ten years less. Using time series data between 1980 and 1999 in conjunction with vector autoregession analysis (VAR), Cárdenas (2007), found that the growth of illicit crops and homicide rates were associated with a 0.3 percentage point reduction in GDP per capita growth due to a decline in factor productivity. The work of Vargas (2003), using a 3SLS model, confirmed this magnitude in reporting a per capita GDP growth that was 0.33% less, on average, during the 1990s.

The social consequences of conflict are generally broader. Attacks on civilians led to the forced displacement of about 3.8 million people (8.4% of the population) between 1999 and 2011. According to Ibáñez (2009a), guerrillas are responsible for nearly half (45.8%) of this displacement, followed by paramilitaries (21.8%), with the remainder attributed to other groups engaging in drug trafficking and more general forms of criminality. These displaced households usually found themselves in a poverty trap due to the loss of assets and a lack of skills to compete in urban labour markets. Between 2002 and 2007, 95% of the displaced households were found to live below the poverty line (with 75% living in extreme poverty).[2]

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[1] This is according to *statistics reported at* www.**verdadabierta**.com/*, taken from* Centro Nacional de Memoria Histórica.

[2] Further information on this can be found at: http://focoeconomico.org/2014/05/27/acabar-el-conflicto-en-colombia-una-eleccion-racional/

The negative consequences of violence are known to persist for several generations. For example, these effects include, for example, an 8.8% decrease in years of education acquired (Rodríguez and Sánchez, 2012); children born into regions with exploding landmines weighed, on average, 8.7 grams less at birth due to high levels of maternal stress (caused by conflict) during the mother's gestation period resulting in poorer cognitive development in the long term (Camacho, 2008).

In the spirit of this work, the current research tackles unexplored research questions regarding conflict impacts using a set of novel Colombian municipal datasets and robust identification strategies.[3]

This thesis is comprised of three empirical essays. The first empirical essay enhances the existing literature by estimating the effect of the conflict on agribusiness contract durations of small-holder farmers. This is defined as the survival of contractual partnerships between small-holder producer organizations and their commercial buyers. In Colombia, despite the fact that the rural population has incurred the economic and social costs of war disproportionately, little is known about how the conflict affects the agribusiness of small-holders. In fact, most of the conflict literature for Colombia has traditionally focused on identifying the ways in which a farmer household copes with violence[4] (See, for example, Ibañez et al., 2013; Arias et al., 2014)

In order to provide a robust analysis on small-holders agribusiness durations and their relationship with specific episodes of violence, this essay employs original data drawn from 434 agri-business contracts. These contracts were established by small-holder producer organizations obtained from the administrative records of the Rural Productive Alliances Project (*Proyecto de Apoyo a Alianzas Productivas* or PAAP, its Spanish acronym). This is a major Colombian initiative linking farmers to markets and is partly sponsored by the World Bank.[5] It is implemented by the Colombian Ministry of Agriculture and Rural Development (MADR, its Spanish acronym). The information on

[3] An identification strategy is the manner in which a researcher uses observational data (i.e., data not generated by a randomized trial) to approximate a real experiment.
[4] Coping strategies involve the decision whether or not to withdraw from markets, which crop to plant, whether to implement a short growing cycle or a long one, which production technique to use, and other possible ways of risk-diversification.
[5] The World Bank co-financed about 70% of PAAP project operations.

the number and types of violent episodes perpetrated by both guerrilla and paramilitary groups in Colombia is obtained from an annual data set at the municipal level constructed by CEDE (Centro de Estudios Sobre Desarrollo Económico, Universidad de los Andes).

The empirical approach uses common non-parametric, semi-parametric, and parametric duration models. The estimation results suggest that the presence of violence in the municipality where the producer organization is located increases the hazard rate of agri-business commercial contract failure. In particular, the presence of terrorism at the start year of the agribusiness contract appears to be a key factor in commercial failure. However, when the duration models allow violent incidents to vary over time, the subversive actions mainly provoked by the guerrillas emerge as the main cause of failure. Thus, this essay confirms the hypothesis that the Colombian conflict had a degrading effect on the overall agri-business climate, constraining farmer capacity to sustain market linkages.

The second empirical essay offers evidence on the relationship between armed conflicts and their environmental impacts. In particular, the overall effect of conflict on the environment remains an open empirical question. From an academic point of view this effect is ambiguous. One strand of the literature emphasizes pressures on environmental degradation with another strand suggesting the opposite. For example, in Colombia there is an environmental friendly attitude adopted by the guerrilla movements usually connected to the prevailing economic and military interests in the area. In other words, forest conservation helps rebel forces to conceal and to establish safe-havens with transit corridors for troops, military and other supplies, drugs, or illegally extracted natural resources (See, for example, Álvarez, 2003; Dávalos et al., 2011).

Thus, the second essay provides evidence as to which of these strands is most likely for Colombia using a unique annual municipality panel dataset (from 2004 to 2012). The estimates for the share of the municipality area covered by the forests are based on satellite images collected by the Department of Geographical Sciences at the University of Maryland partnering with other major research centres[6] in the United States. The

[6] These are Google; the Department of Forest and Natural Resources Management, State University of New York; the Woods Hole Research Center; the Earth Resources Observation and Science, United States Geological Survey; and the Geographic Information Science Center of Excellence, South Dakota State

conflict measure used is forced displacement, which correctly captures the presence of extreme violence perpetrated by guerrilla and paramilitary groups in each municipality. The forced displacement source estimates are obtained from the Information System of Displaced Population (SIPOD, its Spanish acronym), the Central Registry for Victims Office (RUV)[7] and the Observatory of the Presidential Human Rights and International Humanitarian Law of the Vice Presidency of Colombia.

An instrumental variable approach that controls for a possible endogeneity between forest cover and forced displacement is deployed to estimate the causal impact of conflict on deforestation. This essay reveals that there is evidence that the conflict is a force for forest protection and growth. However, the estimated effect found is found to be numerically small. For example, the average estimated effect suggests that an additional person displaced per 1,000 inhabitants increases the percent of forest covered by 0.0028 of a percentage point at the municipality level. Forest degradation often increases in post-war situations. Thus, with the advent of peace in Colombia this research advocates for an appropriate forest conservation strategy.

The third empirical essay estimates the impact of the most recent extreme weather event (EWE) in Colombia, "La Niña" (2010-2011) on the theft rates in the municipalities affected by this weather event. This EWE is labelled by the local media as the "winter wave". In studying the causes of crime researchers often have concentrated their efforts on exploring the role of traditional socio-demographic variables, such as age, gender, race, and socio-economic status. However, very few researchers have investigated the mechanisms including the influence of weather, on criminal behaviour (Hsiang et al., 2013). No studies have investigated to date the climate variability-crime and/or specific natural disaster-crime relationship using appropriate econometric techniques for Colombia.

This essay employs information regarding theft activity in Colombia from the statistical Information System of Delinquency of the National Police, and official records at the municipal level relating to the weather disasters associated with the passing of "the winter

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University.

[7] This registry, established under Act 1448 of 2011, contains the number of registered victims of human rights violations during the armed conflict and over the period from 1985 to the present.

wave"[8] (e.g., floods, avalanches and landslides, tornado, thunderstorm, wind, erosion and hail) directly from the archives of the Colombian Government National Unit for Disaster Risk Management (UNGRD, corresponding to the *Spanish acronym).*

A Difference-in-Difference (D-i-D) procedure is used to estimate the impact of the "winter wave" on theft rates in the municipalities most exposed to adverse climatic effects. In particular, the "winter wave" intensity levels are measured according to the number of houses damaged and destroyed in each municipality. The results reveal that the winter wave brought a decrease in theft rates, especially, the theft from persons, in the treatment group compared to the control groups. This is perhaps viewed as attributable to the emergence of pro-social behaviour in the municipalities most affected. In addition, we also find an increase in theft from houses that is possibly linked to a 'survival mechanism', rather than one that seeks monetary reward like the Becker (1968) model of acquisitive crime. In addition, the D-i-D estimates also reveal that the presence of conflict, in general, discourages theft perhaps due to the establishment of coercive institutions by illegal armed groups.

The 2016 peace agreement that ended 60 years of conflict with the FARC, aside from reducing victimization, is anticipated to yield immense economic benefits for the future. For example, a National Planning Department (DNP)[9] study suggests that Colombia's GDP will grow between 1.1 and 1.9 percentage points more in the wake of the peace accord. In particular, an increased confidence is anticipated to translate into a 2.5 percentage points increase in consumption growth, a 5.5 percentage points increase in the investment rate (as a percentage of GDP), three times more Foreign Direct Investment (FDI), and a 17.7 percentage point increase in the openness to trade (exports plus imports as a share of GDP). From the supply side, the results are anticipated to be promising as well: 1.4 points of additional growth in the agricultural sector, 0.8 points of increased growth in the manufacturing sector, and a 4.4 percentage point increase in the rate of growth in the construction sector.

[8] This information is available from April 2010 to June 2011.
[9] This is based on DNP (2015), "Dividendo económico de la paz". Power point presentation.

It is evident that the social and economic costs decrease sharply once violence has ceased. However, it is important to clarify that the peace dividends do not materialize without the necessary investments. In the aftermath of the peace, one cannot expect to immediately secure an increase of one or two percentage points in GDP growth. The economic benefits will be gradual: they will depend on how solid are the country's foundations for economic development. Thus, an important aspect of these three essays lies in their policy implications. The findings of this thesis suggest greater income opportunities for rural families, especially in places where agribusinesses have been damaged by the conflict, an appropriate forest conservation strategy, and the promotion of the right climate adaptation and mitigation policies given a global context of increasing extreme weather events.

The thesis is organized into six separate chapters. Chapter 2 presents a summary of the Colombian conflict in order to provide the reader with an adequate context within which to interpret the empirical results. Chapters 3 to 5 contain the three empirical essays. Finally, Chapter 6 offers some concluding remarks, a discussion of the limitations of the research, and an agenda for future research.

Chapter 2

2 The timeline and narrative of the conflict

2.1 1958-1964: from political confrontation to subversion

The Colombian armed conflict originated from a civil war known as “La Violencia” involving two main political parties, liberals (leftist) and conservadores (rightist). La Violencia is considered to have started on the 9th of April 1948 with the assassination of Jorge Eliécer Gaitán, the presidential candidate for the liberal party. In 1953, General Gustavo Rojas Pinilla seized power through a political coup d'état intended to restore peace and civil order. After a short period of military dictatorship, democracy returned in 1957 with the National Front, in which the liberal and conservatives parties agreed to allow the opposite party to govern, alternating over a period covering four presidential terms, until 1970.

The National Front imposed limitations on members of third political parties, barring them from participating in the electoral process or even becoming public employees. Major social problems such as poverty, income and land ownership inequality prevailed. In May 1964, Colombian troops launched an assault against less than 50 guerrilla families who had openly rebelled against the government and declared their own republic in the small town of Marquetalia. The objective of the operation was to eradicate a perceived communist threat. Five months after this operation, the survivors regrouped and established their first guerrilla conference, which gave birth to the longest running communist insurgency in Latin America: The Revolutionary Armed Forces of Colombia (FARC).

Other leftist peasant resistance groups formed during La Violencia period and inspired by the Cuban revolution in the late 1950s evolved into the National Liberation Army (ELN). Initially, these were two small groups dedicated to seizing power with the goal of enacting social programs and undertaking radical agrarian reforms.

2.2 1965-1981: The guerrilla’s consolidation and the fight against the state

During the 1970s, the M-19, another largely urban guerrilla group emerged. The M-19 was founded in response to alleged fraud in the presidential election of a conservative politician, Misael Pastrana Borrero.

During this decade, the FARC and ELN began to grow. They were involved in kidnapping to finance their activities, but they also engaged in political kidnappings to increase their bargaining strength with the government in power. At this time, FARC and ELN also began to engage in drug producing and trafficking operations.

2.3 1982-1995: The armed conflict boost, drug lords and paramilitaries

During the 1980s, the growing illegal drug trade and its consequences provided impetus to sustain the armed conflict. The appearance of the Medellin and Cali cartels led to either the bribery or murder of politicians and public servants – and anyone else who opposed them – particularly those who supported the implementation of the extradition of Colombian criminals to the United States.

The kidnapping of drug cartel family members and the imposition of a tax on cattle breeders and land owners by the guerrillas led to the creation of the Muerte a Secuestradores (MAS) death squad (Death to Kidnappers), which was characterized as one of the first expressions of right-wing paramilitarism in Colombia.

In 1985, the M-19 took over the Palace of Justice and held the Supreme Court hostage with the intention of staging a "trial" of President Belisario Betancur. After heavy fighting between the army and the rebels, the building was set alight and almost half of the Supreme Court Justice members, as well as several civilians, died in a subsequent and controversial army rescue operation.

2.4 1996-2002: The armed conflict peak

The M-19 group was successfully integrated into a peace process, which culminated in the elections for a Constituent Assembly of Colombia that would draft a new constitution that would eventually take effect in 1991.

During the 1990s, FARC military activity increased as the group continued to grow financially from both kidnapping and drug-related activities. The illicit crops rapidly spread throughout the countryside. In 1994, the alliance between paramilitaries and drug lords strengthened, both legally and illegally, with the creation of the armed Convivir groups, supported by the National Congress. In 1997, paramilitary forces and several former Convivir members united to create the United Self-Defence Forces of Colombia (AUC), a large paramilitary militia closely tied to drug trafficking which instigated attacks on the FARC and ELN rebel groups.

In 1998, the president Andres Pastrana agreed with FARC commanders to create a demilitarized zone in the region of El Caguán river basin. The Caguán (1999–2002) was a demilitarized zone of 42,000 km^2 in southern Colombia. It was within this zone that the government initiated their first effort at a peace process with the FARC.

2.5 2003- 2015

The Caguán peace process failed and the guerrillas became stronger than prior to the previous 40 years of fighting. A political outsider, Alvaro Uribe, was voted into the presidential office in 2002 on a promise to defeat the FARC. From 2002 onwards, with Mr. Uribe in power, the armed conflict declined. The elected government provided substantial financial resources to the army and a strong national security policy helped to reduce national levels of violence. Simultaneously, in 2003 a disarmament process began with the AUC and successfully concluded in 2006. However, some of their members started up smaller drug-dealing groups, known as the emergent criminal bands (Bacrim, in Spanish). From November 2012, the FARC and the national government were engaged in discussions in an attempt to end South America's longest-running internal conflict.

2.6 From 2016 onwards

After four years of talks in Havana, the Cuban capital, the government and the FARC reached a peace deal. It was put to a referendum in October and the public voted by a narrow margin to reject it (50.2%). The country was divided mainly in regard to some of the terms of the peace deal such as: i) the definition of what's a fair time in prison for crimes committed by the rebels; ii) in what way should rebels found guilty of crimes be barred from jail and running for public office, and; iii) how can FARC use their illicit gains to pay compensation to the victims of the conflict.

In the aftermath of the referendum result, the government and the rebel leaders made changes to the deal. Colombia’s President, Juan Manuel Santos, was awarded the Nobel Peace Prize in recognition of his efforts to end the conflict. Finally, in December 2016, the Colombia's Congress bypassed the majority voter preferences and approved a revised peace deal.

Chapter 3

3 Do violent incidents affects the duration of agribusiness contracts of smallholder farmers? Evidence from Colombia

Summary

This chapter provides a seminal analysis on agribusiness contract durations in Colombia. The empirical focus is on the survival of contractual partnerships between smallholder producer organizations and their commercial buyers, and their relationship with specific manifestations of violence. The study constructed a unique dataset of agribusiness contracts and producer organization attributes from the archives of a public project, whose primary goal is to establish commercial relationships between small producers and formal buyers in Colombia (Proyecto de Apoyo a Alianzas Productivas – PAAP, in Spanish). The empirical approach exploits a set of common non-parametric, semi-parametric, and parametric duration models, as well as discrete time models for completeness. There is evidence that the presence of violence increases the hazard rate of agribusiness contract commercial failure. In particular, a presence of terrorism at the start year of the agribusiness contracts appears as the main cause. When violence incidents vary over time, the subversive action mainly perpetrated by the guerrillas, emerge as the key cause of commercial failure.

Keywords: Conflict, violence, risk, uncertainty, investment climate, agricultural production, agribusiness, firm survival.

3.1 Introduction

It is widely known that violence reduces welfare through its effects on physical or psychological harm, destruction of human capital and physical assets, and forced displacement. Violence also hinders economic efficiency and modifies behavioural norms and social organisational structures (Justino et al., 2013a).

On the one hand, macroeconomic studies offer explanations for the negative correlation between GDP per capita, or broadly defined economic activity, and violence (Barro 1991; Alesina and Perotti 1996; Collier 1999;Gaviria 2002). For example, according to Collier (1999), GDP per capita declines at an annual rate of 2.2% during civil wars on average and *ceteris paribus*. On the other hand, there is a substantial body of research on the effects of violent conflict on its victims. Furthermore, households residing in areas with violence incur a multiplicity of social, economic and political consequences—including decisions regarding education, child nutrition, household consumption, labour market participation, political preferences and/or social engagement.

However, little is known about how violence affects agribusiness contracts. In the developing world, many violent conflicts have their origins in agrarian disputes, such as conflicts over land, and escalate and reproduce fairly quickly in rural areas where state presence and governance is often weak. The research presented here is the first of its kind to utilize data on agribusiness contract durations to investigate the effects of violence on the survival of such contracts.

The information on smallholder agribusiness contracts is obtained from a major public project linking farmers to markets (*Proyecto de Apoyo a Alianzas Productivas* – PAAP, in Spanish) partly financed by the World Bank and implemented from 2002 by the Colombian Ministry of Agriculture and Rural Development (MADR, in Spanish).

The PAAP fosters agribusiness under formal contracts that unite buyers with smallholder Producer Organizations (POs). These agribusiness contracts are known as Productive Alliances (PAs). They are aimed at reducing technical, commercial, financial and social risks in pursuit of potential productivity and income gains in a particular value chain. First, under these contracts sponsored by the government, POs obtain access to critical inputs and markets for their products, while buyers expand food-processing activities by securing supplies from small producers that meet minimum quality standards. Second, these contracts are initially funded through grants, known as modular incentives (MI), which the POs typically invest in technical assistance (production, management and marketing issues), infrastructure and/or equipment to fulfil the contract with the buyer (Collion and Friedman, 2012).

Despite a major reduction in criminal activity in recent decades, Colombia continues to evoke in the minds of many an image of violence and drug trafficking. It is seen as the Latin American country where violence has been the most widespread and persistent, thus providing an ideal setting to study the consequences of violence on an outcome like the duration of agribusiness contracts. Guerrillas, paramilitary groups and drug barons have repeatedly perpetrated attacks that vary in both type and intensity, spanning both space and time.

The information used here regarding the manifestations of violence were obtained via a yearly municipal-level dataset constructed by CEDE (*Centro de Estudios sobre Desarrollo Económico*, Universidad de los Andes, Bogotá), which contains information on violence and conflict between 2002 and 2012.

Regarding the literature that explains how violence degrades the endurance of agribusiness contracts, "violent shocks" and "fear and uncertainty" may act as the main triggers. First, farmers located in conflict-affected areas are exposed to attacks, extortion or crop and livestock appropriation. Thus, violence can be understood as an additional negative shock faced by farmers, in addition to more conventional shocks due to variations in climatic conditions, crop diseases or natural disasters (Ibañez et al., 2013; Blattman and Miguel, 2010). Violent shocks generate a destruction of both physical and human capital. As a consequence, agribusinesses located in violent areas operate in scenarios prone to inefficient economic outcomes (i.e., market failures), leading to high operational costs and low investment levels due to a contraction in the supply of labour and goods, higher transaction costs, higher prices and reductions in existing networks (Abadie and Gardeazabal 2003; Justino 2009; Justino and Verwimp 2013; Justino et al. 2013a).

Secondly, violence increases uncertainty and fear (Camacho and Rodriguez, 2013a; Rockmore, 2016). Farmers adjust their behaviour *ex-ante* in anticipation of a violent shock to minimize risk or exposure, rather than to maximize profits. For example, farmers may shift their production portfolio from long growing cycle crops to short ones, since they can be converted easily into cash (Verpoorten 2009; Arias, Ibáñez, Zambrano 2014). Additionally, farmers are reluctant to make irreversible investments that would otherwise increase productivity, volume and product quality such as investments in greenhouses or irrigation systems. Diversifying income sources by allocating time to off-farm activities provide another coping strategy.

A duration analysis framework was employed to study the impact of violence on the survival rate of agribusiness contracts. The methods of analysis include a non-parametric Kaplan-Meier approach; semi-parametric Cox Proportional Hazard (PH) model; common parametric accelerated failure time duration models (e.g., Exponential, Weibull, and Log-logistic); and discrete time models (Logistic and Cloglog) were all used to estimate the hazard duration function for 434 agribusiness contracts within the PAAP project context. The analysis incorporated information on the presence of violence in the municipalities where the POs are located.

The semi-parametric and parametric model estimates reveal that the presence of violence at the inception of a business hinders the ability of smallholder growers to sustain their agribusinesses contracts with formal buyers. In particular, acts of terror appear to be one of the main causes of agribusiness contract failure.

The main advantage of using discrete time models compared to the semi and fully parametric duration models noted above is that they provide a simple way to permit the variables of interests to change over time. These discrete-time models reveal that subversive actions perpetrated by the guerrillas are the main determinants of agribusiness contract failure.

The next section briefly reviews the existing theoretical and empirical literature on the relevant research question. A third section describes empirical modelling issues. A fourth discusses the data and provides some descriptive statistics. The fifth reports the empirical results and the final section offers some concluding remarks.

3.2 Literature Review

This study enhances the existing literature on conflict and violence in a number of distinct ways. As previously mentioned, to the author's knowledge, no studies currently exist that analyse the impact of violence on agribusiness contract durations, and certainly none for Colombia.

We focus the literature review on the firm-level effects of exposure to violent environments as this appears particularly germane to our analysis. For example, at the cross-country level, Gaviria (2002) used data from a private sector survey[10] and an OLS regression model that controls for firm-level characteristics (sector, size, tenure, public or foreign ownership, public buyer, location, etc.) and country effects. The author reported that firm sales in Latin America grow at a lower rate if entrepreneurs believe crime rates are high enough to interrupt their business activities. The author explains that simply a manager's perceptions of crime and corruption raise a firm's operational costs, causing a loss in valuable human and financial resources and preventing companies from entering profitable business. All of which leads to a lowering of competitiveness and firm-level sales.

At the country level Camacho and Rodriguez (2013a), for the case of Colombia, combine a panel of industrial firms from the Annual Manufacturing Survey with violence and conflict data collected between 1993 and 2004 to study the effect of armed conflict on industrial plant exits. Since the plant exit decision contains the possibility of reverse causality with the escalation of armed conflict, the authors used an instrumental variable approach instrumenting contemporaneous violence using lagged government deterrence measures, such as the number of dismantled laboratories and anti-narcotic operations. Using a two stage least squares estimator for the linear probability panel data model, and after controlling only for plant fixed effects, year effects and duration of the plants, the authors report that an increase in the number of guerrilla and paramilitary attacks in a municipality increases the probability of plant closure by 2.3 percentage points, *ceteris paribus*.

[10] Conducted by the World Bank and the Inter-American Development Bank in 1999.

Pshisva and Suarez (2010) merged information about crime across the 32 departments of Colombia with financial statements from around 11,000 firms operating between 1997 and 2003. Using OLS and controlling for firm and state level characteristics, the authors find that kidnappings that directly target firm managers/owners exerted a statistically significant negative effect on firm level investment. The authors did not find statistical evidence of the impact of other forms of crime—such as guerrilla attacks or homicides–on firm investment decisions.

Collier and Duponchel (2013) studied the impact of the civil war in Sierra Leone from 1991 to 2002. In many ways, this is one of the first papers to investigate how civil conflict affects the economy by studying its impact on firms. Using data from the World Bank 2007 Employers Survey, they employed OLS, IV, binary and ordered probability models to exploit geographical variations in the intensity of conflict in four districts of the country. The study demonstrates that violence and conflict had a negative effect on both the firm's size and income. Additionally, an entrepreneur's willingness to pay for the training of the firm's staff is higher in conflict regions, reflecting a shortage of skilled labour in these areas.

Most of the literature exploring the relationship between violence and agribusiness focuses on identifying ways in which farmers cope with such violence. Coping strategies involve the decision of whether to withdraw from markets, which crop to plant, whether to implement a short growing cycle or a long one, which production technique to use and other possible ways of risk diversification (Brück 2003; Nillesen and Verwimp, 2010). For example, in the face of violence, farmers may reduce the accumulation of livestock in order to reduce their visibility to armed actors, thus decreasing the likelihood of being attacked. The possession of livestock becomes a very risky business due to the collapse of the local economy, a lack of access to services or the possibility of burglary and looting (Brück 2003; Nillesen and Verwimp 2010). Lastly, another potential coping strategy is to plant illicit crops, which also provide funding to the armed actors in a given region.

Arias *et al*. (2014) and Arias and Ibáñez (2012) try to disentangle the effects of direct (violent shocks) and indirect (presence of violence) impacts on the agricultural production of small producers in Colombia. Using a household survey of 4,800 households in four micro-regions, the researchers use OLS technique with an array of explanatory variables including the occurrence of violent shocks, the historical presence of armed groups, and the governance structures imposed on the population to investigate their impact on agricultural decisions. Their research reveals that those farmers most susceptible to violent shocks allocated 19.3% less land to long growing cycle crops, 13.7% more to short growing cycle crops and 14.6% more to grassland. Additionally, farmers living with a violent presence between four and six years allocated 7.7% and 7.3% more land to grass, respectively (Arias and Ibáñez, 2012).

Ibañez et al. (2013) investigated how violence generates incentives for Colombian coffee growers to allocate more land towards the production of illegal crops. Using a unique panel data set of coffee-growers constructed from the Census of Coffee Growers between 1993 and 1997, and using parametric and semi-parametric approaches, the authors found that coffee growers are more likely to reduce the allocation of land devoted to coffee when exposed to high levels of violence and the presence of illegal crops. An increase of 1% in the average number of hectares allocated to coca cultivation at the municipality level reduces the probability of coffee production by between 0.062 and 0.075 percentage points, and decreases the land allocated to coffee by between 0.03% and 0.083%, on average and *ceteris paribus*.

Despite the existence of a fairly extensive literature on the determinants of firm survival using duration analysis[11], no systematic empirical research exists addressing the question of agribusiness contract durations, nor the impact of violence, using this methodology. It is often detected in the literature on the determinants of firm survival literature that a firm's survival rate at the time of market entry depends on pre-entry experience, initial endowments, size, employee skills and capabilities, capital intensity and the firm-level heterogeneous innovation rate at the industry level, among other things (Audretsch and Mahmood 1995; Baldwin and Rafiquzzaman 1995; Klepper and Simons 2000; Agarwal and Gort 2002). This emphasizes the central importance of initial conditions in determining firm survival. Thus, the role of such initial conditions will also be the subject of our contract duration analysis.

[11] See, for example, Disney et al. (2003) and Agarwal and Gort (2002) for the UK and US manufacturing cases, respectively.

3.3 Duration model specifications

Duration models help explain the factors (or covariates) that accelerate or delay the length of time that elapses before an observed transition state – in this case the termination of an agribusiness contract. The time that elapses from the origin until the failure is known as the "spell at risk." It is defined by a continuous random variable $\mathrm{T} \geq 0$; the date on which the initial state begins $(T = 0)$ may not be the same for all observations, and t is the time taken for an observation to actually change states.

T follows the following cumulative distribution function $\mathrm{F}(\mathrm{t})$:

$$\mathrm{F}(\mathrm{t}) = \int_0^{\mathrm{t}} \mathrm{f}(\mathrm{s})\mathrm{ds} = \mathrm{Prob}\ (\mathrm{T} \leq \mathrm{t})$$

A density function $\mathrm{f}(\mathrm{t})$ is defined as:

$$\mathrm{f}(\mathrm{t}) = \frac{\partial \mathrm{F}}{\partial \mathrm{t}}$$

Therefore, the survivor function $\mathrm{S}(\mathrm{t})$ is:

$$\mathrm{S}(\mathrm{t}) = 1 - \mathrm{F}(\mathrm{t}) = \mathrm{Prob}(\mathrm{T} \geq \mathrm{t})$$

Consequently, the probability that an observation exits the original state in the short interval of length $\Delta\mathrm{t}$ after t is given by:

$$\mathrm{Prob}\ (\mathrm{t} \leq \mathrm{T} \leq \mathrm{t} + \Delta\mathrm{t} \mid \mathrm{T} \geq \mathrm{t})$$

Another fundamental concept is "censoring." Often, when collecting spells' data, some of the observations fail to transition from the original state. This does not mean that they will not ultimately terminate in the future. In order to address problems caused by censored observations, a hazard rate approach is often used. This involves modelling the hazard function $(\theta(\mathrm{t}))$ as the conditional probability that the observations will change state over a specified period conditioned on having survived to a particular point in time. The hazard rate can be thought of as the rate at which some observations change state after the duration of the determined time t, given that some others preserve their state at least until time t. Specifically, to obtain the average probability of leaving the state per unit of time period over a short interval after t, the former equation is divided by Δt and the limit is calculated as follows:

$$\theta(t) = \lim_{\Delta t \to 0} \frac{\text{Prob}\ (t \le T \le t + \Delta t | T \ge t)}{\Delta t} = \lim_{\Delta t \to 0} \frac{F(t+\Delta t) - F(t)}{\Delta t\, S(t)} = \frac{f(t)}{S(t)}$$

In practice, the kinds of duration models vary according to the specifications of the hazard rate function. The non-parametric models do not impose rigid structures on exit probability behaviour as a function of the state of duration t. In contrast the parametric models assume distribution functions that exhibit different (sometimes fairly rigid) types of duration dependence.

The Kaplan-Meier hazard estimator, a traditional non-parametric estimator, is the simplest form of a hazard estimator. Its main advantage is that it does not force the hazard function to take a particular shape. Further, it can be augmented within a discrete time framework to incorporate covariates.

In the Kaplan-Meier, the hazard function is defined by the following equation:

$$\widehat{\theta}(T_k) = \frac{h_k}{n_k}$$

where the spells are sorted by duration in ascending order up to K different survival times T_k, h_k is the number of spells completed at T_k, and n_k is the size of the risk set (failures) at time k.

The popular Cox Proportional Hazard (PH) is generally viewed a more complete model that explicitly incorporates covariates, and one that is not fully parameterized in terms of the baseline hazard. The hazard function is given by:

$$\theta(x,t) = \theta_0(t)\exp\left(\beta_1 x_1 + \cdots + \beta_k x_k\right)$$

or sometimes expressed taking logs as:

$$\ln(\theta_{it}) = \beta_i x_i + \ln(\theta_0(t))$$

A baseline hazard $\theta_0(t)$ is common to all units and does not vary across observations – it is left un-parameterized and is not explicitly estimated. Meanwhile, the relative effects of covariates are parameterized in the following form as: $\exp(\beta_1 x_1 + \cdots + \beta_k x_k)$. An implication of the latter is that the ratio of the hazards for any two observations, say the ones indexed by *i* and *j*, depends on the regressors but not on time t.

By using an estimation method known as the partial likelihood method, it is possible to obtain consistent estimates of the parameters without specifying the baseline hazard. The interpretation of the estimated coefficients is also a fairly straightforward exercise. Thus, the Cox PH is generally viewed as one of the econometrically most convenient procedures – hence its use in the current chapter.

The disadvantage of Cox is in its assumptions. For example, there is no reason to assume that the hazards are proportional. Furthermore, the model encounters estimation problems when there are many ties in the failure times (i.e., several failures in the same period). In contrast to the Cox Proportional Hazards model, there are a variety of parametric models that explicitly give structure (shape) to the hazard function. Regarding these parametric models, if the hazard function for a particular distribution slopes upwards (downwards), then the distribution has a positive (negative) duration dependence. Positive (negative) duration dependence implies that the likelihood of failure at time t, conditional on duration up until t, is increasing (decreasing) in t. The type of behaviour displayed by the hazard function depends upon the distribution selected (and the estimated shape parameter). First, the "Exponential" distribution displays constant duration dependence. The hazard function is thus expressed as:

$$\theta(t) = \frac{f(t)}{1 - f(t)} = \frac{f(t)}{F(t)} = \frac{\theta\exp(-\theta\, t)}{\exp(-\theta t)} = \theta$$

Thus, the hazard is completely described by one positive parameter (θ). Each unique value of θ determines a different exponential distribution implying the existence of a family of exponential distributions. Second, the "Weibull" distribution for which the hazard function is either monotonically increasing or decreasing. The hazard function is denoted as:

$$\frac{f(t)}{F(t)} = \theta(t) = \alpha\lambda^{\alpha} t^{\alpha-1}$$

where λ is a positive scale parameter and α is a shape parameter. In particular, if $\alpha > 1$ this implies a positive duration dependence ($\frac{\partial\theta(t)}{\partial t} > 0$), $\alpha = 0$ suggest no duration dependence ($\frac{\partial\theta(t)}{\partial t} = 0$), and if $\alpha < 0$ indicate a negative duration dependence ($\frac{\partial\theta(t)}{\partial t} < 0$). It is clear from the above that the use of the exponential distribution could be problematic if the duration data are characterized by either positive or negative duration dependence.

The "Log-Logistic" distribution is one choice for non-monotonic hazards. It can display increasing duration dependence initially, followed by decreasing duration dependence. It is also possible that the log-logistic distribution will display only negative duration dependence. The hazard function is defined as:

$$\theta(t) = \frac{\alpha\, \lambda^{\alpha} t^{\alpha-1}}{1 + [\lambda t]^{\alpha}}$$

Consequently, $\theta(t)$ increases and then decreases if $\alpha > 1$; or monotonically decreasing when $\alpha \leq 1$. The parameters of these parametric models are estimated by the standard method of maximum likelihood.

In duration modelling the problem of neglected heterogeneity or 'frailty' arises as a result of an incomplete specification. Thus, duration analysis can be extended to handle neglected heterogeneity. Unobserved differences between observations are introduced in the specification for the hazard function via a multiplicative scaling factor, v_i generally as follows:

$$\theta_i(x, t) = v_i \theta_i(x, t)$$

where v_i is an unobservable random variable independently and identically distributed as Inverse Gaussian (which is right-skewed with a heavy tail) or Gamma. These two distributions have been the most commonly used. After some extensive algebra, it can be shown that the heterogeneity introduces a tendency for a decreasing hazard rate. Estimation of this model is undertaken using maximum likelihood techniques and for the Gamma case it involves the estimation of an additional parameter σ^2. It should be noted that if $\sigma^2 = 0$ (i.e., the variance of v_i is zero), then there is no heterogeneity present in the data and the model collapses to $\theta^*(x, t) = \theta(t)$, or the standard Weibull model in this particular case.

The empirical literature has generally confirmed that if one (mistakenly) ignores unobserved heterogeneity the non-frailty model will over-estimate the degree of negative duration dependence in the (true) baseline hazard, and under-estimate the degree of positive duration dependence. In such circumstances, the proportionate effect (β_k) of a given regressor (x_k) on the hazard rate is no longer constant and independent of the survival time, and the estimate of a positive (negative) β_k derived from the (wrong) no-frailty model will underestimate (overestimate) the 'true' parameter estimate.

The failure time econometric modelling explained earlier is actually situated in a continuous framework. However, Jenkins (1995) suggested an approach to the estimation of discrete-time duration models using a binary logistic regression model (among other models). The motivation behind is that usually research data are collected retrospectively in a cross-sectional survey, where the dates are recorded to the nearest, month or year, or prospectively in waves of a panel study. This give rise to discretely-measured durations or also called interval-censored (i.e., we only know that an event occurred at some point during an interval of time).

The discrete duration modelling requires re-organization of the data set away from the individual as the unit of observation to the spell at risk of event occurrence. Thus, for each individual, there are as many data rows as there are time intervals at risk of the event occurring for each individual. In other words, we move from the data set discussed previously, with one row of data per individual unit, to another data set in which each individual unit contributes T_i rows, where T_i is the number of time periods *i* was at risk of the event occurring. Naturally, an unbalanced panel data set-up emerges with a maximum of N individuals observed over T discrete time periods. Consequently, a binary dependent variable Y is created. If subject i's survival time is censored, the binary dependent variable is equal to 0 for all of i's spell periods; if subject i's survival time is not censored, the binary dependent variable is equal to 0 for all but the last of i's spell periods (period 1..., T_i-1) and equal to 1 for the last period (period T_i).

The logistic regression model can be formulated as:

$$\text{Prob}(y_{i,t} = 1) = \frac{\exp[\beta x_{i,t} + \gamma \text{BaselineHazard}_{i,t}]}{1 + \exp[\beta x_{i,t} + \gamma \text{Baseline Hazard}_{i,t}]}$$

where the dependent variable represents the probability of individual i exiting in an interval around period t conditional on having survived to period t, where $x_{i,t}$ is a vector of covariates, which may or may not vary over time. The final step prior to estimation is to choose a functional form for the baseline hazard. They are, for example, the fully non-parametric $(\gamma' D_{i,t})$, where $D_{i,t}$ represents a set of duration-interval-specific dummy variables, one for each spell, a log time baseline ($\log(t_i)$), the time ($\gamma\ t_i$) baseline, the quadratic polynomial baseline ($\gamma_1 t_i + \gamma_2 t_i^2$) and the cubic polynomial baseline ($\gamma_1 t_i + \gamma_2 t_i^2 + \gamma_3 t_i^3$).

In summary, the discrete duration modelling allows the introduction of time-varying covariates, and the development of a very flexible non-parametric baseline hazard that is ultimately determined by the data rather than a specific distributional assumption. However, there are some disadvantages using these types of models. First, the sample size is inflated but the estimates obtained remain maximum likelihood and retain the asymptotic properties. Second, the data re-organization also leads to the potential for correlation across observations that likely introduce some degree of inefficiency in the estimates and a potential downward bias in the sampling variance. Hence, a solution to this problem is the introduction of an error term of the type introduced to model neglected heterogeneity.

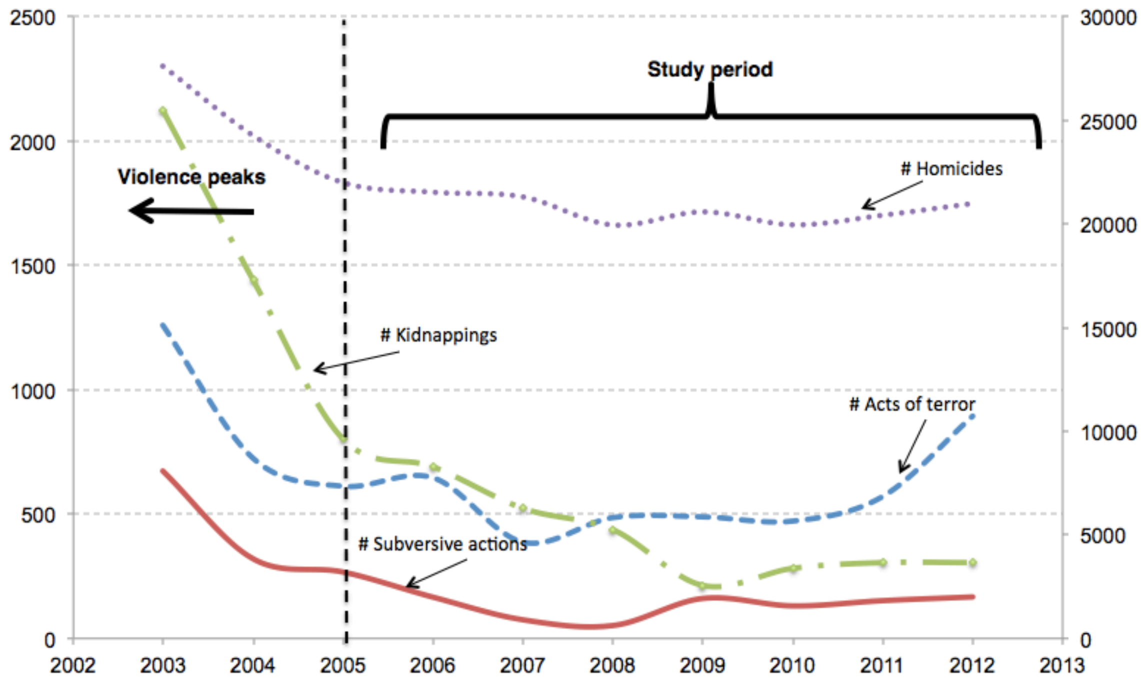
The empirical analysis of this chapter will include the explained variety of common non-parametric, semi-parametric, parametric duration models, and discrete time models. First, the Kaplan–Meier smoothed-baseline hazard estimator is plotted. Second, there is a discussion of the Cox PH model estimates. Third, the standard parametric models such as the Exponential (constant hazard), the Weibull, and the Log-Logistic, either incorporating or not incorporating a control for neglected heterogeneity, are employed. Fourth, moving beyond the continuous framework and, thus, situating the analysis within a discrete-time context a logistic form is used for the hazard modelling.

3.4 Failure time econometric modelling for the PAAP

3.4.1 The conflict in Colombia

During the period covering this study (2005-2013), the armed conflict in Colombia was still active but declining from its 2002 levels (Figure 3.4.1 Selected incidents of violence in Colombia). In 2003 a disarmament process began with a paramilitary group named the United Self-Defence Forces of Colombia (AUC, its Spanish acronym) that successfully concluded in 2006. Nonetheless, some elements remained active due to lower level organization of some members, who started smaller drug-dealing and criminal bands, known as the Bacrim.

Figure 3.4.1 Selected incidents of violence in Colombia



Kidnappings, acts of terror and subversive actions (Y-right axis); and homicides (Y-left axis).
Source: based on data from Centre of Development Economics Studies (*Centro de Estudios sobre Desarrollo Económico, CEDE* in Spanish) from Universidad de los Andes in Bogotá, Colombia.

The Revolutionary Armed Forces of Colombia (FARC), the oldest and largest active guerrilla group in Colombia engaged in discussions with the national government in November 2012 in an attempt to end the conflict. Peace negotiations concluded successfully in December 2016, though the second most important guerrilla group known as the National Liberation Army (ELN) remained active.

3.4.2 The PAAP

The agribusiness contracts data are obtained from the administrative records of the Rural Productive Alliances Project (*Proyecto de Apoyo a Alianzas Productivas* or PAAP, to give it its Spanish acronym). This is a major Colombian government rural development project partly financed by the World Bank[12] and implemented by the Colombian Ministry of Agriculture and Rural Development (MADR, its Spanish acronym). Between 2002 and 2015 around 775 Productive Partnerships were sponsored by PAAP, covering 31

[12] The World Bank co-financed about 70% of all PAAP project operations.

departments [13]in the country. These partnerships have benefited over 49,000 families and 430 commercial partners, principally buyers in the processing sector. Over 90% of these partnerships are still operating today. The total value of agribusinesses sponsored is approximately US $434 million, of which 23% corresponds to investments made by the MADR.[14]

The PAAP enables Producer Organizations (PO) to overcome problems faced by individual small-scale producers in accessing markets (buyers) in a sustainable way by means of establishing formal Agribusiness Contracts (AC) with a commercial buyer (CB). POs receive full support to sustain this new formal business opportunity with technical assistance and capacity building (Figure 3.4.2 PA business model). These agribusinesses contracts are called Productive Alliances (PAs).

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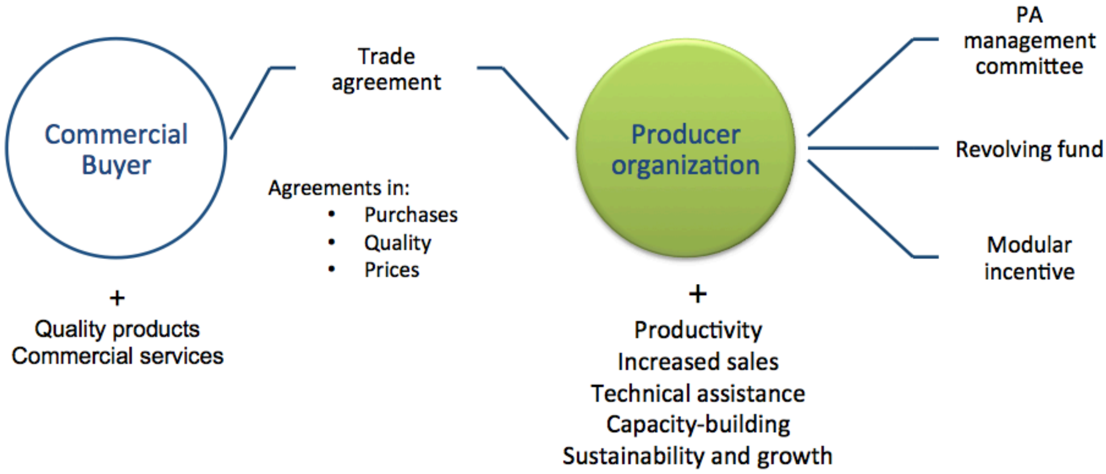
[13] Colombia is formed by 32 departments and Bogotá DC, which is a Capital District. Each department has a Governor and a Department Assembly elected by popular vote for a four-year period. Departments as an administrative division are formed by a grouping of municipalities. Thus, Colombia has 1,122 municipalities in total headed by a Mayor and administered by a Municipal Council elected also for a four-year period.

[14] The period of our study only covers PAAP operations from 2005 to 2012.

Figure 3.4.2 PA business model



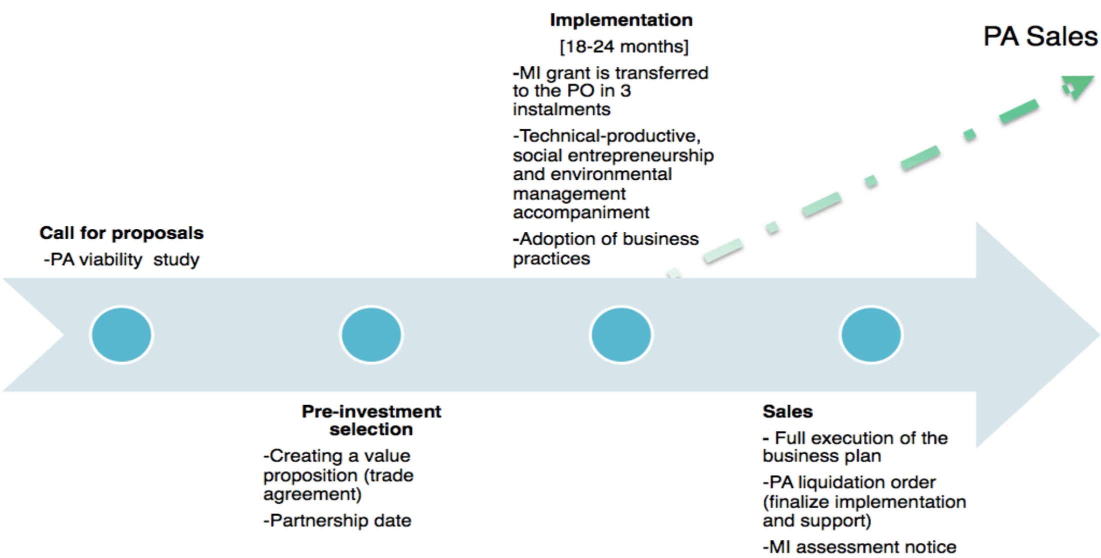
Source: authors

PAAP is a project exclusively for smallholder farmers as only poor farmers are permitted to apply for its funding and benefits. Major pre-requisites include: i) at least one family member is literate; ii) the subsidy beneficiary is an adult and head of household; iii) the family net income must not exceed twice the value of the minimum wage (USD 2*315.39= 630.79); iv) at least 75% of the household income is derived from agriculture; v) family asset value must not exceed 200 times the minimum wage (USD 63,780.5) and vi); the parcel size must not exceed two Family Agricultural Units (Unidades Agrícolas Familiares, or UAF, to give it its Spanish acronym[15]).

The project cycle begins with a call for proposals (Figure 3.4.3 PA Life cycle below) where POs and CBs prepare and submit a basic proposal for a prospective business plan. The business plan must assist PO smallholders in responding to market demand. Eligible proposals that best meet the requirements and indicate a higher likelihood of long-term business relationships are subjected to a feasibility study. Multi-stakeholders review both the prospective plan and the feasibility study. Only those with satisfactory technical, financial and market feasibility obtain funding and full support.

[15] This size usually reflects subsistence households whose production is sufficient to meet only the basic needs of the family. UAFs (*Unidades Agrícolas Familiares, in Spanish*) vary depending on municipality.

Figure 3.4.3 PA Life cycle



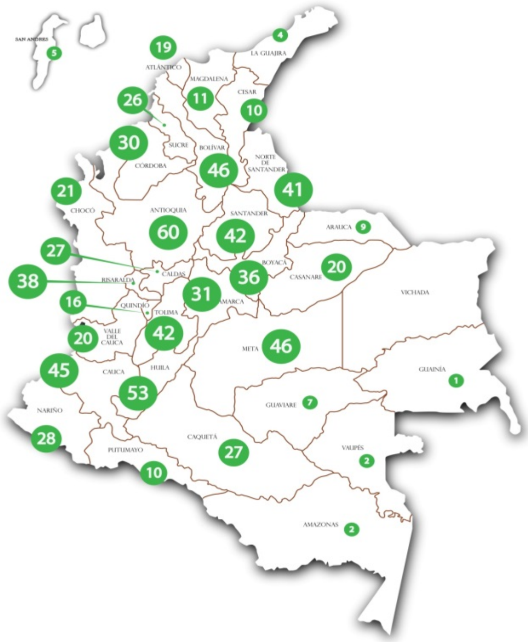
Source: authors.

A subsidy known as a Modular Incentive (MI) is then granted in three instalments to POs. Its value cannot exceed 35% of the total projected investment stated in the business plan nor exceed COP $6,000,000 (USD 2,988) per beneficiary. MI resources may finance a wide range of investments to improve a producer's productive efficiency. For example, MIs can be used to finance technical assistance in production or to co-finance infrastructure or equipment investments (such as irrigation equipment for individuals or collective storage and packing facilities).[16] In addition, part of the subsidy is used to strengthen PO capacity building (both, technical and organizational), allowing producers to meet the market requirements defined by the buyer.

In the implementation stage, an agribusiness contract is formally signed and a Rural Productive Alliance (PA) management committee is formed. An AC usually specifies product characteristics (size and varieties), quantity (produced/bought), production modalities (deliveries, how, by whom, when, grading and packing requirements), payment modalities and price determination criteria. It stipulates a buyer's contribution to the PO, such as technical assistance, specific inputs and arrangements for input reimbursement (for example) at the time of sale.

[16] In fact, some PAs use this grant to buy seeds, inputs or as start-up capital.

Figure 3.4.4 Number of AC by department



Source: PAAP M&E Unit, 2014.

During a period covering 18 to 24 months, POs receive technical assistance in production and business skills and environmental management training (sustainable water and land management techniques) by a Regional Accompaniment Organization (*Organizaciones Gestoras Acompañantes* – OGA, in Spanish), which are assigned depending on the location of the PO.

In order to promote AC survival, subsidy recipients should ideally repay a share of it. Repayments are deposited in a Revolving Fund (RF) that will provide credit to farmers once PAAP interventions are ended.[17] Finally, during the sales stage, POs are left alone and should be able to sustain their new business opportunities, ideally maintaining or increasing sales over time. POs are also empowered to develop direct formal links with other CBs offering better deals.

A data set comprising 434 agribusiness contracts covering the period from 2005 to 2012, including the start-up characteristics of the POs such as municipality location, tenure, PO size, PO labour, was constructed based on confidential files of the PAAP. Monitoring and

[17] This is a requirement but is not enforced by the project.

Evaluation (M&E) Unit[18] exclusively for the empirical analysis conducted in this research.

3.4.3 The definition of the contract spell

A major challenge to survival analysis is defining the origin and failure points. In the PAAP context, the point of origin is the date when PAAP managers approve the agribusiness contract before the PAAP implementation stage starts. This point ensures the availability a larger sample size. More than half (57.4%) of the PAs have not finished the implementation stage (See Section 3.5).

The selection of the failure point was more complicated. A failure point may be understood as a situation in which the PO defaults the agribusiness contract established with the CB. This happens when the commercial ties between parties are over, therefore causing PO sales to decline. Each semester, which in Spanish is equivalent to a period of six months, PAAP inspectors visit POs in the field to survey and assess the implementation of their operational plan, as well as to assess their productive, organizational and environmental management performance. Field surveys ask if the PO currently has active commercial ties with one or more CBs. If so, there is not an agribusiness contract, but somehow a trade agreement is enforced, the answer is 'yes', otherwise the answer is 'no'. This question is taken to define a failure point. The major limitation is that information on responses to this question is only available after January 2010. Therefore, for a group of agribusiness contracts, failure time could have occurred before then. There is no way to identify exactly when before this time due to a lack of information. This is one reason why we use time-invariant covariates in the first phase of our empirical analysis.

The 'yes' responses include several default positions. Often, their combination contributes to the termination of an agribusiness contract. For example: i) PO beneficiaries revert to traditional ways of production and markets since they find that more profitable, they simply cannot sustain the original deal with the secured CB; ii) the selected PO lacks social cohesion and displays an inability to manage conflicts, ultimately

[18] The M&E unit tracks POs even after the termination of the implementation stage.

leading the agribusiness contract to failure; iii) the PO is inefficient in providing services to its members; and/or iv) the PO lacks adequate management, organizational, commercial or professional skills, such as the management of a revolving fund. Basically, the overall strength of the PO is a prerequisite for a successful agribusiness contract (Collion and Friedman, 2012).

Finally, there are also cases in which the buyer goes out of business. Commercial failure may not be always a fault of the PO. Inherent reasons about this situation are unknown given the nature of the data.

3.4.4 The key explanatory variables

Since this study's interest is on the effect of violence on the duration of agribusiness contracts of smallholder growers, the selection of the conflict variables is guided empirically by their potential impact on the municipal business climate environment. The information on violent incidents is obtained from a confidential dataset constructed by the Centre of Development Economics Studies (*Centro de Estudios sobre Desarrollo Económico*, CEDE in Spanish) from Universidad de los Andes in Bogotá, Colombia. The dataset contains information on various manifestations of violence and is event-based and available on an annual basis. The type of violence, date and location are recorded for each event.

Four conflict-intensity measures, which are set to their initial values before the start of the contract, are constructed using information available at the municipal level where the POs are located:

i) **Acts of terror:** total number of acts of terror including explosions, incendiaries or other type of terrorist acts;

ii) **Subversive actions:** total number of subversive actions undertaken by the illegal armed groups including attacks on private property, attacks on entities or facilities, attacks on military headquarters, political attacks, roadblocks, ambushes, harassments, raids and car hijackings;

iii) **Kidnappings:** total number of kidnappings of civilians, politically active individuals, or members of the army per 100,000 inhabitants; and

iv) **Homicides:** the total number of homicides per 100,000 inhabitants.

The choice of covariates to include in the analysis of agribusiness contract duration were selected on the basis of prior expectations, which also are primarily set to initial values before the start of the contract. Three broad groups of variables are assumed to have a potential impact on agribusiness contract durations:

i) **PO-characteristics:** The total number of PO beneficiaries at the time when PAAP managers approved the agribusiness contracts is used in order to emphasize the importance of the PO size. It is likely that bigger POs uphold the agreement with the commercial buyer for longer based on scale economies in production and superior bargaining power.

PO tenure is also an important explanatory factor related to the survival of the agribusiness contract. A dummy variable is constructed that distinguishes POs remaining in the implementation stage of PAAP from those that have completed it. In particular, the POs that have completed this stage have implicitly gained technical assistance in production, management and marketing from the technical service provider of PAAP, and also used the MI instalments (e.g., to cover investments in infrastructure or equipment), which would allow them to honour more easily the agribusiness contract with the commercial buyer.

The average share of PO beneficiaries that work fulltime on the farm at the start of the agribusiness contract is also constructed. The inclusion of this variable proxies the level of engagement and commitment of the beneficiaries to the contract between the PO and the CB. Given this, it is anticipated that the contract is likely to endure longer given the extent of beneficiary commitment to the contract.

ii) Product-specific: The supported product type may have significant effects on agribusiness development and the duration of the contract. Typically, producers of long growing cycle crops (of more than 12 months' maturity) require additional resources to support their livelihoods. In addition, long growing cycle crops require huge amounts of pre-harvest investments, implying a need for backup resources. Alternative revenues outside of the farm are limited and not very stable. Therefore, in order to achieve business success, producers must have access to additional land often devoted to cultivating short growing cycle crops (three to 12 months of maturity) for either their own consumption or sales. A dummy variable for product cycle is constructed in order to establish its impact on agribusiness contracts durations.

Furthermore, PAAP not only supports agricultural crops[19] but also supports some non-crop activities that take place in the countryside. The following dummy variables are included to capture a product's inherent non-crop features: livestock, milk, fish and other non-crop products (beekeeping, silk thread and unrefined sugar cane).

iii) Market access: The presence of wholesale food markets near the PO denote lower transportation and transaction costs, less post-harvest losses for producers and a higher number of clients, along with more possibilities to establish better business deals outside agribusiness contracts with current buyers. Conversely, remoteness relative to markets increases sales uncertainty, unless there already exists an enforced agribusiness contract.

3.4.5 The determinants of agribusiness contract failure

There is no systematic empirical research addressing the issue of agribusiness contract duration determinants, nor its relationship with violence. The research question is tackled empirically by using duration models.

As an example, Equation (3.1) illustrates the form of the Cox Proportional Hazards model to be estimated:

$$\theta(x_{ij}, t) = \theta_0(t) \exp(\beta_1 \ \text{Violence}_{i,t=0} + \beta_2 \text{PO}_{\text{Specifics}_{j,t=0}} + \beta_3 \text{Prod}_{\text{Cycle}_{j,t=0}} + \beta_4 \text{Prod}_{\text{Type}_{j,t=0}} + \beta_5 \text{Market Access}_{i,t=0}) \tag{3.1}$$

where *i* is the municipality, *j* the agribusiness contract and *t* the semester, which is

[19] PAAP support around 70 crops. The ten most popular are cocoa, specialty coffee, blackberry, plantain, rubber, mango, avocado, oil palm, fique, and pineapple.

equivalent (in Spanish) to a period of six months. Therefore, $\boldsymbol{\theta}(\mathbf{x}_{ij}, \mathbf{t})$ is the hazard rate of agribusiness failure, $\boldsymbol{\theta}_0(\mathbf{t})$ is the baseline hazard common to all units – this is ultimately swept out of the Cox partial likelihood estimation procedure and not explicitly estimated; **Violence** represents alternative measures of violence in the municipalities where producers are located at the start of the agribusiness contract; **PO_Specifics** are the producer organization's characteristics also at the start of the contract (tenure, PO size, PO labour); **Product_Cycle** is a dummy variable that distinguishes between a crop type produced in either a long (more than six months) or a short growing cycle and sold by the PO; **Product_Type** is a dummy categorizing other non-crop products produced and sold by the PO under the agribusiness contract – specifically livestock, fish, milk, and other non-crop products like beekeeping, silk thread and unrefined sugar cane. Finally; **Market Access** is the Euclidean (straight-line) distance between the municipalities where producers are located and the closest wholesale food market.

In Equation (3.1) all of the explanatory variables are calibrated at the time of the start of the agribusiness contract and are thus time invariant. Hence, this particular equation is useful to explore the effects of the initial conditions of violence on the future of agribusiness contract durations.

However, the use of time-invariant covariates is restrictive, particularly when some key measures relating to violence are time-varying. The introduction of time-varying covariates is difficult in parametric models but considerably easier to do within a discrete spell at risk framework. Once the data are transformed into spells at risk, as explained above in the failure time econometric modelling section, the estimation of the hazard model is done using a conventional logit model. For example, Equation (3.2) illustrates the discrete time hazard model to be estimated:

$$\mathrm{Prob}(y_{i,t} = 1) = \frac{\exp[\beta' x_{i,t} + \gamma \mathrm{BaselineHazard}_{i,t}]}{1 + \exp[\beta' x_{i,t} + \gamma \mathrm{Baseline\ Hazard}_{i,t}]} \tag{3.2}$$

where

$$\beta' x_{i,t} = \beta_0 + \beta_1 \text{Violence}_{i,t} + \beta_2 \text{PO}_{\text{Specifics}_{j,t=0}} + \beta_3 \text{Prod}_{\text{Cycle}_{j,t=0}} + \beta_4 \text{Prod}_{\text{Type}_{j,t=0}} + \beta_5 \text{Market Access}_{i,t=0_{i,t=0}}$$

In the current case the discrete time models are estimated by maximum likelihood techniques using a logit cumulative distribution function operator. The subscript *i* is the municipality, *j* is the agribusiness contract and *t* is the semester. A binary dependent variable Y is created. If the agribusiness contract *j*'s survival time is censored, Y is equal to 0 for all of *j*'s spell semesters; if the agribusiness contract *j*'s survival time is not censored, Y equals 0 for all but the last of *j*'s spell semester (semester 1,... *Tj*–1), and equal to 1 for the last semester (semester *Tj*) and no further data are recorded for a contract after it expires and exits the state.

Regarding the variables now listed above, once again **Violence** includes alternative measures of violence in the municipalities where producers are located. However, now we allow them to vary yearly. The duration of agribusiness contracts of smallholder growers for the PAAP are expressed in semesters, but the alternative measures for violence vary yearly (there is no availability of six-monthly data). Therefore, we have the same data point for the two semesters for each year. The **PO_Specifics**, **Product_Cycle**, **Product_Type**, and the **Market Access** variables are the same as in the Cox Proportional Hazards model.

In addition, note that in Equation (3.2), the whole dataset is re-organised so that for each agribusiness contract there are as many data rows as there are time intervals at risk of the event of failure occurring for each one. The data now resemble an unbalanced panel. Consequently, this estimation is based on transforming the data set discussed earlier from one row of data per agribusiness contract, to another data set in which each agribusiness contract contributes *Tj* rows, where *Tj* is the number of time periods (semesters) that *j* was at risk of the event of contract failure occurring.

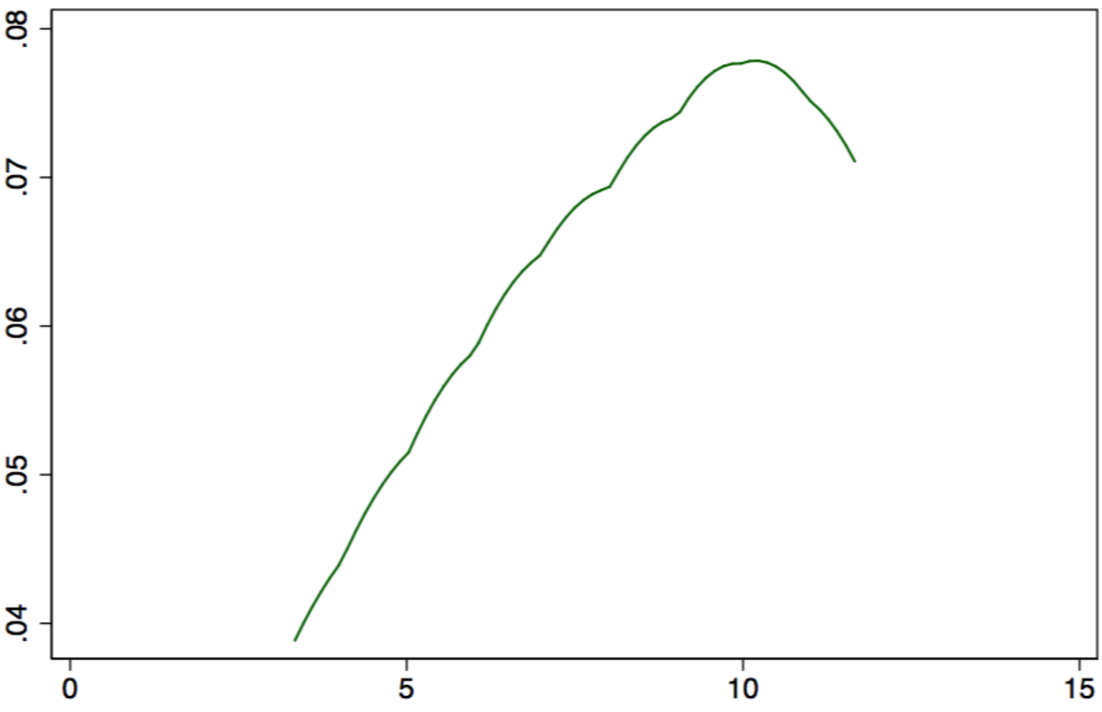
The final step prior to estimation of Equation (3.2) is to choose a functional form for the **Baseline Hazard** function. Several alternative specifications for each failure time period are considered such as the fully non-parametric ($\gamma' D_{i,t}$), where $D_{i,t}$ represents a set of duration-interval-specific dummy variables, one for each spell, a log time baseline

($\log(t_i)$), the time ($\gamma \; t_i$) baseline, the quadratic polynomial baseline ($\gamma_1 t_i + \gamma_2 t_i^2$) and the cubic polynomial baseline ($\gamma_1 t_i + \gamma_2 t_i^2 + \gamma_3 t_i^3$).

3.5 Data and Selected Summary Statistics

There is no reason to assume that the baseline hazard follows a particular form. Thus, the Kaplan–Meier smoothed-baseline hazard estimator is plotted in (Figure 3.5.1). The hazards rate of agribusiness contract failure increases until the tenth semester, when it begins to decline. Since the tail turning point is fairly late, this suggests that a Weibull distribution that exhibits a positive duration dependence could fit the data reasonable well. However, this has to be investigated further.

Figure 3.5.1 Smoothed hazard estimate for agribusiness contract durations under PAAP context



X-axis semesters.
Source: authors.

Two different sets of estimates are presented in the results section. The first corresponds to the set of variables at the time of the start of the agribusiness contract and the second estimation allows these variables of interest to vary over time. Table 3.5.1 and Table 3.5.2 provide respectively a description of the variables used in both analyses and their summary statistics. See Table 8.1.1 Variable models definitions found in the Appendix chapter 3 for a full set of variable model definitions.

Data on 434 agribusiness contract durations signed in 27 of the 32 departments of Colombia for the period 2005 to 2013 are available for empirical analysis. The summary statistics for these variables are reported in Table 3.5.1 and range in length from one to 17 semesters. While 320 durations were ongoing at the time of this analysis (73.7% censored), 114 experienced the failure event (26.3% non-censored) and exited the state of interest.

The municipalities where the POs are located have suffered from the presence of violence along various dimensions and intensities over the period covered by this study. For example, within the dataset, at the start of each agribusiness contract municipalities experienced an average number of 1.7 acts of terror, including explosive, incendiary or other type of terrorist acts, with the maximum at 26. The average number of subversive actions, mainly caused by the guerrillas, include kidnapping and killing rates per 100,000 inhabitants, are 0.36, 1.20 and 52.95, respectively.

On average, POs have 60 members and around 56.91% of these work in agriculture as their main income producing activity. More than half (57%) of the agribusinesses remain in the implementation stage of PAAP. The average distance to the nearest wholesale food markets in the departments where these POs are located is 65.53 kilometres.

Table 3.5.1 Summary stats set at the start of agribusinesses contracts

VARIABLES	Mean	Sd	Min	Max
Duration (in semesters)	5.42	3.22	1	17
Failure event	0.26	0.44	0	1
Average failure time	5.4	3.2	1	17
Acts of terror, at start	1.69	3.77	0	26
Subversive actions, at start	0.36	1.07	0	8
Kidnappings per 100,000 population at contract start	1.20	3.67	0	30.4
Homicide rate per 100,000 population at contract start	52.95	49.83	0	413
Number of PO beneficiaries selected, at contract start	60.06	32.1	14	203
Avg. share of beneficiaries that work on the farm/UPA at start (0-100)	56.91	27.7	0	100
PA still at implementation stage	0.57	0.50	0	1
Distance to the nearest wholesales food markets in the department	65.53	57.5	0	379.4
Crops	0.78	0.42	0	1
Short growing cycle crop	0.04	0.19	0	1
Livestock	0.03	0.16	0	1
Fish	0.03	0.18	0	1
Milk	0.13	0.33	0	1
Other no crop product	0.03	0.17	0	1

N: 434 agribusiness contracts
Source: authors own calculations.

Approximately 80% of the POs produce and commercialize crop products. About 4% of the sample trade in short growing cycle crops, 13.0% produce milk, 3% livestock, 3% fish and the other 3% produce non-crop products such as beekeeping, silk thread and unrefined sugar cane.[20]

As mentioned previously in Table 3.5.2, the data are also re-organised for further analysis so that for each agribusiness contract, there are as many data rows as there are time intervals at risk of the event of failure occurring within each contract. While the conflict variables differ yearly (half-year data are not available), the other covariates remain set at the start of the agribusiness contract due to the absence of updated information on these particular variables. However, since the key variables that are evolving over time are the conflict measures, we do not believe this represents a significant constraint in the current analysis.

[20] In view of some of these dummies have very small cell sizes, the interpretation of their estimates need to be done with care.

In addition, as mentioned earlier a limitation on agribusiness contract information is that failure is only detected after January 2010. Hence, the discrete time survival models employ a subsample of agribusiness contracts starting in 2007 onwards. This time is enough for the POs to complete the implementation stage of PAAP, and also establish commercial relationships with the buyers. After three years, it could be argued that the incidence of violence may cause contract failure.

Table 3.5.2 Summary stats for spell at risk data

Variable	Mean	Sd	Min	Max
Failure (dummy)	0.05	0.22	0	1
Acts of terror	1.39	3.39	0	34
Subversive actions	0.33	1.03	0	8
Kidnappings per 100,000 inhab, at start	1.21	3.83	0	59.4
Killings per 100,000 inhab, at start	52.31	47.21	0	459.3
PO beneficiaries selected, at start (#)	62.22	31.04	14	203
Avg. share of beneficiaries that work on the farm, at start (0-100)	56.94	27.39	0	100
PA still under implementation stage	0.40	0.49	0	1
Avg. distance to nearest wholesales food markets in the department	64.48	58.03	0	379.42
Short growing cycle crop	0.04	0.20	0	1
Livestock	0.02	0.15	0	1
Fish	0.03	0.17	0	1
Milk	0.13	0.33	0	1
Other no crop product	0.04	0.19	0	1
Ln(t)	1.12	0.73	0	2.64
num_semester = t	3.94	2.75	1	14
t2	23.04	31.59	1	196
t3	173.55	352.84	1	274

N: 2195 observations.
Source: authors.

The new dataset has 2195 observations. The probability of failure is 5%. The average number of acts of terror, subversive actions (mainly attributable to the guerrillas), kidnappings and killings (both per 100,000 inhabitants) are 1.39, 0.33, 1.21 and 52.31 respectively. Regarding the other covariates, a degree of caution should be employed in the interpretation of the summary statistics in view of the reorganization of the data set, creating as many data rows as there are time intervals at risk of the event of failure occurring for each agribusiness contract.

3.6 Empirical Results

3.6.1 The Cox PH model Estimates

Attention now turns to a discussion of the Cox PH model estimates reported in Table 3.6.1. This realization for all the covariates are fixed at the time of the start of the agribusiness contract. Hence, this estimation explains the agribusiness contracts with respect to initial conditions prevailing in terms of both the conflict as well as the other covariates. The difference between Columns 1 and 2 in Table 3.6.1 is that the latter column includes the departmental fixed effects (dummies).

The estimates suggest that agribusiness contract durations are negatively affected by the acts of terror at the point when the contract was initially signed. Overall, their effect on the hazard rate is positive, meaning that one additional act of terror at the contract start increases the hazard rate of agribusiness contract failure by 9.4% (see Column 2, Table 3.6.1), on average and *ceteris paribus*.

The threat of terror degrades the overall business environment. It may well be the case that the buyer business delegates, such as transporters, decide not to travel to municipalities where acts of terror occur, ultimately making it quite complicated for PO farmers to uphold or maintain an agribusiness contract with the nominated buyer.

Table 3.6.1 Cox PH model estimates for commercial agreement failure

VARIABLES	(1)	(2)
Acts of terror, at start	0.069**	0.094**
	(0.032)	(0.048)
Subversive actions, at start	-0.150	-0.172
	(0.119)	(0.124)
Kidnappings per 100,000 inhab, at start	0.026	0.000
	(0.030)	(0.033)
Homicide rate per 100,000 inhab, at start	-0.003	-0.005
	(0.003)	(0.003)
PO beneficiaries selected, at start (#)	-0.011***	-0.005
	(0.004)	(0.004)
Avg. share of beneficiaries that work on the farm, at start (0-100)	-0.007**	-0.012***
	(0.003)	(0.004)
PA still under implementation stage	0.852***	0.900***
	(0.223)	(0.231)
Avg. distance to nearest wholesales food markets in the department	0.001	0.007*
	(0.001)	(0.004)
Short growing cycle crop	0.118	0.031
	(0.353)	(0.426)
Livestock	1.059***	1.169***
	(0.335)	(0.418)
Fish	0.389	1.083**
	(0.436)	(0.448)
Milk	-0.633	-0.849**
	(0.398)	(0.428)
Other no crop product	-0.412	0.024
	(0.572)	(0.475)
Dummy Department (26)	No	Yes
Observations	434	434
Test of joint significance of department fixed effects (Prob>chi2)	n/a	0.00
Test of joint significance of type of product (Prob>chi2)	0.015	0.001
Model chi2	43.6	130.2
Df	13	39
Pseudo-Log(L)	-581.9	-554.7
AIC	1190	1187
N. of fails (without a business partner)	114	114

Cox regression -- Breslow method for ties.
Robust standard errors in parentheses *** p<0,01, ** p<0,05, *p<0,1
Source: authors.

The PO characteristics matter for the duration of the PAs. For example, due to scale-economies in the use of inputs and possibly stronger bargaining power, it is likely that bigger POs (with a higher number of beneficiaries at inception) may have the capacity to produce and sustain the volume and product quality requested by the buyer. Thus, adding one beneficiary to the PO at the start of the contract reduces the hazard rate of failure by 1.1%, on average and *ceteris paribus* (Column 1, Table 3.6.1). However, this coefficient is not statistically significant in column 2, when the departmental fixed effects are included.

In addition, agribusiness contracts endure when POs have a higher number of household members that work directly in agriculture. A one percentage point increase in the average share of beneficiaries that work on the farm at contract start decreases the hazard rate of contract failure by 1.2%, on average and *ceteris paribus* (see Column 2, Table 3.6.1).

The POs still involved in the implementation stage of PAAP are 146% more likely to fail than more mature ones that have received the full package of benefits of PAAP (technical assistance in production, business skills and environmental management training) on average and *ceteris paribus* (Column 2, Table 3.6.1).

Access to markets also matters**.** Each additional kilometre between POs and the nearest wholesale food markets increases the hazard rate of agribusiness contract failure with the buyer by 0.7%, on average and *ceteris paribus* (Column 2, Table 3.6.1).

Finally, product growth cycles (short or long growing cycle crops) do not appear to have an effect on agribusiness contract durations. However, product type does matter with respect to crops (the base category). Livestock and fish have 221.9% and 195.4% higher hazard rates of agribusiness contract failure than crops, respectively. In addition, milk displays a 57.2% smaller hazard rate of failure than crops, on average and *ceteris paribus*. However, some caution is required in all these cases as they represent a very small number of the contracts in the sample.

Departmental differences in soil, altitude, climate (temperature and rainfalls), availability and quality of resources (such as infrastructure) determine agricultural products supply and demand and therefore agribusiness patterns. These are captured with the inclusion of the departmental fixed effects (dummies), which are found to be statistically significant overall (p-value 0.001).

Finally, further diagnostic analysis is undertaken to determine the robustness of the Cox PH results. First, on the one hand, perhaps the violence incidents at the start year of the agribusiness contract are atypical, while on the other, producers' expectations based on past violence experiences may affect intrinsic decisions relating to a producer's agribusiness contract duration. Thus, the conflict variables are recomputed as the average of the previous three years before the start period of the agribusiness contract. These estimates are reported in Table 8.1.2 Cox PH model estimates for commercial agreement failure (Violent incidents average 3 years before start) found in Appendix chapter 3. Once more, in Column (1), the acts of terror at the start of the spell appear to be one of the main channels through which agribusiness contract durations are reduced. However, in Column (2), the departmental dummies absorbed most of the effect of violence variables since conflicts have a strong geographical dimension.

Second, suspicion about the presence of spatial correlations often arise when using municipal-level data. Intuitively, no spatial correlation is expected in this dataset: spell origins occur in different times and the distance between municipalities is quite large due to the fact that PAAP is distributed around the whole country. Using a formal test, we find no evidence of spatial correlations.[21]

3.6.2 Parametric models

The standard parametric models such as the Exponential (constant hazard), the **Weibull**, and the **Log-logistic**, either incorporating or not incorporating a control for neglected heterogeneity,[22] are now employed to test the robustness of Cox PH model results.

[21] A spatial error model was estimated as part of an exploratory exercise. The durations again providing the dependent variable with the same covariates in Equation (3.1) included. This type of model is appropriate when there is an interest in correcting for spatial autocorrelation. First, we constructed a spatial weight matrix (W) based on POs municipalities' distances (longitude and latitude). Second, the spatial dependence was added to a regression in a spatial error. The regression model is $y = \beta x + e$, the errors are spatially correlated $e = \lambda W e + u$ or $(I - \lambda W)e = u$, thus, the spatial error regression reduced form equation is defined by $(I - \lambda W)y = (I - \lambda W)\beta x + e$. The multipliers in front of the dependent and independent variables are the variation that cannot be explained by the neighbours' values. Moran's I test statistic is used to test if the data have spatial dependence. It is similar but not equivalent to a correlation coefficient. It varies from -1 (perfectly dispersed) to +1 (perfectly clustered). The Moran's I test statistics applied to this model reveals no spatial dependencies (p-value 0.248).

[22] This distributional assumption is often made in this literature.

Table 3.6.2 Parametric models for commercial agreement failure

VARIABLES	Exponential	Weibull	Weibull with I.G
Acts of terror, at start.	0.080*	0.104*	0.104*
	(0.043)	(0.053)	(0.053)
Subversive actions, at start	-0.232*	-0.195	-0.196
	(0.119)	(0.130)	(0.130)
Kidnappings per 100,000 population at contract start	-0.009	-0.014	-0.014
	(0.031)	(0.037)	(0.037)
Homicide rate per 100,000 populations at contract start	-0.003	-0.005	-0.005
	(0.003)	(0.003)	(0.003)
PO beneficiaries selected, at start (#)	-0.003	-0.004	-0.004
	(0.003)	(0.004)	(0.004)
Avg. share of beneficiaries that work on the farm/UPA at start (0-100)	-0.010**	-0.011**	-0.011**
	(0.004)	(0.005)	(0.005)
PA still under implementation stage	0.248	1.009***	1.009***
	(0.185)	(0.228)	(0.228)
Avg. distance to nearest wholesales food markets in the department	0.005	0.007*	0.007*
	(0.003)	(0.004)	(0.004)
Short growing cycle crop	0.027	0.041	0.041
	(0.383)	(0.439)	(0.439)
Livestock	0.851**	1.096**	1.096**
	(0.360)	(0.445)	(0.445)
Fish	1.011***	1.400**	1.400**
	(0.383)	(0.557)	(0.557)
Milk	-0.855**	-0.849*	-0.849*
	(0.400)	(0.437)	(0.437)
Other no crop product	-0.039	-0.047	-0.047
	(0.440)	(0.472)	(0.472)
Constant	-2.048***	-3.823***	-3.823***
	(0.541)	-0.669	(0.669)
Ln(alpha)		0.680***	0.680***
		(0.074)	(0.074)
Ln(theta)			-12.732***
			(1.234)
Departments dummies (26)	Yes	Yes	Yes
Observations	434	434	434
Overall test (Prob>chi2) of product dummies	0.002	0.003	0.003
Overall test (Prob>chi2) of departmental dummies	0.000	0.001	0.001
Model chi-square	129.7	123.7	123.7
Df	39	39	39
Pseudo-Log(L)	-270.1	-243.3	-243.3
AIC	620.1	568.6	570.6
N. of fails (without a business partner)	114	114	114

Robust standard errors in parentheses *** p<0,01, ** p<0,05, * p<0,1.
Source: author

The estimation confirms that the acts of terror at the start of the contract shortens the duration of agribusiness contracts under PAAP thus increasing the hazard rate of failure. According to the Akaike Information Criterion (AIC)[23] the standard Weibull model with positive duration dependence (alpha=1.974) fits the data better, which is consistent with the Kaplan–Meier smoothed-baseline hazard estimator with positive slope plotted in Figure 3.5.1 earlier above

Thus, one additional act of terror at the contract start increases the hazard rate of agribusiness contract failure by 10.4% (Column 2, Table 3.6.2), on average and *ceteris*

[23] The Akaike information criterion (AIC) is a measure of the relative quality of statistical models for a given set of data. Given a collection of models for the data, AIC estimates the quality of each model, relative to each of the other models.

paribus. It is worth noting that the direction and the significance of the control variables remain similar to those reported for the Cox PH model.

Often in the literature the models incorporating a control for neglected heterogeneity dominate any other parametric form. However, this is not the case here. Perhaps the departmental fixed effects and the product dummies are absorbing the plausible presence of neglected heterogeneity. Alternatively, the Inverse Gaussian distribution used to model the neglected heterogeneity is not fit for purpose.

It should be noted that the AIC values obtained from the Cox PH model estimation cannot be compared with the ones obtained from the parametric models estimation. This is because the Cox PH model is estimated by a method known as the partial likelihood, while the parametric models are estimated using a standard maximum likelihood method. However, given the positive slope of the Kaplan–Meier smoothed-baseline hazard estimator plotted in Figure 3.5.1, we actually can say with some degree of confidence that a very flexible hazard it is likely not required in this case, which provides further support for using the standard Weibull model with positive duration dependence rather than the Cox PH model.

Moreover, another reason why we might be sceptical in using the Cox PH results relates to a high number of ties.[24] In particular, 114 contracts experienced the failure event (26.3% non-censored) and exited the state of interest, the mean exit number is 5.4 per semester, with a maximum of 17 per semester. Table 8.1.3 in the Appendix chapter 3 shows the contract durations statistics per semester.

Finally, see Table 8.1.4 and Table 8.1.6 in the Appendix chapter 3 for the Accelerated Failure Time (AFC[25]) duration models results where similar findings are detected.

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[24] The proportional hazards model assumes a series of comparisons of those subjects who fail to those subjects at risk of failing (the risk pool). For example, let's assume that there are five subjects—x1, x2, x3, x4, and x5—in the risk pool, and that x1 and x2 fail. The "Breslow method" employed here for handling tied values says that because we do not know the failure order, we will use the largest risk pool for each tied failure event. This method assumes that both x1 and x2 failed from risk pool x1 + x2 + x3 + x4 + x5. However, if there are many ties, this approximation will not be accurate because the risk pools include too many observations.

[25] The AFT models are also parametric and provides an alternative to the commonly used proportional hazard models. Whereas a proportional hazards model assumes that the effect of a covariate is to multiply the hazard by a constant, an AFT model assumes that the effect of a covariate is to accelerate or decelerate the spell by some constant.

3.6.3 Discrete time survival models

The incidence of violence in Colombia has varied in intensity both across regions and over time. The violent shocks, fear and uncertainty generated by the armed conflict have weakened economic activity. In fact, in the agricultural sector, farmers often invest and produce less and avoid engaging in more profitable activities due to the higher costs of production and the perception of living potentially in a shorter time horizon in the midst of war (See Arias et al. 2014; Arias and Ibáñez, 2012).

Thus, the main advantage of using discrete time models over the semi-parametric and parametric duration models is that the former allows the violence variables to vary over time within the spell at risk. In other words, it permits the inclusion of time-varying covariates.

Since contract failure can only be detected after January 2010 given that there is information available on the answers to the question "does the PO currently has active commercial ties with one or more CBs?" in the dataset (See Section 3.4.3), the discrete time survival models employ a subsample of agribusiness contracts starting in 2007.

This sub-sample essentially removes from the analysis those old contracts that are not so fragile, and we focus especially on an interval of time that allows the precise time for agribusiness to mature. In other words, it is assumed that three years before failures are detected provides enough time for the POs to complete the implementation stage of PAAP, and to establish concrete and prosperous commercial relationships with the buyers. Moreover, this particular sub-sample permits the inclusion of time-varying violence variables that match better the lifespan of the contracts in the dataset. Hence, after three years, the incidence of violence may emerge as a cause of contract failure.[26]

In addition, in order to run the discrete time survival models some adjustments to the violence variables are required. The duration of agribusiness contracts of smallholder growers for the PAAP is expressed in semesters. However, the violence measures vary

[26] For the continuous-time duration analyses doing this subsampling exercise was not necessary due to the covariates are fixed at the time of the start of the agribusiness contract.

yearly, because there is no availability of six-monthly data of these statistics. Therefore, the yearly data point is used twice for the two semesters within each year.

The functional forms for the Baseline Hazard function considered included in the estimations are the fully non-parametric baseline ($\gamma' D_{i,t}$) , where $D_{i,t}$ represents a set of duration-interval-specific dummies, one for each spell, a log time baseline ($\log(t_i)$), the time ($\gamma\ t_i$) baseline, the quadratic polynomial baseline ($\gamma_1 t_i + \gamma_2 t_i^2$) and the cubic polynomial baseline ($\gamma_1 t_i + \gamma_2 t_i^2 + \gamma_3 t_i^3$).

Figure 3.5.1 provides some hints about which Baseline Hazard function would be most appropriate. Given the positive slope of the Kaplan–Meier smoothed-baseline hazard estimator plotted with a very late turning point, it is likely that the quadratic or a cubic polynomial baseline are fit for purpose. On the other hand, whereas it is expected that the last set of duration-interval-specific dummies of the fully non-parametric baseline may capture the tail at the end. The log time ($\log(t_i)$) would captured it too softly and the time ($\gamma\ t_i$) baseline may not be enough to do the job.

The discrete time models coefficients expressed in Equation (3.2) are estimated by maximum likelihood using the logistic cumulative distribution function (See Table 3.6.3).[27] In particular, although not reported in the table to save space, in the fully non-parametric model [28] the last set of duration-interval-specific dummies that are statistically significant yield negative sign coefficients, and as time increases their magnitude decreases. On the other hand, regarding the cubic baseline, both estimated quadratic and cubic coefficients are statistically significant; while $\hat{\gamma}_2$ is positive, $\hat{\gamma}_3$ is negative and smaller, thus, capturing the late and not so deep turning point seen in Figure 3.5.1.

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[27] All models estimations report their correspondingly log pseudo likelihood value, which is always negative, and with higher values (closer to zero) indicating a better fitting. As expected, and according to the lecture of the log pseudo likelihood values, the fully non-parametric and the cubic baseline fits the data better.

[28] The inclusion of a full set of duration-interval-specific dummies, one for each spell, somehow over parametrize the model, for example, two dummies predicts failure perfectly ($D_{i,t=12,}, D_{i,t=14,}$) and two others generate collinearity problems ($D_{i,t=15,}, D_{i,t=16,}$) causing estimations problems. That's why the final estimation of this model include only 14 dummies and have 27 observations less than the others.

Table 3.6.3 Discrete time models coefficients (logistic regressions)

Variables	Baseline				
	Fully non-parametric	Log(t)	(t)	Quadratic	Cubic
Acts of terror	-0.044	-0.044	-0.046	-0.046	-0.046
	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
Subversive actions	0.234*	0.223*	0.234*	0.234*	0.228*
	(0.134)	(0.130)	(0.131)	(0.131)	(0.133)
Kidnappings per 100,000 inhab	0.010	0.012	0.012	0.012	0.010
	(0.020)	(0.019)	(0.020)	(0.020)	(0.020)
Killings per 100,000 inhab	0.001	0.001	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
PO beneficiaries selected, at start (#)	-0.006	-0.005	-0.006	-0.006	-0.006
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Avg. share of beneficiaries that work on the farm at start	-0.013**	-0.012**	-0.013**	-0.013**	-0.013**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
PA still under implementation stage	1.076***	0.843***	0.959***	0.961***	1.051***
	(0.258)	(0.231)	(0.246)	(0.244)	(0.251)
Avg. distance to nearest wholesales food markets in the department	0.007	0.006	0.006	0.006	0.007
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Short growing cycle crop	0.064	0.076	0.078	0.077	0.061
	(0.540)	(0.538)	(0.544)	(0.544)	(0.545)
Livestock	1.425***	1.258**	1.333**	1.333**	1.384***
	(0.536)	(0.529)	(0.534)	(0.534)	(0.532)
Fish	1.362**	1.420**	1.390**	1.390**	1.306**
	(0.591)	(0.571)	(0.566)	(0.566)	(0.571)
Milk	-0.908**	-0.912**	-0.920**	-0.919**	-0.915**
	(0.451)	(0.444)	(0.445)	(0.447)	(0.447)
Other no crop product	0.238	0.198	0.243	0.242	0.235
	(0.612)	(0.622)	(0.616)	(0.613)	(0.606)
Ln(time=semester)		0.635***			
		(0.173)			
Time			0.187***	0.192	-0.406
			(0.039)	(0.118)	(0.292)
Time^2				-0.000	0.119**
				(0.009)	(0.057)
Time^3					-0.006**
					(0.003)
Constant		-3.096***	-3.153***	-3.165***	-2.441***
		(0.756)	(0.773)	(0.784)	(0.872)
Semesters dummy (14)	Yes	No	No	No	No
Departments dummy (26)	Yes	Yes	Yes	Yes	Yes
Observations	2,168	2,195	2,195	2,195	2,195
Log pseudolikelihood	-368.8	-380.7	-378.0	-378.0	-375.7

Table 3.6.4 shows the discrete time models marginal effects. The estimation results show that a one-unit increase in the number of subversive actions (mainly provoked by the guerrillas) raises the probability of agribusiness contract failure by 0.0065-0.0069 probability points (0.65%-0.69%) on average and *ceteris paribus*.

Table 3.6.4 Discrete time models marginal effects (logistic regressions)

Variables	Baseline				
	Fully non-parametric	Log(t)	(t)	Quadratic	Cubic
Acts of terror	-0.0012	-0.0013	-0.0014	-0.0014	-0.0013
	(0.0011)	(0.0012)	(0.0012)	(0.0012)	(0.0011)
Subversive actions	0.0065*	0.0068*	0.0069*	0.0069*	0.0066*
	(0.0036)	(0.0039)	(0.0038)	(0.0038)	(0.0038)
Kidnappings per 100,000 inhab	0.0003	0.0004	0.0004	0.0004	0.0003
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Killings per 100,000 inhab	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
PO beneficiaries selected, at start (#)	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Avg. share of beneficiaries that work on the farm at start	-0.0004***	-0.0004**	-0.0004***	-0.0004***	-0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
PA still under implementation stage	0.0344***	0.0284***	0.0320***	0.0321***	0.0349***
	(0.0090)	(0.0082)	(0.0087)	(0.0087)	(0.0091)
Avg. distance to nearest wholesales food markets in the department	0.0002*	0.0002	0.0002	0.0002	0.0002*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Short growing cycle crop	0.0018	0.0024	0.0024	0.0024	0.0018
	(0.0159)	(0.0174)	(0.0172)	(0.0172)	(0.0166)
Livestock	0.0783	0.0690	0.0740	0.0740	0.0772
	(0.0489)	(0.0459)	(0.0479)	(0.0478)	(0.0487)
Fish	0.0720	0.0835	0.0787	0.0787	0.0697
	(0.0493)	(0.0531)	(0.0504)	(0.0504)	(0.0474)
Milk	-0.0188***	-0.0206***	-0.0202***	-0.0202***	-0.0197***
	(0.0072)	(0.0077)	(0.0075)	(0.0075)	(0.0073)
Other no crop product	0.0074	0.0066	0.0080	0.0080	0.0075
	(0.0209)	(0.0224)	(0.0224)	(0.0223)	(0.0215)
Ln(time=semester)		0.0192***			
		(0.0054)			
Time			0.0055***	0.0057	-0.0117
			(0.0012)	(0.0035)	(0.0085)
Time^2				-0.0000	0.0034**
				(0.0003)	(0.0017)
Time^3					-0.0002**
					(0.0001)
Constant					
Semesters dummy (14)	Yes	No	No	No	No
Departments dummy (26)	Yes	Yes	Yes	Yes	Yes
Observations	2,168	2,195	2,195	2,195	2,195
Log pseudolikelihood	-368.8	-380.7	-378.0	-378.0	-375.7

In general, these tables exhibit similar findings to those detected when the parametric models are used. The number of beneficiaries and the average share of beneficiaries that work on the farm (both at business contract inception) yield a negative relationship with the probability of agribusiness contract failure. In contrast, when the productive alliances remain in the implementation stage, the probability of agribusiness contract failure increases. Furthermore, when the POs produce livestock and fish, the probability of agribusiness contract failure is higher compared to producing crops. However, when they produce milk, the probability of agribusiness contract failure decreases. The marginal effects vary across the estimation methods as does the shape of the baseline hazard function.

Finally, see also **Table 8.1.5** in the Appendix chapter 3 for results when the cloglog[29] form is employed for the hazard discrete time modelling. Similar findings are detected.

[29] The Complementary Log-Log (cloglog) transformation is defined as $Log\{-log[1 - \mathrm{Prob}(y_{i,t} = 1)]\} = \beta x_{i,t}$. Like the logit transformation, it takes a response restricted to the (0,1) interval and converts it into something in $(-\infty, +\infty)$ interval. Since $[1 - \mathrm{Prob}(y_{i,t} = 1)]$ is always a negative number, this is changed to a positive number before taking the log a second time. Therefore, the model can also be written as $\mathrm{Prob}(y_{i,t} = 1) = 1 - \exp[-\exp(\beta x_{i,t})]$.

3.7 Conclusions

The findings of this chapter fill an important gap in the existing violence and conflict literature. Until now, to the author's knowledge, there are no studies exploring the performance of agribusiness contracts that use econometric models. In addition, there is no study that has linked agribusiness data with violence at the municipal level. Going beyond studies that often use cross-country information, firms or individual farmer surveys, this investigation employs an original dataset of smallholder farmer agribusiness contracts to explore the relationship between their duration and violence in Colombia using data from a project focused on linking farmers to markets – PAAP.

This chapter attempts to disentangle the channels through which violence affects agribusiness contract durations. Terrorism, at the start of the agribusiness contract, appears to be the main cause of smallholder agribusiness contract failure. When violent incidents vary over time, the armed conflict (i.e., the number of subversive actions) emerged as the cause of agribusiness contract failure. Thus, the Colombian armed conflict has had a degrading effect on the overall agribusiness climate, constraining farmer capacity to sustain market linkages.

The empirical analysis of this chapter is subject to some data limitations. For example, non-state armed actors, such as the FARC, occasionally impose a 'war tax' on farmers, a payment of monthly dues to the guerrillas that allow them to continue working on their farms. The existence of the 'war tax' (*vacunas*, in Spanish) may affect agribusiness contract durations. However, the dataset used includes only smallholder producer organizations, which do not necessarily provide a lucrative tax base for such purposes.

In addition, it is not possible to identify with the current dataset who is the actor that defaults from the original partnership. Buyers may also be tempted to look for other providers and the inherent reasons for contract failure, whether it is sourced on the supply-side or the demand-side or indeed both, are unknown.

Finally, failure from the original partnership is not necessary something bad. Indeed, if the PAAP, as a linking farmer to markets program, is effective, smallholder farmer beneficiaries at some point after its implementation may be able to link with buyers in more sophisticated supply value chains that offer better business growth opportunities. Thus, contract failure may actually be a positive outcome. However, this again is something we cannot inform directly on given data constraints.

Chapter 4

4 Forests and Conflict in Colombia

Summary

This chapter offers evidence on the relationship between armed conflict and its environmental impacts. For the case of Colombia, using a unique annual municipality panel dataset (from 2004 to 2012) and an instrumental variable approach to control for possible endogeneity between forest cover and forced displacement, there is evidence that the armed conflict is a force for forest protection and growth. In December 2016, the Colombian government concluded the negotiations with the Revolutionary Armed Forces of Colombia (FARC) to end South America's longest-running internal conflict. Forest degradation often increases in post-war situations. These findings highlight a need for increased protection of Colombia's forests in the wake of the peace settlement.

Keywords: forest cover, forest change, reforestation, deforestation, armed conflict, violence, forced displacement, land abandonment, coca crops

4.1 Introduction

The toll of civil conflict goes well beyond human suffering and the damage to physical infrastructure. Conflicts may also cause the degradation and destruction of local environments and biodiversity. This paper offers evidence on the relationship between armed conflicts and forest cover for the case of Colombia.

Little attention has been given to the impact of conflicts on the environment. In fact, most conflict studies investigate the effects of conflict on socioeconomic and institutional outcomes, such as a country's' macroeconomic performance, human capital and asset accumulation, or civil political participation. For example, from a macroeconomic perspective Collier (1999) using a cross-country dataset (92 countries, 1960 to 1992) estimates a GDP per capita annual decline of 2.2% for a country that experienced a civil war relative to its counterfactual, on average. Likewise, Hoeffler and Reynal-Querol (2003) using a global dataset (211 countries, 1960 to 1999) report that civil wars that last five or more years reduce the country's average annual growth rate by 2.4% on average.

Regarding human capital accumulation Justino *et al*. (2013) examine the impact of violence in Timor Leste using data from 1999. In the short term, the authors found supporting evidence that school attendance was reduced. In the longer-term, primary school completion declined particularly for boys exposed to peaks of violence during the 25-year conflict. Similarly, Shemyakina (2011) for the case of Tajikistan, found that girls aged between 7-15 years old in 1999 are about 11 percentage points less likely to be enrolled in school if their household's dwelling was damaged during a conflict period (1992-1998).

In terms of asset accumulation Deininger (2003), using household data from Uganda, found that the conflict negatively affected investment and non-agricultural enterprise formation between 1992 and 1999. The household income decision on investment was affected by the imposition of war taxes by the rebel forces.

On the subject of civil political participation, Bellows and Miguel (2006) investigate the socioeconomic and institutional outcomes in 2004 and 2005 in Sierra Leone, some years after the civil war period (1991-2002) had ended. The empirical evidence shows that political mobilization measures became higher in areas that experienced more violence.

Understanding how conflict affects forest cover could provide insights on the need to promote natural resource conservation with the corresponding governmental engagement in structural forest governance regulations particularly important in preventing the escalation of conflict.

The 2016 peace deal was intended to end the 60 years of conflict with the FARC. Apart from reducing victimization, it is anticipated to generate immense economic benefits for the country. For example, a National Planning Department (DNP)[30] study suggests that Colombia's GDP will grow between 1.1 and 1.9 percentage points more with the arrival of peace. However, it is important to clarify that the 'environmental' peace dividend would not necessarily be positive. In particular, in Colombia the effect of the conflict on forest cover is often regarded as ambiguous.

On the one hand, the presence of illegal armed groups[31] in protected areas restricts colonization trends and assist these areas to remain free of environmental damage (Álvarez, 2003; Dávalos et al. 2011). In fact, guerrilla groups often served as the local environmental protection authority, taking explicit decisions on nature conservation, enacting and enforcing unofficial laws limiting hunting, fishing, and deforestation (Dávalos, 2001; Sánchez-Cuervo and Aide, 2013).

The environmental friendly attitude of the guerrilla movement in Colombia is usually linked to their prevailing economic and military interests in the area. Conserving the forests helps rebel forces conceal their activity and establish safe-havens with transit corridors for troops, military supplies, drugs, or illegally extracted natural resources such as timber or minerals (Álvarez, 2003; Dávalos et al. 2011).

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[30] This is based on DNP (2015), "Dividendo económico de la paz".
[31] During the period covering this study the armed conflict comprised mainly two guerrilla organizations known as the Revolutionary Armed Forces of Colombia (FARC) and the National Liberation Army (ELN). In addition, there exists in the shadows a third actor, a right-wing paramilitary group known as the United Self-Defence Forces of Colombia (AUC), which even though signing a demobilization agreement in 2003 remains active in criminal and drug-related activities.

On the other hand, in other areas, illegal armed groups have caused devastating effects on the ecosystem, destroying oil pipelines, engaging in illegal mining, and clearing forests to acquire land for the cultivation of illicit crops. The war on drugs has exacerbated this situation. Chemically or manually, coca eradication automatically causes localized deforestation in the area in which it is conducted. In response, coca producers tend to move to even more remote locations such as national parks or other protected areas where chemical fumigation is prohibited. New coca plantations are then established which ultimately lead to a cycle of deforestation (Dávalos et al., 2011).

This paper complements and enhances the existing literature by identifying the direction of the relationship between armed conflicts and forestation in Colombia. The identification strategy used relies on exploring the causal effect that forced displacement exerts on forest cover at the municipal level.

According to official figures more than 5.2 million persons were forcibly internally displaced between 1990-2012. This represented 11.2% of the population. Illegal armed groups are the main implicated parties. In fact, it well known that violence against civilians has not been random. Instead, it has been a deliberate strategy of war. Illegal armed groups have displaced peasants in order to secure control of valuable land rich in natural resources. This enables the armed groups to engage in legal or illegal economic activities such as mining or planting illicit crops, or use the land to establish camps for troops, or store illegal drugs and weapons. Selective killings, massacres, death threats, disappearances, forced recruitment and property damage are consequences of attacks perpetrated by these groups to frighten and intimidate local inhabitants, which eventually leads to forced displacement (Roche-villarreal, 2012; Moya, 2012; Ibáñez, 2009).

The research presented here provides an important contribution to the existing literature on conflict. In particular, the scope of existing studies has been limited by data restrictions regarding the availability of forest cover and conflict statistics at the sub-national level. Thus, while some studies have focused on examining a conflict's environmental impacts, others exclusively deal with the impacts generated by a single conflict actor. In addition, few studies employ appropriate econometric techniques to tackle this research question. Therefore, this chapter goes beyond others studies by using a unique annual Colombian panel dataset of forest cover satellite imagery at the municipal level over the period from

2004 to 2012. Furthermore, the research also investigates and tests for the endogeneity problem between forest and conflict presence using an array of appropriate econometric techniques. Specifically, a fixed effects (FE) Instrumental Variable (IV) approach is used to address the potential endogeneity problem between forest cover and forced displacement. In exploiting forced displacement as the main conflict-specific explanatory variable we not only capture the effect of multiple perpetrators of violence, but also its link or relationship to land use. This allows us to explore the conflict's impact on forest coverage given armed conflicts invariably induce large flows of displaced persons either from the countryside to urban centres, or to unexploited frontier lands elsewhere.

The main finding of this study is that the armed conflict has been a beneficial force for forest protection and growth in Colombia, but the estimated effect of the conflict on forestation is found to be small in magnitude. Consequently, the positive yield of conflict conservation is overwhelming offset by the negative consequences of violence which involve, for example, a high number of deaths in the fighting, the destruction of human capital and physical infrastructure, educational and health outcomes and market disruption, and the increments of drug production which undermines governance, among other things. Hence, the major achievement of the 2016 peace deal that ended 60 years of conflict with the FARC was reducing victimization. Yet, since forest degradation frequently increases in post-conflict situations the government may need to play an active role in developing conservation policies in those developing areas currently under the control of the guerrillas when the peace finally arrives. Otherwise, the peace dividend for the environment will not emerge.

The paper is structured as follows. The next section presents a literature review which is followed by a section describing empirical modelling issues. A fourth section describes the data and some descriptive statistics. A fifth reports the empirical results, while a sixth section examines the role of a set of time-invariant variables on explaining forest cover. A final section offers some concluding remarks and the policy implications for the analysis.

4.2 Literature review

Most of the literature linking conflict and the environment emphasizes the connection between abundant natural resources, armed conflict, and underdevelopment. This is generally known as the "resource curse" which makes reference to a situation in which the natural resources are mismanaged by a certain interest group (See, for example, Auty (2004); Ross (1999); Collier and Hoeffler (1998)[32]; and Sachs and Warner (1995))

The findings are somehow mixed in terms of the duration of conflicts and the presence of forests. For example, Collier *et al*. (2004) investigates the causes of civil war, exploiting a database of 161 countries over the period 1960-1999 (79 civil wars) and reports that the extent of forest cover is not statistically associated with longer conflicts. In contrast, De Rouen and Sobek (2004) exploit a database containing information on 114 civil wars in 53 countries between 1944 and 1997, and find that highly forested countries are associated with a significantly decreasing probability[33] of the civil war ending.

However, studies that use cross-country data are subject to criticism. Often the forest cover is calculated for the whole country, but it is likely that only some parts of the country experienced the conflict. Hence, Lujala (2010) shows that the location of the natural resources are key determinants of conflict durations using a dataset known as PETRODATA [34], which contains the geographic coordinates on the location of hydrocarbon (i.e., crude oil and natural gas) reserves for 111 countries. According to the author's research, if these resources are located inside the actual conflict zone, the duration of the conflict actually doubles.

There is also a growing literature that tries to explicitly link the relationship between civil war and forest cover. In particular, progress has been made in terms of incorporating spatially explicit forest cover in to empirical analysis given the evolution and development of user-friendly satellite data. Once again, these studies offer mixed results regarding the direction of the impact of conflicts on forests, and are usually subject to the

[32] In the Collier and Hoeffler (1998) paper on the economic causes of conflicts, countries experiencing civil wars were found to have marginally lower forest cover (29%) than their counterparts who did not experience civil war (31%).
[33] In this study, a logit model is used to explain what determines the probability of civil war outcomes (i.e., government victory, rebel victory, truce, or treaty), whereas a hazard analysis identifies the factors that determine the time to reach such an outcome.
[34] This dataset includes 890 onshore and 383 offshore locations with geographic coordinates and information on the first oil or gas discovery and production year. PETRODATA allows researchers to control for both the spatial and temporal overlap of regions with hydrocarbon reserves and armed conflict. PETRODATA is available at http://www.prio.no/CSCW/Datasets/Geographical-and-Resource .

inherent mechanics of country conflicts, which demonstrate the need for more focused research.

Focusing on the experience of Colombia, Fergusson *et al*. (2014) is one of the few studies that addresses the endogeneity problem between conflict and forests. In particular, the authors focus on examining the deforestation impact of the paramilitary expansion, which was characterized by the perpetration of selective massacres and by forcing large populations to flee in order to secure territory during the late 1990s. They instrument paramilitary attacks with the distance to the Urabá region, the epicentre of the paramilitary activity. The forestation data were based on satellite images for the years 1990, 2000, 2005 and 2010. The authors detected a negative effect of the paramilitary expansion on forest cover using cross-sectional models controlling for, among other things, municipality fixed effects,

Dávalos *et al*. (2011), examining the case of Colombia, use forest cover maps at 1-km grid[35] spatial resolution to quantify forest changes in the northern Andes, Chocó and the Amazon regions. These represented the largest coca leaf producing zones between 2002 and 2007. The authors use logistic regressions and control for the grid distance to the closest newest coca fields and the area of coca cultivation around 1 km^2, and the population, road accessibility and climate controls, among other things. The study finds that the cell probability of transition from forest to no forest increases with shorter distances to the newest coca fields and with the area of coca cultivated in its boundaries. This paper suggests that establishing larger protected areas could help reduce deforestation and preserve biodiversity.[36]

Viña *et al.* (2004) concentrate their analyses on the region along the Colombia-Ecuador border using satellite data between 1973 and 1996. The authors compare images to calculate the rates and patterns of land-cover changes along the border. Their comparison suggests that forest cover loss is higher on the Colombian side of the border with 43% on that side compared to 26% on the Ecuadorian side. They do not use an econometric model to identify specific factors driving these results. However, they suggest that the illegal

[35] These comprise a network of lines that cross each other to form a series of squares.
[36] Fjeldså (2005) report similar results, concluding that the eradication campaigns lead to a constant relocation of drug dealers, thus making illicit crops one of the main causes of deforestation.

coca production, occurring mainly along the Colombian side, might explain the differences in deforestation rates.

Álvarez (2003) using information obtained through semi-structured interviews with local civilians and members of the guerrilla groups situated in the main forested regions of Colombia (e.g., the Macarena mountains, Munchique National Park, Tambito Nature Reserve, the San Lucas mountain range, and the Churumbelos mountains) emphasize that the relationship between conflict and forest cover is ambiguous. On the one hand, the author finds evidence of 'gunpoint' conservation in some sites, which means that the guerrilla groups, such as the ELN in the San Lucas mountain range, undertook conservation activities. In this particular case, this was done by placing landmines[37] or posting signs that warn of landmines in patches of the forests. In turn, the forests served the guerrillas as cover from government surveillance and air strikes. On the other hand, guerrilla groups have also expedited deforestation. For example, in the Choco Department lowlands, forests were actually converted into cattle ranches or coca plantations.

Among the international studies on this subject that are of relevance is Stevens *et al.* (2011). Their paper investigates the forest cover changes on two sites, with a total area of circa 160,000 hectares located along the Atlantic Coast of Nicaragua over a period covering the civil war (1978 to 1993). Based on a forest and non-forest image pixels[38] classification detection methods[39], the authors find that in the first five to 7 years of the conflict, reforestation was greater than deforestation due to forced displacement. However, once the conflict terminated people returned to their lands and the level of deforestation was almost double the level of reforestation that had occurred during the conflict.

Hecht and Saatchi (2007), using a visual interpretation of satellite imagery data of forest cover between 1990 to 2007 for El Salvador, highlight the expansion of woody vegetation, especially in the northern provinces, in mountainous zones at the edge of

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[37] Landmines are in effect a 'negative capital stock' that society accumulates during a conflict. They continue to kill and mutilate people long after the actual fighting has ended (see Hoeffler & Reynal- Querol, (2003)).
[38] Pixels are the smallest elements of an image that can be individually processed in a digital screen.
[39] Based on a classification scheme, the pixel classes were divided into specific land cover categories, which included forests (deciduous, mixed, secondary) and non-forest (agriculture, rangeland, and barren land) types.

agricultural frontiers, and in regions that had been under the control of the Farabundo Martí Front for National Liberation. They conclude that woodland resurgence is positively correlated with the occurrence of the civil war. They note that many people fled the country to avoid being killed in the conflict.

Nackoney et al. (2014) for the Democratic Republic of Congo, comparing satellite imagery data across two decades (1990–2010) with an algorithm that uses surface reflectance to detect image changes, report that primary forest loss and degradation rates occurring during the conflict decade (1990–2000) were over double the rates of the post war decade (2000–2010). This suggests pressure on the forests during periods of conflict. Despite the fact that their images do not consider forest regrowth, the authors note that after the end of the war in 2003, the rate of primary forest loss taking place within the agricultural zones increased, meaning that in the post-war era people returned from remote forested areas to their homes, and cleared forests in order to regenerate food production activity.

Table 4.2.1 Selected studies on the relationship between conflict and forests

Author	Published Journal	Sample coverage	Methodology	Conflicts impacts on forests
Collier et al (2004)	Journal of Peace Research	Cross-country overtime (1960 - 1999) 161 countries	Probability model (logit)	No impact
Fergusson et al (2014)	Working paper CEDE series, Universidad de los Andes, Colombia	Colombia overtime (1990, 2000, 2005 and 2010)	Cross-sectional and instrumental variables models	Negative (due to paramilitary activity expansion)
Dávalos (2001)	Environmental science technology	Colombian regions (Northern Andes, Chocó and the Amazon) overtime (2002 - 2007)	Probability model (logit)	Negative (due to coca production)
Viña et al (2004)	Journal of the Human Environment	Colombia & Ecuador border region overtime (1973 - 1996)	Satellite imagery analysis	Negative (due to coca production)
Alvarez (2003)	Journal of Sustainable Forestry	Colombia main forested regions (Macarena mountains, Munchique National Park, Tambito Nature Reserve, the San Lucas mountain range, and the Churumbelos mountains) 2003	Not Econometrics (interviews)	Ambiguous (due to "gunpoint" conservation)
Stevens et al (2011)	Biodiversity and Conservation	Nicaragua's Atlantic Coast (160,000 ha) overtime (1978-1993)	Satellite imagery analysis	Positive (due to displacement)

Hecht and Saatchi (2007)	BioScience	El Salvador overtime (1990 - 2007)	Satellite imagery analysis	Positive (due to displacement)
Nackoney et al (2014)	Biological Conservation	Democratic republic of Congo overtime (1990-2010)	Satellite imagery analysis	Negative (due to pressure on natural resources)
Burgess et al (2015)	Environmental Research Letters	Sierra Leone overtime (1990 and 2000)	Log linear regressions	Positive (due to displacement)

In contrast, Burgess *et al.* (2015) for Sierra Leone, merged satellite imagery of forest cover with chiefdom-level conflict incidents (151 observations) for the years 1990 (prior to the civil war) and 2000 (just prior to the end of the civil war) and found that conflict prevented local deforestation. In particular, conflict-ridden chiefdoms experienced significantly less forest loss relative to their counterparts due to forced displacement.

Table 4.2.1 provides a short summary of the research done in this topic reviewing data sources, methodologies and key findings. The major constraint on research progress on this topic have been a lack of data on both conflict and forest cover at the sub-national level. Some studies concentrate their analysis only on particular biomass areas (eco-regions), while others are confined to the effects of a single perpetrator of violence. Very few adopt a clear or clean identification strategy, and address the endogeneity problem between the conflict and forestation or deforestation. Although, it is acknowledged the potential problem may not be present in the current application since, as we have found, it depends on the choice of the conflict variable used in the empirical analysis. The aim of this paper is to fill these lacunae.

4.3 Empirical and identification strategy

The research question is addressed empirically by using instrumental variables and panel data methods. The variation of the dependent and explanatory variables over time and across municipalities is exploited to identify the effects of the armed conflict on forest cover. Equation (4.1) outlines the specification to be estimated:

$$Forest_{i,t} = \gamma FD_{i,t} + \beta X_{i,t} + \alpha_i + \lambda_t + \varepsilon_{i,t} \tag{4.1}$$

where $Forest_{i,t}$ is the share of municipality *i*'s area covered by forest in year *t.* The conflict variable is the forced displacement rate per 1000 of the municipal population ($FD_{i,t}$). Following the literature review, the main reason as to why forced displacement was chosen as a variable to measure the impact of the armed conflict on forests is because it not only represents a deliberate[40] strategy used in war, but also is linked to land use and conservation trends.[41] Similar to areas with harsh environmental conditions[42] that may experience agricultural abandonment and a subsequent spontaneous ecosystem recovery, productive areas abandoned by humans due to conflict may experience a reduction on land pressure, which leads to forest regrowth (See Sanchez-Cuervo and Aide, 2013).

CNMH (2015), using statistics from the Central Registry for Victims Office (RUV) (1985-2014), suggest that 62.5% percent of the victims of forced displacement declared that the perpetrator was an illegal armed group (41.4% of which were guerrillas and 21.1% paramilitaries, respectively). The emergent criminal bands (known by the name of Bacrims in Spanish) accounted for 4% of the total displacement, while various state forces were found to be directly responsible for only 0.8%. Unfortunately, the remainder of the victim statements (32.7%) contained in the RUV do not offer a detailed description of the actors identified by the victims as the displacement perpetrators.

In Colombia, illegal armed groups promoted forced displacement often to reduce the offensive capacity of the "enemy", expropriate and concentrate land, exploit and usufruct the dispossessed territory, or to establish and sustain illegal economies (e.g., money laundering, planting of illicit crops, development of drug trafficking routes). Forced displacement is not an unintended result of the internal conflict. Instead, groups attack the civil population to strengthen territorial strongholds, expand territorial control, weaken support for the opponent, and accumulate valuable assets (Ibáñez and Vélez, 2008).These actions are the standard modus operandi of a warlord who seeks territorial control and appropriation of the revenues of the territory (CNMH, 2015; Duncan, 2004). Thus, forced displacement is provoked by any threats or direct attacks by an armed group, regional indiscriminate violence, or even the mere presence of armed groups. Civilians

40 According to Ibáñez (2009) violence against civilians is not a random act.
41 Forced displacement is the conflict consequence most connected to forestation trends.
42 Environmental variables can explain the patterns of forestation because they can restrict or encourage different land uses.

are displaced to avoid direct victimization, or, simply as a way of preventing a confrontation (Ibáñez, 2009a).

In particular, Engel and Ibáñez (2007) and Ibáñez and Vélez (2008) investigate displacement determinants using logistic regression models for a sample of 376 households conducted during the year 2000. The data cover displaced households (200) from the departments of Antioquia and Cordoba (the expulsion zones) which migrated to Bogota, Medellin and Cartagena, and others (176) that remained at their place of origin. The probability of displacement is determined by variables capturing the strategies pursued by armed groups, state presence, income generation possibilities, and household characteristics. For example, the study finds that a household is significantly more likely to opt for displacement if there were violent acts committed in its surrounding area, the presence of a subversive group (either paramilitary or guerrilla), if it owns larger landholdings or high levels of livestock[43], it is far from economic markets, or it is located in a region with a high index of basic needs. On the contrary, the probability of household displacement is reduced when there is an active presence of military forces and the national police, there is access to social services (education and health), and when the age of the household head and the level of education is high.

Dueñas et al. (2014) present similar results based on fixed effects panel data estimation for the period 2004–2009. In particular, the authors show that the rate of expulsion of a displaced person is positively and strongly correlated with the conflict intensity (attacks undertaken by illegal armed groups), the presence of coca crops, royalties (which is a proxy for the presence of natural resources) and low economic and security conditions at the municipal level.

In summary, violence and security perceptions are the major determinants of displacement and are, therefore, viewed as the key levers in preventing displacement (Ibáñez and Vélez, 2008).

[43] Livestock can be transformed into cash relatively easily (more easily than land). Thus, it provides financial resources that help to cover the costs of displacement and provide a basis for a new start in the receiving location.

Authors such as Aide and Grau (2004) and Meyerson et al. (2007) have shown that rural–urban forced displacement promotes ecosystem recovery due to the reduction of human pressure on land. The research findings in this thesis is in line with that hypothesis. Despite the fact that rural to rural displacement might also increase forest degradation, in Colombia most of the forced displacement is actually rural to urban in nature. In other words, it goes from forested areas and most often to the larger cities. According to official figures during the study period (2004-2012) around 60% of the total displaced people were expelled from a “strictly”[44] rural municipality, and around 75% of the displaced was received by a “strictly” urban municipality.

In Equation (4.1), γ is the primary parameter of interest in the empirical analysis. In order to identify the causal effect of forced displacement on forest coverage, the error term ($\varepsilon_{i,t}$) needs to be uncorrelated with the forced displacement rate per population (i.e., the main variable of interest ($FD_{i,t}$) must be exogenous). The standard econometric literature suggest that there are at least three possible reasons why the $FD_{i,t}$ may be endogenous (i.e,. correlated with the error term): i) measurement error, ii) simultaneity, and iii) omitted variables. Yet, in this particular case it should be noted that one cannot rule out the possibility that the measurement error bias dominates the other two endogeneity causes.

First, it is expected that **measurement error** may play a role in the estimation of γ due to data on $FD_{i,t}$ may be subject to underreporting. In particular, precise statistics for the number of people who have been internally displaced in Colombia are unavailable.

The government Registry for Displaced Populations (RUPD) consolidates forced displacement statistics. The RUPD objective is to legally recognize displaced households, and, therefore, quantify the demand for public aid. Displaced persons approach local government authorities to declare, under oath, the circumstances of their displacement.

[44] The municipal urban and rural classification follows the theoretical framework developed by the “National Mission for Rural Transformation of Colombia” led by the National Planning Department during 2014-2015, which defined four categories of municipalities according to its degree of “rurality” (cities and agglomeration, intermediate, dispersed rural, and rural) based on three variables: the number of inhabitants, the population density per square kilometre, and the share of people that reside in their main cities. In particular, whilst the categories “cities and agglomerations” and “intermediate” are assumed “urban”, the “dispersed rural” and "rural" are assumed “rural”.

Then, public servants confirm whether or not this is truthful. According to Ibáñez (2009) approximately 30% of the displaced population is believed not to be registered.

Displacement is not confined to remote or isolated municipalities as it extends throughout the whole of Colombia. Underreporting in displacement is due to a person's unwillingness to become registered in the official registration system for reasons including a fear it places on an individual's personal and household security at risk, the desire of anonymity because of the situation of displacement, reticence or mistrust towards the state and its institutions, the lack of information on the existence of the registration system, or unawareness about the system registration benefits, among other factors (Ibáñez, 2009; Silva and Sarmiento, 2013).

On the other hand, there are registration inefficiencies and bureaucratic procedures that could vary regionally. For example, it can be the case of refusal to register by an official in charge of feeding the system in a region due to the non-recognition of certain causes of displacement (e.g., due to a state-caused displacement through the aerial fumigation of coca crops in the region). Finally, depending on the case, the regional authorities may not record the number and the reasons for the rejection. Similarly, there aren't records about the number of appeals or of the responses to appeals (See Rivadeneira, 2009). In conclusion, under-registration makes the true extent of displacement impossible to quantify with certainty. All of these explanations are random and municipality case-specific. Therefore, although the levels of registrations may be affected, we do not believe that the variation in registrations are affected given the random nature of under-reporting. Hence, we believe it is a reasonable assumption to make that measurement error in the forced displacement variable is likely to be random in nature. Furthermore, we believe that the IV estimation procedure used would address the issue of measurement error if it were systematic (rather than random) in nature.

Bottom-line, measurement error may conceal the true impact of $FD_{i,t}$ on forest cover. Since underreporting is likely to be negatively correlated with the $FD_{i,t}$ the estimate of γ is likely to be downward biased if estimated by OLS.

Second, **simultaneity** issues may also bias the parameter estimate of γ . $Forest_{i,t}$ and

$FD_{i,t}$ are possibly determined simultaneously. On the one hand, $FD_{i,t}$ may be particularly widespread in forested regions. The illegal armed groups are profit-driven actors and therefore, natural resources such as faunae, timber, minerals, and tree crop booms attract them to the forests for harvesting purposes. These groups often then enter into conflict with the local people or with each other causing civilian displacement. For example, it is well known that the FARC and other criminal gangs, known locally as "Bacrims", have sought control of illegal mining activities in the more remote forest lands. In the department of Choco illegal armed groups have violently secured control of territories, which are used by locals to carry out illegal gold mining. The FARC then charges the miners a gold production tax and a fee for using each unit of machinery (i.e., excavators).[45]

On the other hand, the presence of illegal armed groups affects forest conservation efforts. Historically, the Colombian government has often neglected remote regions and their inhabitants. As a result, local populations have limited loyalty to local governments, and look to other groups to perform traditional government functions. Thus, the guerrillas have taken advantage and have performed natural resource management and conflict resolution to legitimize their role as a local political actor in these regions. For example, it has been well documented that the ELN protected forests in the Serranía de San Lucas, a forested massif located in the department of Bolívar, northern Colombia, because of their major role in the local hydrology (See Álvarez, 2003; and Dávalos et al., 2011). In the Serranía de la Macarena, a set of mountains located in the Department of Meta, eastern Colombia, FARC violently enforced environmental protection. A noteworthy example is a ban they established on yellow catfish harvesting, a threatened species, especially when it is migrating up rivers and streams to spawn.[46]

Therefore, if there is a simultaneity bias one could expect a negative correlation between the unobservables determining $Forest_{i,t}$ and $FD_{i,t}$, ($\varepsilon_{i,t}$) and ($u_{i,t}$), respectively, that might explain a downward bias in the estimate of γ if OLS is used in preference to an appropriate IV estimation procedure. However, looking for unobservables and also a

[45] For example, see the article entitled "El medio ambiente: la víctima olvidada" an online special edition of Semana Magazine retrieved from: http://sostenibilidad.semana.com/medio-ambiente/multimedia/medio-ambiente-conflicto-colombia/33709
[46] Ibid.

convincing narrative that leads to this particular result is hard. In fact, it is more likely that the correlation between unobservables is weak.

Third, **omitted variables** could also potentially affect the estimate for this key parameter as well. The set of controls ($X_{i,t}$) may neglect some time-varying factors that are difficult to capture but are also correlated with forest cover and forced displacement. For example, Acevedo (2015) argues that in coca areas the increase in coca yield is associated with a decrease in forced displacement mainly due to the establishment of 'coercive' institutions enforced by illegal actors. Thus, forced displacement only occurs when farmers are able to escape safely from the coca-farming contract entered into with the guerrillas and local drug barons. The negative correlation between the establishment of coercive institutions by guerrillas and forced displacement could potentially downward bias the OLS estimate of γ, though the direction of bias cannot be known a priori. However, the inclusion of municipal fixed effects may attenuate this particular bias in this circumstance.

It is likely that the measurement error bias dominates the other two endogeneity sources due to a presence of increased underreporting found in the forced displacement variable. First, even if the simultaneity and measurement error act in opposite directions, the correlation between unobservables determining $Forest_{i,t}$ and $FD_{i,t}$ is likely to be weak, which means that simultaneity bias is largely offset by the measurement error bias. Second, since inclusion of municipal fixed effects controls for permanent unobserved heterogeneity, the omitted variable problem is attenuated.

In order to tackle these endogeneity concerns, an instrumental variable (IV) technique is employed. Therefore, equation (4.1) represents the structural model and comprises the second-stage equation in a two-stage estimation procedure.[47] The IV estimation seeks to separate the exogenous part of the total variance of the variable of interest from a part that is endogenous and thus correlated with the error term in equation (4.1). Under the assumption that this separation is undertaken correctly, the final least squares estimates

[47] One alternative way to bypass the endogeneity problem is to use the lag of the $FD_{i,t}$ variable. It could be argued that this might solve the simultaneity problem as it could be argued that today's forest cover will not influence armed conflict activity in the past. However, the weakness of this approach is that if there is any inertia in the variables, the lags will not necessarily resolve the endogeneity problem. In any event, exogeneity, in its most stringent form, requires the unobservables to be independent of past, present and future values of the conflict variable. In general, this condition is rarely satisfied.

will be unbiased and consistent. In practice, it is necessary to find a set of variables, known as instruments, which are independent wither respect to forest cover, but strongly correlated with the variable of interest (i.e., displacement). The three important features of a good instrument are that: i) it should be correlated with the endogenous variable (i.e., relevance); ii) it should be uncorrelated with the error term (orthogonality) ; and most importantly iii) there should be a persuasive narrative about the use of the instrument(s). The first two of these requirements can be investigated empirically.

Thus, the first-stage Equation (4.2) is defined as:

$$FD_{\mathrm{i,t}} = \pi Z_{i,t} + \delta X_{i,t} + \alpha_i + \lambda_t + u_{i,t} \qquad (4.2)$$

where (Z_{it}) is the set of instruments that includes the lagged values of the victims of massacres per 100,000 inhabitants and the number of conflict kidnappings per 100,000 inhabitants. Exploiting various valid instruments can improve precision, hence, the use of a third instrumental variable is also explored. In particular, it is considered the percentage of the agricultural frontier with coca crops fumigated[48] and manually[49] eradicated; or expressed as the percentage of the municipal area with coca fumigated and manually eradicated. The vector $X_{i,t}$ is comprised of exactly the same set of variables assumed exogenous in Equation (4.1). The key point here is that the predicted variable $\widehat{FD_{\mathrm{1,t}}}$, by construction, is independent of $u_{i,t}$ and thus the estimation yields unbiased and consistent estimates. The $u_{\mathrm{i,t}}$ is an error term assumed to be identically independently distributed with zero mean and a constant variance.

The rationale underlying the "relevance" of these instruments is now discussed. First, forced displacement is usually preceded by an escalation of violence, driven by exposure to more than one type of violence. In such instances, displacement becomes the last resort to survive. One of the main reasons driving people to flee their homes is the occurrence of massacres. Massacres are defined as those events in which four or more people are murdered at once. Usually, illegal armed groups have conducted massacres as a deliberate tool to instil fear and intimidate the civilian population in order to seize assets,

[48] Aerial spraying is undertaken using an herbicide called glyphosate, commercially sold as Roundup. It kills the plants inhibiting their ability to produce amino acids. The herbicide is sprayed from small aircrafts as closely as possible to the coca crops.
[49] Manual eradication is performed by a group of men who destroy coca crops by hand.

disintegrate entire communities, and appropriate territory (Calderón-Mejía and Ibáñez, 2015; Roche-villarreal, 2012).[50] According to Ibáñez (2009a) the occurrence of massacres account for about one fifth (21.1%) of the total forced displacements.

Forced displacement and massacres are strongly linked at the municipal level in Colombia. In particular, high incidences of displacement and massacres coincide in 66.2% of Colombian municipalities; conversely, municipalities with low incidences of forced migration also exhibit a low incidence of massacres (Ibáñez and Vélez, 2008).

Second, kidnappings, just like other acts of violence, serve to remind the local inhabitants that coercive threats are real, and that a violent event could happen to anyone within the community boundaries (See Moya (2012)). According to Ibáñez (2009a) kidnappings explain 7.6% of the total forced displacements.

Third, there is evidence of a positive effect of the drug trade on violence (Dell, 2015; Dube and Vargas, 2013; and Angrist and Kugler, 2008). The presence of coca has fuelled Colombia's long enduring civil conflict. Despite the fact that coca production appears to improve crop producers' income, violence increases sharply in the coca-growing regions. Guerrillas derive substantial income by taxing coca-growers. Violence, or the threat of violence, is regularly used to enforce coca farming contracts in this illegal industry, which ultimately leads to displacement (See Acevedo, 2015; Rabasa and Chalk, 2001).

In particular, coca leaf production and forced displacement are potentially related. According to Ibáñez (2009,a) the growth in illicit crop areas adds pressure on land and displacement not only because of the acquisition of lands for cocaine and poppy crops by illegal armed groups but also due to the importance of establishing transport routes for drugs. This is tested empirically by Dueñas et al. (2014). The authors, using fixed effects municipal panel data estimation for the period 2004–2009, report that the rates of expulsion of the forced displaced is positively correlated with the higher areas under coca cultivation.

[50] Most massacres were committed during the time of the right-wing paramilitary activity between 1999 and 2003, rendering this armed group responsible for 58% of these cases.

Angrist and Kugler (2008) explain that coca crops generate only modest economic gains by farmers, mostly in the form of increased self-employment earnings[51] , and increased labour supply provided by teenage boys. However, rural areas which experience accelerated coca production subsequently become more violent due to an increase in the economic resources available to illegal armed actors. This in turn leads to increased forced displacement. In contrast, Acevedo (2015) suggests that coca production by farmers in some situations is not a voluntary choice. Instead it is forced by the illegal armed groups. In particular, coca planting, harvesting and processing into cocaine are activities that may be enforced with violence or the threat of violence. This is consistent with some anecdotal evidence that suggests that the economic benefits of coca growing are largely taxed. This kind of reasoning postulates that an increase in coca productivity should be associated with expansion efforts by the coercive non-state armed groups and a decrease in forced displacement. The Acevedo (2015) results confirm that an additional millimetre of precipitation above the municipality mean, which positively affects the yield of the crops, decreases forced displacement by 1.22% in coca-suitable areas with rich harvest data. An inference to be drawn from this is that forced displacement occurs only when farmers are able to leave "safely" the coca farming contract (and the region) thus mitigating the risks of retaliation.

Finally, programs to eradicate illicit crops may also produce displacement. According to Engel and Ibáñez (2007) aerial fumigation of illicit crops destroys farmer assets, generating a negative income shock. This exacerbates violence in coca crops regions. Especially, the Forced Eradication Anti-Drug Programs in Colombia is one of the most aggressive programs in the world.[52] Data from the Colombian Anti-narcotics Police (DIRAN) suggest that in 2014 these programs treated around 68,050 hectares (UNODC, 2015). According to Rozo (2013), when the share of municipality area sprayed increased by 1%, the homicide rates increased by 4.56 per 100,000 inhabitants, the number of armed engagements increased by 1.69 per 100,000 inhabitants and the number of displaced people increased by around 41.6 per 100,000 inhabitants in the municipality.

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[51] Coca cultivation *per se* may do little to enrich the cultivators. The price of raw coca leaf makes up a small fraction of the price of cocaine.

[52] Aerial spraying was first implemented in Colombia in 1978. Manual eradication programs began in 2007 and are modest in size given its high cost in terms of human lives. Reports from the Anti-narcotics National Police estimate that since its implementation, 135 men have been killed through explosions of mines hidden in the ground to prevent the eradication (Gaviria and Mejía, 2011).

In regard to the "orthogonality" of these instruments, which imply that they are independent of forest cover, all three instrument are as good as randomly assigned. First, the massacres reflect a complex interaction between gangs, paramilitaries, guerrillas and drug trafficking interests, which together have created several cycles of extreme violence in different geographies independently of forest cover presence. Second, forest cover has nothing to do with kidnappings. Kidnap victims are frequently targeted for their political beliefs or their wealth, and even others due to being in the wrong place at the wrong time. Today kidnapping is becoming not as lucrative as drug trafficking, is riskier and requires more resources than other crimes like extortion. And, third, the monitoring of coca crops cultivation in Colombia is based on the interpretation of satellite images and the validation of the data obtained through aerial or terrain reconnaissance each semester. Hence, eradication depends on detection. It can also be said that the cultivation of coca occurs in agricultural hubs, which means that it is not necessary to clear forests to plant coca bushes (See Dávalos et al., 2011)

The vector $X_{i,t}$ represents the municipal characteristics that affect forest cover. In particular, equation (4.1) controls for the legal[53] extraction of valuable minerals such as gold, silver or platinum in municipality *i* in year *t.* Due to the potential bias that its inclusion might cause through a potential simultaneity problem with the dependent variable, the lag of the mining presence variable is used. In particular, mining is expected to have a negative environmental impact. It involves increased erosion, loss of biodiversity, and the contamination of soil, ground and surface waters by chemicals. Mining also often requires the clearance of large areas of forest, both for the mine itself, but also to create space for the storage of the created debris, and for the roads and other required infrastructures. Mining can be interpreted as part of the mechanisms enhancing conflict driven deforestation. For example, when the prices of minerals increase and/or national security policies reduce the incomes of the guerrilla groups and/or criminal gangs (e.g., the illegal incomes earned from kidnapping and drug trafficking), these illegal actors frequently finance themselves through mining. For example, it is well known that FARC controls mines legally or illegally either through having direct stakes in operations

[53] There are only official statistics for the legal extraction of minerals. At the moment, the government is trying to formalise the status of traditional miners who operate without licenses, while concurrently cracking down on those which serve the rebel groups and criminal gangs.

or through extortion, respectively.[54]

Mining usually occurs in those municipalities rich in environmental resources - from the Pacific lowlands and rivers of the Amazon to the coffee-growing regions. Around 18%[55] of Colombia's territory has been licensed to national and multinational corporations in order to develop mining projects. This fact reflects the government's objective to turn the country into a mining powerhouse. Some mining requests have even been granted in protected forested areas such as national parks, indigenous territories and collectively held lands occupied by communities of African heritage.[56]

In Equation (4.1), the additional time varying controls included are the municipal population and municipality urbanization levels. Both variables account for the pressure of human activities on forests, capturing the increased demand for food products and timber which leads to both the need for converting forests into land for agriculture and an over-exploitation of forests.

The income tax revenue per inhabitant, which mirrors the heterogeneity in the overall economic activities at the municipality level, is also included as a control variable. Due to the high degree of fiscal decentralization, Colombian municipalities differ in terms of their fiscal abilities. There is significant dispersion in terms of a municipality's ability to raise local taxes or to invest tax revenues generated locally (Cardenas et al., 2016).

A potential question is whether any of the explanatory variables in the model, might also be affected by the presence of conflict. Although there is a link, the yearly effect of the conflict on population and urbanization is not sizeable when compared to the more standard natural drivers of population such as births and deaths. Thus, according to

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[54] According to governmental estimates around 80% of all gold in the country is mined illegally, and as much as 20% of the profits from these illegal activities go to the FARC, ELN and other criminal organizations. See also the article entitled "El medio ambiente: la víctima olvidada" in an online special edition of Semana Magazine retrieved from: http://sostenibilidad.semana.com/medio-ambiente/multimedia/medio-ambiente-conflicto-colombia/33709

[55] This is according to statistics from the Mining and Energy Planning Unit (UPME, acronym in Spanish). This share corresponds to the current and potential mining areas estimates. See also the article entiled "En sus 130 años, la U. Externado entrega estudio sobre minería" in El Tiempo newspaper retrieved from: http://www.eltiempo.com/estilo-de-vida/educacion/universidad-externado-entregara-estudio-sobre-mineria/16510296.

[56] See the article "Fiebre minera se apoderó de Colombia" in Semana magazine retrived from http://www.semana.com/nacion/articulo/la-fiebre-minera-apodero-colombia/246055-3

official statistics during the study period (2004-2012) the average yearly rate of reception[57] of displaced people is 8.6 per 1000 inhabitants (8.0 per 1000 inhabitant in urban municipalities). On the other hand, while the average yearly birth rate is 15.7 per 1000 inhabitants (16.1 per 1000 inhabitants in urban municipalities), the average yearly deaths rate is 4.3 per 1000 inhabitants (4.5 per 1000 inhabitants in urban municipalities). Hence, the rate of natural increase of the population (and urban populations) is greater than the rate of reception of displaced people (also with respect to urban municipalities). Migration, which is not necessarily directly related to conflict in many cases and is difficult to quantify, is likely to have an effect on urban population growth. In any event, the key purpose of the variables relating to population and urbanization are to act as controls. There is no research interest in this study to causally identify the impact of conflict on municipal population and urbanization levels. That represents a different research question and is not the primary one investigated here.

Finally, the inclusion of municipality fixed effects (α_i) controls for any municipality-specific characteristics that are assumed constant over time. The time fixed effects (λ_t) control for aggregate time trends in forest cover, and thus potentially capture macroeconomic shocks and outcomes to any shifts in deforestation policies that may have occurred in particular years. The standard errors are clustered at the municipality level and are thus robust to the presence of both autocorrelation and heteroscedasticity (Stock and Watson, 2008).

4.4 Data

The panel dataset used consists of annual municipal-level observations from 2004 to 2012 (inclusive). Colombia has a total of 1,123 municipalities. However, we use only 859 of these municipalities given the requirement around the availability of satellite data to compute the forest coverage variable. The forest cover variable calculations were done by research staff at the International Centre for Tropical Agriculture (CIAT) using satellite images (at 30-meter resolution) compiled by the Department of Geographical

[57] It corresponds average number of displaced people that arrived to municipalities divided by its population per 1000 inhabitants in the study period.

Sciences at the University of Maryland partnering with other major research centres[58] in the United States (Hansen et al., 2013). For 265 of the municipalities, the forest cover estimates using satellite images were either not available at all, or only available for one or, in some exceptional circumstances, just two years. The criterion used here for the empirical analysis is that the data panel requires observations on forest cover must be available for a minimum of three continuous years.

Although this may be viewed as a limitation, we present three reasons why we believe this should not be a major concern for the empirical analysis undertaken here. First, the Figure 8.2.1 in the Appendix 8.2, which presents the final sample map, reveals that the location of the municipalities excluded are in fairly remote parts of the country.[59] In particular, some are situated in the Amazon Jungle, South East Colombia bordering Brazil, while others are in the Chocó Department, Northwest Colombia, which borders Panama, and is also a jungle area and rich in natural resources. The other missing areas included are in the Orinoquía Region, East Colombia, which borders Venezuela, also known as the "Eastern Plains" ("Llanos Orientales" in Spanish), where traditionally raising beef cattle and oil exploitation occurs; the Cesar Department, North Colombia, part of the Caribbean regions with valleys; and in Norte de Santander Department bordering Venezuela, with a mixed geography comprising mountainous areas, deserts, plateaux, plains and hills.

Second, in order to examine the relationship between the conflict and the forestation impacts using relevant maps, Figure 8.2.1 in Appendix 8.2 presents a map of the main locations of forced displacement in Colombia for the last decade[60], which reflects visual testimony of where in Colombia the armed conflict has had an incidence. The considerable overlay between maps, Figure 8.2.2 (which proxies the presence of conflict) and Figure 8.2.1 (which maps the final sample locations), both reported in the Appendix 8.2, suggest a plausible correlation between the conflict locations and the forest cover areas that are available to us for analysis. We highlight that we do not know a priori the sign of the direction of a causal relationship. However, since the municipalities excluded

[58] Google; the Department of Forest and Natural Resources Management, State University of New York; the Woods Hole Research Center; the Earth Resources Observation and Science, United States Geological Survey; and the Geographic Information Science Center of Excellence, South Dakota State University.

[59] The final sample includes municipalities with prominent economic *activity*.

[60] 2005-2014.

from the analysis are fairly remote, we can say with some degree of confidence that their exclusion is unlikely to affect the sign of the correlation that we are trying to disentangle empirically in the econometric analysis.

Third, Table 4.4.1 presents the summary statistics for the final sample. In addition, Table 8.2.1 and Table 8.2.2 reported in Appendix 8.2 reports the mean statistics for the key variables for the omitted municipalities, and the means statistical differences t-test between both samples. The mean values for the direct conflict kidnappings per 100.000 inhabitants (lagged one year), the percentage of the agricultural frontier with coca crops fumigates and manually eradicated (lagged one year), the percentage of the municipal area with coca fumigated and manually eradicated (lagged one year), mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year), and the income tax revenue per inhabitants are broadly similar between samples. The sample mean values of the share of municipality area with forest coverage [0-100], the forced displacement per 1000 inhabitants, victims of massacres per 100,000 inhabitants (lagged one year), the percentage of urban population, and the municipal population are statistically different between these samples. Overall, the variable means are not necessarily similar for these two sets of municipalities.[61] It should be stressed that these comparisons are likely to be unreliable given the significant presence of missing values in the set of remote and excluded municipalities.

However, given the differing geographical and socio-economic nature of the included and excluded municipalities, the detection of differences in observables is to be anticipated. Our argument is that the econometric results are conditional on the sample used. We acknowledge the data that we are employing may not be representative of the country. This does not vitiate the analysis nor does it undermine our attempt to identify the size and the sign of the effect of conflict on forest cover in those areas where conflict has had the most pervasive effect.

Table 4.4.1, as mentioned, presents the descriptive statistics employed in the regression analysis for coefficients interpretation purposes. Note that the sample period is adjusted to start at year 2005. This is because the 2004 observations are "lost" when the set of

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[61] This result is not surprising, as mentioned, due to the absence in the final sample of a significant part of the Amazon Jungle and the forests of Chocó Department.

instruments are lagged one year. As noted above, the primary outcome is the share of municipality area covered by forest. Between 2005 and 2012, the average share of the municipality area covered with forest is more than half (58.4%) the land size of Colombia.

Table 4.4.1 Summary statistics

Variable	Mean	SD	Min	Max
Share of municipality area with forest [0-100%]	58.40	25.85	0.67	98.93
Forced displacement per 1000 of the municipal population	10.09	22.87	0.00	702.72
Victims of massacres per 100,000 inhabitants (lagged one year)	0.43	4.98	0.00	187.62
Direct conflict kidnappings per 100.000 inhabitants (lagged one year)	1.04	5.56	0.00	185.56
Hectares of coca fumigated and manually eradicated (lagged one year)	173.23	1091.46	0.00	34432.53
Percentage of the agricultural frontier with coca crops fumigates and manually eradicated [0-100%] (lagged one year)	0.12	0.75	0.00	27.63
Percentage of the municipal area with coca fumigated and manually eradicated [0-100%] (lagged one year)	0.11	0.68	0.00	24.81
Mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year)	0.16	0.36	0.00	1.00
Population	32027.15	80091.16	885	1200513
Log Population	9.58	1.10	6.79	14.00
Percentage of urban population [0-100]	43.10	23.79	1.68	99.89
Income tax revenue per inhabitants (COP[62])	86762.13	126009.15	385.47	2749220
Log income tax revenue per inhabitants	10.93	0.97	5.95	14.83

Statistics refer to N = 6826 observations for 859 municipalities over the period 2005-2012.

[62] Colombian peso.

Satellite images issues such as persistent cloud cover in the tropics, shadows from the tree canopy, and the complexity of forest structure can all lead to (random) small errors in forest cover calculations. Furthermore, the ambiguity in the concept "forest" leads to different assessments of the extent of forest cover. For example, geographers and ecologist have long called for the definition to be more standardized. One scientist could consider that the area is forested if 30 percent of the land is covered with trees (the definition employed here by CIAT), while another could argue that a forest exits when there is 10 percent tree cover and excluding areas of intermediate tree cover, such as savannahs, scrublands, mountain ridge forests, and boreal taiga. Thus, many researchers currently claim that there should be either a single, unambiguous definition of forest/non-forest that can be used globally or, preferably, that the research community should shift to the use of measureable ecological characteristics such as tree cover, canopy height, and/or biomass.

The use of satellite images for forest cover is not free from critics. However, if the estimation manages to yield statistically significant coefficients with an apparent mis-measured dependent variable, this is actually good news. Measurement error in the dependent variable does not cause the slope coefficients to be biased, but it does cause the standard error for the slope coefficients to be larger, which suggests that in this case a statistical significant coefficient is way more significantly different from zero.

The primary conflict variable is the forced displacement rate per 1,000 of the population ($FD_{\mathrm{i,t}}$) and is calculated based on estimates from the Information System of Displaced Population (SIPOD, its Spanish acronym), the Central Registry for Victims Office (RUV)[63], and the Observatory of the Presidential Human Rights and International Humanitarian Law of the Vice Presidency of Colombia. As discussed in Section 3, the main drawback on displacement statistics is under-reporting. In the dataset, an average of 10.09 people per 100,000 inhabitants were forcibly displaced due to violence at the municipal level. One municipality experienced a displacement of 702.7 people per 100,000 of its population in one year (see Table 4.4.1).

[63] This registry, established under Act 1448 of 2011, contains the number of registered victims of human rights violations during the armed conflict and over the period from 1985 to the present.

Regarding the data sources for the identifying instrumental variables, the victims of massacres per 100,000 inhabitants are based on data from Colombia's National Centre of Historical Memory. The statistics on the direct conflict kidnappings[64] per 100,000 inhabitants are taken from a conflict panel dataset constructed by the Centre of Development Economics Studies (Centro de Estudios sobre Desarrollo Económico, CEDE in Spanish), Universidad de los Andes, Bogotá, Colombia.

The number of hectares of coca fumigated and manually eradicated in the municipalities is calculated using satellite-based information from the Integrated Monitoring System of Illicit Crops of the United Nations Office of Drugs and Crime (SIMCI[65]-UNODC) and the Anti-Narcotics Directorate of the Ministry of National Defence in Colombia. The municipal agricultural frontier area corresponds to the sum of agricultural, agroforestry, animal husbandry and forest vocation areas calculated by the Geographic Institute Agustin Codazzi (IGAC, in Spanish).

In the municipality dataset used in the regressions, around 0.43 people per 100,000 of the population were killed in massacres, with a maximum reported of 187.6 per 100,000 inhabitants. Armed groups kidnapped one person 1.04 per 100,000 inhabitants and the military fumigated and manually eradicated a total of 173.2 hectares of coca plants on average, which corresponds to circa 0.12% and 0.11% of the average municipal agricultural frontier and municipal area, respectively (see Table 4.4.1).[66]

A dichotomous variable [Yes=1; No=0], representing the extraction of elements such as gold, silver or platinum, is constructed using data on municipal mining records from the Colombian Mining Information System (SIMCO, its Spanish acronym). About 16% of the municipalities have mining activities, producing gold, silver or platinum (see Table 4.4.1).

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[64] Bear in mind that these types of kidnappings mainly target businessmen, political leaders and senior members of the army.

[65] This is known as the Integrated System for Monitoring Illicit Crops (SIMCI, according to its Spanish acronym).

[66] Not all municipalities of the country produce coca. In fact, only 16% of municipalities produce coca, on average.

The information on socioeconomic and geographic covariates such as the municipal population, the percentage of urban population, and the income tax revenue per inhabitant was provided by the National Administrative Department of Statistics (DANE, according to its Spanish acronym) and the National Planning Department (DNP, according to its Spanish acronym). The municipality average population is 31,846 inhabitants and almost half of these (43.1%) live in cities, and their inhabitants pay yearly on average COP 82,389.69 in income tax.

4.5 Empirical results

4.5.1 Validity of the instruments

The first stage regression results employing initially two instruments are presented in Table 4.5.1 with the standard IV-diagnostic tests presented in the bottom panel of this table.

Table 4.5.1 First stage reduced form results (two instruments)

Dependent variable: Forced displacement per 1000 inhabitants
Two instruments: a) Victims of massacres per 100,000 inhabitants (lagged one year); and b) Direct conflict kidnappings per 100.000 inhabitants (lagged one year)

	(1) 1st Stage FE
Victims of massacres per 100,000 inhabitants (lagged one year)	0.19**
	(0.083)
Direct conflict kidnappings per 100.000 inhabitants (lagged one year)	0.15**
	(0.070)
Mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year)	-1.69
	(1.69)
Log Population	-22.2**
	(10.4)
Percentage of urban population [0-100]	-1.21**
	(0.53)
Log income tax revenue per inhabitants	-0.57
	(0.75)
Year 2006	1.39*
	(0.74)
Year 2007	2.8***
	(1.05)
Year 2008	1.51
	(0.95)
Year 2009	-3.51***
	(0.99)
Year 2010	-5.32***
	(1.14)
Year 2011	-3.89***
	(1.37)
Year 2012	-4.03**
	(1.59)
Observations	6826
Cragg-Donald Wald F statistic	16.99
Hansen J statistic	0.000
Hansen p-value	0.999

Std. Err. (in parentheses) adjusted for clusters in municipality
* $p < .10$, ** $p < .05$, *** $p < .01$

The IV estimator is based on asymptotic properties. Thus, it is subject to finite sample bias which can only be reduced through using stronger and more relevant instruments. In addition, using stronger instruments ensures that the estimator follows a normal distribution. That's why the relevance condition is so important.[67]

[67] It is possible to attempt to bypass the endogeneity issue by using explicitly the lagged values of $FD_{\mathrm{i,t}}$ (See Table 8.2.3 in the Appendix chapter 4), however, the correct method of estimation is IV.

The Cragg and Donald (1993) test yields a value 16.99, indicating that the instruments are relevant. However, the result comfortably passes the 'rule-of-thumb'[68] value of 10. The Hansen (1982) J-test provides a p-value of 0.999. Thus, the null hypothesis of zero correlation between the instruments and the error term is upheld at the conventional significance levels, though the prob-value is acknowledged to be on the high side.

We now turn to an interpretation of the estimates for the selected identifying instruments. The individual significance of these identifying instrument imply that the military strategies adopted by the illegal armed groups and forced displacements are strongly correlated. Indirect violence, including massacres and directly related conflict kidnappings, play a strong role in determining civilian displacement. If the number of victims of massacres per 100,000 municipality inhabitants in the previous year increases by 1, which is a sizeable increase relative to the mean, approximately 1.9 persons per 10,000 of the population are forced displaced, on average and *ceteris paribus*. The empirical estimates also reveal that an increase in 1 conflict-related kidnapping in the previous year per 100,000 inhabitants, which is effectively a doubling relative to the sample mean, is associated with an increase of 1.5 displaced persons per 10,000 of the municipal population, on average and *ceteris paribus*.

In order to improve IV models efficiency, the use of a third instrumental variable related to drug production in municipality *i* is explored as well. The first stage regression results including the percentage of the agricultural frontier with coca crops fumigated and manually eradicated; or the percentage of the municipal area with coca fumigated and manually eradicated, along with the standard IV-diagnostic tests are presented in Table 4.5.2 and Table 4.5.3, respectively. In both cases, the estimated coefficient associated with the instrument with coca crops presence is borderline statistically significant with a t-ratio of 1.6. However, overall all three instruments are jointly statistically significant with a F-test of 14.26 and 14.34, respectively, which exceed the conventional 'rule-of-thumb' of 10.

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[68] This rule-of-thumb means that we are tolerating a 10% finite sample bias in the IV estimator relative to the OLS estimator.

Table 4.5.2 First stage reduced form results (Three instruments A.)

Dependent variable: Forced displacement per 1000 inhabitants
3rd instrument: Percentage of the agricultural frontier with coca crops fumigates and manually eradicated (lagged one year)

	(1) 1st Stage FE
Victims of massacres per 100,000 inhabitants (lagged one year)	0.18**
	(0.082)
Direct conflict kidnappings per 100.000 inhabitants (lagged one year)	0.15**
	(0.070)
Percentage of the agricultural frontier with coca crops fumigates and manually eradicated (lagged one year)	1.19
	(0.74)
Mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year)	-1.62
	(1.68)
Log Population	-22.1**
	(10.3)
Percentage of urban population [0-100]	-1.21**
	(0.53)
Log income tax revenue per inhabitants	-0.59
	(0.75)
Year 2006	1.31*
	(0.75)
Year 2007	2.68***
	(1.04)
Year 2008	1.41
	(0.95)
Year 2009	-3.59***
	(0.99)
Year 2010	-5.35***
	(1.14)
Year 2011	-3.89***
	(1.36)
Year 2012	-4.03**
	(1.59)
Observations	6826
Cragg-Donald Wald F statistic	14.26
Hansen J statistic	0.0883
Hansen p-value	0.957

Std. Err. (in parentheses) adjusted for clusters in municipality
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 4.5.3 First stage reduced form results (Three instruments B.)

Dependent variable: Forced displacement per 1000 inhabitants
3rd instrument: Percentage of the municipal area with coca fumigated and manually eradicated (lagged one year)

	(1) 1st Stage FE
Victims of massacres per 100,000 inhabitants (lagged one year)	0.18**
	(0.082)
Direct conflict kidnappings per 100.000 inhabitants (lagged one year)	0.15**
	(0.070)
Percentage of the municipal area with coca fumigated and manually eradicated (lagged one year)	1.32
	(0.83)
Mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year)	-1.62
	(1.68)
Log Population	-22.1**
	(10.3)
Percentage of urban population [0-100]	-1.21**
	(0.52)
Log income tax revenue per inhabitants	-0.59
	(0.75)
Year 2006	1.31*
	(0.75)
Year 2007	2.68***
	(1.04)
Year 2008	1.41
	(0.95)
Year 2009	-3.59***
	(0.99)
Year 2010	-5.35***
	(1.14)
Year 2011	-3.88***
	(1.36)
Year 2012	-4.02**
	(1.59)
Observations	6826
Cragg-Donald Wald F statistic	14.34
Hansen J statistic	0.0923
Hansen p-value	0.955

Std. Err. (in parentheses) adjusted for clusters in municipality
* $p < .10$, ** $p < .05$, *** $p < .01$

The disruption of drug production and forced displacement are also correlated. If a municipality is subject to a one percentage point increase of the agricultural frontier with coca crops fumigates and manually eradicated, or a one percentage point increase in the municipal area with coca fumigated and manually eradicated, both in the previous year (and representing substantial increases of circa 8.3 and 9 times their mean, respectively), this leads to an increase of 11.9 and 13.2 forced displaced persons per 100,000 municipality inhabitants, on average and *ceteris paribus*. If the scale of disruption activities is correlated with the scale of drug production activities, this result is consistent with the literature indicating that coca production is associated with the establishment of coercive institutions governed by the illegal armed groups. Thus, forced displacement only occurs when farmers are able to escape safely from the region (Acevedo, 2015).

The instruments related to victims of massacres and conflict kidnappings maintain their expected sign, size and statistical significance.

4.5.2 IV Estimates of the Causal Effect

Table 4.5.4 provides evidence on the relationship between the armed conflict and forest coverage in Colombia using initially two instruments. In particular, it provides estimates based on treating forced displacement per 1000 of the municipal population endogenously and instrumenting it (FE-IV). Under this context the results are a causal effect and, in some sense, a Local Average Treatment Effect (LATE). The treatment effect estimate is local, because it only applies to the subset of municipalities who are exposed to the treatment and experience forced displacement, because of variation in the instruments.[69] The model also includes the controls described in Section 4.3.

[69] The IV estimate can be interpreted under weak conditions as a weighted average of LATEs, where the weights depend on the elasticity of the endogenous variable to changes in the instruments. This means that the effect of a variable is only revealed for the sub-populations affected by the observed changes in the instruments, and that sub-populations which respond most to changes in the instruments will have the largest effects on the magnitude of the IV estimate.

Table 4.5.4 Forest cover FE-IV equation estimates (two instruments)

Dependent variable: Share of municipality area with forest [0-100]
Two instruments: a) Victims of massacres per 100,000 inhabitants (lagged one year); and b) Direct conflict kidnappings per 100.000 inhabitants (lagged one year)

	(2) 2nd Stage FE-IV
Forced displacement per 1000 of the municipal population	0.012
	(0.0074)
Mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year)	-0.076
	(0.056)
Log Population	-2.89***
	(0.51)
Percentage of urban population [0-100]	-0.035
	(0.025)
Log income tax revenue per inhabitants	0.054*
	(0.029)
Year 2006	-0.20***
	(0.017)
Year 2007	-0.43***
	(0.030)
Year 2008	-0.60***
	(0.033)
Year 2009	-0.81***
	(0.051)
Year 2010	-0.96***
	(0.066)
Year 2011	-1.17***
	(0.069)
Year 2012	-1.40***
	(0.077)
Observations	6826
R-Squared	0.536
F-stat	105.0
Exogeneity test statistic	2.027
p-value (Ho: Regressor is exogenous)	0.155

Std. Err. (in parentheses) adjusted for clusters in municipality
* $p < .10$, ** $p < .05$, *** $p < .01$

On the basis of the instruments used, the exogeneity assumption for the forced displacement variable is not rejected by a Hausman test (p-value of 0.155), thus, confirming there is no need to use IV techniques in the application using two instruments. The same happens when employing a third instrument related to drug production in the municipality. In particular, the Hausman test p-values are 0.12 and 0.13, respectively (See Table 4.5.2 and Table 4.5.3).

Table 4.5.5 Forest cover FE-IV equation estimates (three instruments A.)

Dependent variable: Share of municipality area with forest [0-100]
3rd instrument: Percentage of the agricultural frontier with coca crops fumigates and manually eradicated (lagged one year)

	(2) 2nd Stage FE-IV
Forced displacement per 1000 of the municipal population	0.011*
	(0.0063)
Mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year)	-0.077
	(0.055)
Log Population	-2.90***
	(0.50)
Percentage of urban population [0-100]	-0.036
	(0.024)
Log income tax revenue per inhabitants	0.054*
	(0.029)
Year 2006	-0.20***
	(0.016)
Year 2007	-0.42***
	(0.028)
Year 2008	-0.60***
	(0.032)
Year 2009	-0.81***
	(0.049)
Year 2010	-0.97***
	(0.063)
Year 2011	-1.17***
	(0.066)
Year 2012	-1.41***
	(0.075)
Observations	6826
R-Squared	0.541
F-stat	105.5
Exogeneity test statistic	2.314
p-value (Ho: Regressor is exogenous)	0.128

Std. Err. (in parentheses) adjusted for clusters in municipality
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 4.5.6 Forest cover FE-IV equation estimates (three instruments B.)

Dependent variable: Share of municipality area with forest [0-100]
3rd instrument: Percentage of the municipal area with coca fumigated and manually eradicated (lagged one year)

	(2) 2nd Stage FE-IV
Forced displacement per 1000 of the municipal population	0.011*
	(0.0063)
Mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year)	-0.077
	(0.055)
Log Population	-2.91***
	(0.50)
Percentage of urban population [0-100]	-0.036
	(0.024)
Log income tax revenue per inhabitants	0.054*
	(0.029)
Year 2006	-0.20***
	(0.016)
Year 2007	-0.42***
	(0.028)
Year 2008	-0.60***
	(0.032)
Year 2009	-0.81***
	(0.049)
Year 2010	-0.97***
	(0.063)
Year 2011	-1.17***
	(0.067)
Year 2012	-1.41***
	(0.075)
Observations	6826
R-Squared	0.541
F-stat	105.5
Exogeneity test statistic	2.260
p-value (Ho: Regressor is exogenous)	0.133

Std. Err. (in parentheses) adjusted for clusters in municipality
* $p < .10$, ** $p < .05$, *** $p < .01$

4.5.3 The OLS fixed effects (FE-OLS)

The OLS fixed effects (FE-OLS) estimation are presented in Table 4.5.7. The downward bias of the OLS fixed effects (FE-OLS) of γ (0.0028) relative to the IV models (0.012 and 0.011, using two and three instruments, respectively) estimates suggests that measurement error is a probable source of the downward bias reported, which dominates the simultaneous reverse causality problem. Note that the use of municipal fixed effects is likely to attenuate the omitted variable bias problem here. Nonetheless, the more appropriate method to make inferences is the OLS fixed effects (FE-OLS) model, in the light of the Exogeneity tests involving the selected set of instruments used.

Table 4.5.7 Forest cover FE-OLS equation estimates

Dependent variable: Share of municipality area with forest [0-100]	
	FE-OLS
Forced displacement per 1000 of the municipal population	0.0028^{**}
	(0.0011)
Mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year)	-0.090^{*}
	(0.051)
Log Population	-3.07^{***}
	(0.48)
Percentage of urban population [0-100]	-0.046^{**}
	(0.023)
Log income tax revenue per inhabitants	0.048^{*}
	(0.029)
Year 2006	-0.19^{***}
	(0.012)
Year 2007	-0.40^{***}
	(0.023)
Year 2008	-0.59^{***}
	(0.031)
Year 2009	-0.84^{***}
	(0.041)
Year 2010	-1.01^{***}
	(0.050)
Year 2011	-1.21^{***}
	(0.059)
Year 2012	-1.44^{***}
	(0.067)
Observations	6826
R-Squared	0.571
F-stat	108.6

Std. Err. (in parentheses) adjusted for clusters in municipality
* $p < .10$, ** $p < .05$, *** $p < .01$

We now focus, therefore, on the FE-OLS model estimates for our discussion of the causal estimate of interest. The estimate in column two is well determined statistically and suggests that an increase in one forced displaced person per 1,000 of the municipal population, which represents a 9.91% increase with respect to the sample mean, increases the share of the municipality covered by forest by 0.0028 of a percentage point, on average and *ceteris paribus*. This represents a small effect relative to the mean forest coverage rate of 58.4%. In other words, an approximate 10% increase in displaced person per 1,000 of the population leads to a 0.003% increase in forest cover.

Although the estimated effect is economically small in terms of its magnitude, the explanation for this is straight-forward. The presence of armed groups means that large rural areas become inaccessible and thus are preserved and protected from the economic forces and rural production activities that encourage deforestation. In this case, the armed conflict appears to be a force that favours forest protection and growth, albeit in extremely modest terms. As mentioned previously, this is because some of the armed groups practice a form of forest conservation, although one situated within a highly localized and coercive framework and entirely to the benefit of such groups rather than the environment.

Regarding the other municipality-level characteristics that are statistically significant, the presence of mining, as expected, has a negative environmental impact. A municipality in which there was extraction of elements such as gold, silver or platinum compared to another that did not experience extraction, in the previous year, exhibits a reduction of 0.09 percentage points in the share of municipality area covered by forest, on average and *ceteris paribus*.

On the other hand, a 10 percent increase in the municipality population is associated with a 0.307 percentage points decrease in the share of municipality area covered by forest. This effect is anticipated as it reflects the impact of population pressure on forest resources and their conservation. The population effect could be easily interpreted as an increase of one person per 1,000 of the municipal population, which is equivalent to a 3.12% increase in the population. This increase is associated with a 0.096 percentage point reduction in the share of municipality area covered by forest. Population pressure reduces the forest cover thirty-four times (34.2) more than the effect induced by forced displacement when using the same metric (i.e., one person per 1,000 increase of the municipal population). This confirms the relatively small magnitude of the forced displacement effect on forest cover compared to conventional demographic pressures on forestation.

An increase of 10 percentage points in the percentage of urban population is related to a 0.46 percentage point decrease in the share of municipality area with forest cover, on average and *ceteris paribus*.

In addition, an increase of 10 percentage points in the income tax revenues per inhabitant is associated with a 0.0048 percentage point increase in the share of municipality area covered with forest. This may reflect the fact that revenues are being used to conserve forests. The estimate may also reflect the role of governance and the rule of law. However, revenues are mainly generated in major cities reflecting the strength of local economies already in place. The concentration of people in cities leaves room for nature. It is likely that major cities do not have large sized forests left to clear. Large industrial farms have already taken over rural areas and expanded further into the nearest forests.

Finally, the estimated time dummy effects reveal sizeable annual reductions in forest coverage. The average effects per year are about one-fifth of a percentage point, *ceteris paribus*. This does suggest a secular trend in deforestation, the magnitude of which is sizeable compared to the estimates corresponding to the other regressors included in this specification.

4.6 Are coca crops to blame for forest cover loss?

In this section, we explore some alternative expressions of the conflict to test the sensitivity of the IV results obtained in the last section. Often when exposed to high levels of violence, farmers tend to reduce the allocation of land devoted to legal crops. Illegal crops are planted instead and additional forest clearing occurs (Ibañez et al., 2013). Between 2001 and 2014, it is estimated that planting coca has caused the deforestation of around 290,992 hectares of forest, which is equivalent to a little over twice the area of Bogotá city (UNODC, 2015). Therefore, we use the presence of coca crops to re-estimate Equation (4.1) with the presence of coca crops replacing the forced displacement variable.

The conflict variable in Equation (4.1) is now represented by the presence of coca crops in the municipalities. The selected set of instruments that meet the econometric requirements for valid instruments are the lagged number of dismantled coca crystal laboratories and the confiscation of cocaine paste base (tons).[70] In particular, both measures are taken to reflect the government's capacity to counteract criminal activity in the municipalities, and are also highly correlated with the armed conflict. In addition, it is difficult to argue they are correlated with forest cover.[71]

Table 4.6.1 Summary statistics when the presence of coca crops is used as an explanatory variable

Variable	Mean	SD	Min	Max
Presence of coca crops [Yes=1; No=0]	0.16	0.37	0.0	1.0
Dismantling of coca crystal laboratories (number, lagged one year)	0.22	1.34	0.0	45.0
Confiscation of cocaine pasta base (tons, lagged one year)	0.052	0.420	0.0	18.72

Statistics refer to N = 6826 observations for 859 municipalities during 2004-2012.

Around 16% of the municipalities report the presence of coca crops. Regarding the set of instruments, the police dismantled 0.22 coca crystal laboratories and confiscate 0.052

[70] The "extraction" laboratories called "kitchens", "Chagres", "Chongos, "Saladeros", "Picaderos" are basic constructions at the farmers houses for the extraction of coca paste base by processing raw materials (plant material) using organic solvents. Thus, the coca pasta base is an extract of the leaves of the coca bush. It contains coca alkaloids, and its purification yields cocaine. Then, the coca crystal laboratories are those in which the cocaine is obtained through the chemical processes.

[71] Camacho and Rodriguez (2013) provide support for these instruments. In their study, the authors used an instrumental variable approach, in which contemporaneous armed conflict was instrumented with lagged government deterrence measures.

tons of cocaine paste base on average[72] (see Table 4.6.1). The data source for these variables is the Anti-Narcotics Directorate of the Ministry of National Defence of Colombia.

[72] The confiscation of cocaine paste base obviously is quite low in most of the municipalities, however, more than 90 experienced one ton or more up to a maximum of 18.72 tons.

Table 4.6.2 First stage results when the presence of coca crops is used as an explanatory variable

Dependent variable: Presence of coca crops [Yes=1; No=0]	(1) 1st Stage FE
Dismantling of coca crystal laboratories (lagged one year)	0.0098*
	(0.0050)
Confiscation of cocaine paste base (lagged one year)	0.014*
	(0.0081)
Mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year)	0.0091
	(0.011)
Log Population	0.091
	(0.073)
Percentage of urban population [0-100]	0.0024
	(0.0035)
Log income tax revenue per inhabitants	-0.0058
	(0.0065)
Year 2006	0.0078
	(0.0065)
Year 2007	0.0026
	(0.0071)
Year 2008	0.0096
	(0.0086)
Year 2009	0.015
	(0.0091)
Year 2010	0.0079
	(0.010)
Year 2011	0.012
	(0.011)
Year 2012	0.0085
	(0.012)
Observations	6826
R-Squared	0.89
Cragg-Donald Wald F statistic	13.87
Hansen J statistic	0.0372
Hansen p-value	0.847
Exogenity test statistic	0.021
Exogeneity p-value (Ho: Regressor is exogenous)	0.885

Std. Err. (in parentheses) adjusted for clusters in municipality
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 4.6.2 presents the first stage results. Both instruments signal the municipality's potential of producing coca. The strength of the instruments is assessed using the Cragg-Donald Wald F statistic (1993). The hypothesis of weak instruments is rejected, though again the relevance of the instruments is not strong with the Wald-transformed F-test for exclusion of instruments 13.87, only marginally above the threshold of 10. The Hansen (1982) J-test p-value is 0.84, hence, instruments are orthogonal to the error structure in the structural equation. However, the proposition that the presence of coca crops is exogenous cannot be rejected in this case. Therefore, the use of IV is not required. This indeed is confirmed by the exogeneity test, which yields a p-value of 0.885.

Table 4.6.3 Effect of the presence of coca crops on forest cover

Dependent variable: Share of municipality area with forest [0-100]

	FE-OLS
Presence of coca crops [Yes=1; No=0]	0.027
	(0.073)
Mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year)	-0.095*
	(0.052)
Log Population	-3.13***
	(0.49)
Percentage of urban population [0-100]	-0.049**
	(0.023)
Log income tax revenue per inhabitants	0.046
	(0.029)
Year 2006	-0.19***
	(0.012)
Year 2007	-0.40***
	(0.022)
Year 2008	-0.59***
	(0.031)
Year 2009	-0.85***
	(0.041)
Year 2010	-1.03***
	(0.050)
Year 2011	-1.22***
	(0.060)
Year 2012	-1.45***
	(0.068)
Observations	6826
R-Squared	0.568
F-stat	107.3

Std. Err. (in parentheses) adjusted for clusters in municipality
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 4.6.3 present the FE-OLS model results which is the more efficient method of estimation. Thus, the FE-IV results can be found in Table 8.2.4 in the Appendix 8.2.[73] Consistent with FE-OLS model results, the presence of coca crops has no effect on forest cover, on average. These results are plausible since coca crops account for only a small percentage of total deforestation rates. In addition, compared to a root vegetable like cassava, which requires a lot of space and effort to harvest but brings in a relatively small amount of money, the coca plant has a dense leaf cover and fetches high prices. This means that coca farmers obtain higher value per areas cultivated.

4.7 An Analysis of the forest cover OLS fixed effects estimates

Forests play a crucial role in biodiversity conservation. It helps to purify the air, sustain the quality and availability of freshwater supplies, and provide essential services to local

[73] The coefficients and the standard errors from the FE-IV estimates are almost identical to those from FE.

populations. Furthermore, forest preservation has been attracting increased attention in the fight against climate change. The FE-OLS model cannot accommodate time-invariant variables. Thus, any time-invariant variables are absorbed within the fixed effects. However, understanding which time-invariant factors potentially influence forest coverage is of considerable interest and may provide some insights that aid the design of policy interventions.

Equation (4.3) describes the model that examines the determinants of the estimated fixed effects retrieved from the estimation reported Table 4.5.7. These fixed effects are regressed on a set of time-invariant covariates and thus provide insights on the impact of time-invariant factors on municipality forest cover. The model is specified as:

$$\hat{\alpha}_i = c_i + \delta_i W_i + v_i \text{, with } i = 1; \ldots, n. \quad (4.3)$$

$\hat{\alpha}_i$ is the estimated municipality i specific fixed effect estimate corresponding to the coefficient on the municipality dummy variables in Equation (4.1). W_i is a vector of time-invariant covariates assumed to affect forest cover, which for the purposes of the analysis here include the municipality's degree of elevation, average monthly precipitation, the distance to the department capital, and a soil quality index. The variable c_i is the constant and the term v_i represents the error assumed to satisfy the standard assumptions. The analysis is conducted using only 848 (of 859) municipalities for which forest coverage and the other time-invariant covariates data is available.[74]

[74] In particular, we lost 11 data points due to the presence of missing values in the soil quality index. This index is calculated by the Geographic Institute Agustin Codazzi (IGAC, in Spanish) based on georeferenced information regarding topography types, drainage presence, municipality climates, and others fundamentals that affect soils quality.

Table 4.7.1 Time-invariant covariates summary statistics

Variable	Mean	SD	Min	Max
Municipality elevation (m)	1225.8	1221.9	2.0	25221.0
Avg. precipitation monthly (mm)	176.1	85.6	52.8	712.0
Distance to the department capital (km)	76.6	54.3	0.0	376.1
Soils quality index [1-8]	2.7	1.2	0.0	8.0

N=848 municipalities during 2004-2012.

The data source for the time-invariant covariates is the Centre of Development Economics Studies (Centro de Estudios sobre Desarrollo Económico, CEDE in Spanish), Universidad de los Andes, Bogotá, Colombia, which treasures official statistics produced by the National Administrative Department of Statistics (DANE, in Spanish), the Geographic Institute Agustin Codazzi (IGAC, in Spanish) and the National Planning Department (DNP, in Spanish). Table 4.7.1 above reports the summary statistics.

An average municipality has an elevation of 1,229.4 meters and the precipitation levels reach 173.5 millimeters (mm)[75] of rain monthly. The soil quality index measures the suitability of the land for agricultural activities depending on land topography and soil type. It ranges from 1.0 (not suitable for agriculture) to 8.0 (fully suitable for agriculture). The average municipality has a soil quality index value of 2.73.

Table 4.7.2 reports the estimates for a regression of the fixed effects estimates from the FE-OLS model (Section 4.5.3) on this set of time invariant variables using a Weighted Least Squares (WLS) method.[76] The weights are proportional to the estimated standard errors from the FE-IV model. Thus, the fixed effects that are more precisely estimated secure a higher weight in the WLS estimation procedure. Since each weight is inversely proportional to the standard error variance, it reflects the information contained in that fixed effect.

(See the

[75] The standard instrument for the measurement of rainfall is the 203mm (8 inch) rain gauge. This is a circular funnel with a diameter of 203mm which is kept in an open area, so that it collects the rain into a graduated and calibrated cylinder. The measuring cylinder can record up to 25mm of precipitation. The precipitation value in mm is referring to the amount of rain per square meter in one hour. One millimeter of rainfall is the equivalent of one liter of water per square meter.

[76] See Table 8.2.5 for the determinants of forest cover fixed effects using the OLS model.

Table 4.7.2 Determinants of forest cover fixed effects

Dependent variable: Estimated municipal fixed effects

	WLS
Municipality elevation (m)	0.0015*
	(0.00078)
Avg. precipitation monthly (mm)	0.14***
	(0.011)
Distance to the department capital (km)	0.028*
	(0.015)
Soils quality index [1-8]	-3.70***
	(0.70)
Constant	72.3***
	(3.58)
Observations	848
R-Squared	0.244

Robust (heteroscedasticity correction) std. err. (in parentheses)
WLS model weighting proportional to the u_i Std.Err.
$^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$

Most of the regressors have strong explanatory power.[77] This is confirmed by the R-squared indicating that the regressors explain almost a quarter (24.4%) of the variation in the FE-OLS coefficients. Fluctuations in temperature and rainfall levels are due mainly to changes in elevations. Elevation also affects biodiversity. The lowlands are often more easily accessible and thus more suitable for agriculture. Thus, according to Table 4.7.2 , an increase in elevation of 100 meters is associated with a 0.15 percentage points increase in the share of the municipality covered by forest. Forests are often located in tropical climates where precipitation is high and occurs all year-round. Therefore, an increase in 10 millimetres of average monthly precipitation (which represents about a 5.7% increase in monthly precipitation relative to the sample mean) is associated with a 1.4 percentage point increase in the share of the municipality covered by forest.

There is more pressure to convert forest land to non-forest uses particularly when forest land is located near main cities. In contrast, remote forest land tends to be less valuable and, therefore, more likely to be conserved. The estimates above confirm this dichotomy. Thus, an increase of 10 km in the distance to the department capital is associated with a 0.28 percentage points increase in the share of municipality area covered by forest, on average and *ceteris paribus*.

[77] We also included in the regression a land concentration measure based on a Gini coefficient. We found no impact of land holding inequality on deforestation. The estimated effect for the land concentration index is not found to be well determined at a conventional level.

On the other hand, agriculture is identified as a key factor implicated in forest degradation. This is likely to be exacerbated by poor agricultural technologies, which means that more land is cleared for agriculture. Areas with soil quality more suited to agricultural activity are likely to be associated with greater levels of deforestation. There is nothing wrong with deforestation due to agriculture production provided it is well planned and managed. The estimates reported here suggest that an increase of 1 unit in the soil quality index (approximately an increase of over 1/3 relative to the sample mean and implying better soil suitability for agriculture) is associated with a 3.7 percentage point decrease in the area of a municipality covered by forest.

Overall, the foregoing estimates suggest considerably stronger effects on deforestation mediated through elevation, precipitation, and soil quality compared to the magnitude detected for displacement effects due to conflict.

4.8 **Conclusions**

The literature on the impact of conflict and violence on forestation is ambiguous and many studies fail to address the endogeneity issue of the empirical relationship. On the one hand, violence could lead to more deforestation as armed groups exploit natural resources. On the other, the presence of armed groups also means that large rural areas become inaccessible and thus are preserved and protected from deforestation. So, the impact could go in either direction in theory and, therefore, the direction as well as the magnitude of the effect remains an empirical question.

A major challenge for this chapter was obtaining accurate estimates of the share of municipality area covered by the forest. However, the availability of satellite-based information on forest coverage for not less than three years in the period of the study restricts the panel data we use here to 859 municipalities, which represents about 76.6% of all municipalities in Colombia.[78]

The final sample used for the analysis excluded the more remote municipalities. Using suggestive mapping, the spatial distribution overlaps fairly well with the Colombian

[78] Accounting for 62.4% of the population.

conflict locations. Hence, the main challenge of this chapter is to disentangle the sign of the direction of a plausible causal relationship using econometric analysis. In addition, the summary statistics comparing mean outcomes between the included and excluded municipalities reveal that the mean values are not necessarily similar for some key variables. However, a summary analysis of differences in mean statistics between samples is fraught with difficulty. For example, the extent of missing values for some variables in the sub-set of municipalities excluded is large. Nevertheless, it is difficult to argue that the set of municipalities used for our analysis is not subject to some degree of selection bias. However, the problem of missing values in the end dictates the sample we focus down on.

In addition, our main and preferred econometric specifications are influenced by the work of Fergusson et al. (2014), which sets the framework for our research question. This framework is primarily concerned with how the presence conflict affects the changes in the level of forest coverage in Colombia. However, since only a number of models are presented and discussed in this chapter, there obviously exists space for further research on this topic. For example, a different research approach could try to identify the determinants of the rate of growth of deforestation. This can be done using the change in (log of) forest cover (or the log differences) as a dependent variable. The deforestation growth is not necessarily explained by the structural drivers (e.g., the role of population or urbanization) as captured by the explanatory variables used in our estimation. Instead, the deforestation growth is closely linked to market forces and policy incentives (e.g., changes in food prices, the presence of taxes, or conservation laws, etc.) and may be viewed short-run in nature. Often, econometric deforestation growth models include the market forces or policy incentives variables expressed in terms of their changes. In addition, deforestation growth models often encounter significant econometric problems since market forces and policy incentives are potentially endogenous to decisions of deforestation. Finally, their estimation includes a lag of the dependent variable (log of forest cover) which by construction is an endogenous variable in a panel setting. Therefore, GMM and dynamic panel data models estimations are required (for example, see, for example, Hargrave and Kis-Katos, 2013). Overall, this represents an agenda for future research and is not one that is pursued in this chapter.

Our empirical analysis attempted to causally identify the impact of civilian displacement through violence (or the threat of violence) on forestation. We believe the identifying instruments used are valid and provide us with some confidence that the estimated effect is causally identified. Our estimates suggest there is evidence that the armed conflict is indeed a force for forest conservation. In particular, the alignment between rural underdevelopment and the rural–urban displacement as a result of the violence contributed to the protection of forests. The estimated effect suggests that an additional person displaced per 1,000 inhabitants increases the percent of forest covered by 0.0028 of a percentage point at the municipality level.[79] The magnitude of this effect is relatively small, and even more so when compared to more conventional forestation drivers such as the effects associated to average precipitations monthly (0.14), the distance to the department capital (0.028) and the soils quality index (3.7). In addition, based on the same metric of one person per 1,000 increase of the municipal population, the population pressure reduces the forest cover thirty-four times (34.2) more than the effect in which forced displacement increases it.

A naïve view of the result of this chapter may interpret the armed conflict as something good for the country since it brought a positive environmental yield. However, it is important to emphasize the fact that the major achievement of the 2016 peace deal that ended 60 years of conflict with the FARC was reducing victimization. According to official figures during the study period (2004-2012) at least 150,164 people were killed in the fighting, 6016 killed and permanently 1476 wounded by landmines, 4,990 people kidnapped, and approximately 2.6 million forcibly internally displaced. All of this reflects an immense human toll of suffering against which any environmental gains from forestation induced by conflict pales into insignificance.

The results of this research are also consistent with the literature that emphasizes that rural–urban displacement due to violence promotes ecosystem recovery due to the reduction of human pressure on natural resources (for example, Aide and Grau 2004; and Meyerson et al. 2007). Forest degradation frequently increases in post-conflict situations. Some studies show that after the end of a conflict people resettled and expanded

[79] According to the sample used in the regressions, the average share of the municipality area covered with forest is more than half (58.04%), which corresponds to 51,168.57 hectares (511.7 km2). The estimated effect suggests that one person displaced per 1,000 inhabitants increase the municipality covered by forest by 1.43 hectares (0.0016% of the total municipality area), on average and ceteris paribus.

agricultural lands (see, for example, Stevens et al. 2011 for the case of Nicaragua's Atlantic coast). Governments also pacify former rebels and provide patronage to demobilize forces by promoting rural and agricultural development. In addition, those civilians forced displaced by the conflict return to areas abandoned during the conflict, and so new people enter into forest zones previously seen as too dangerous within which to live.

It is imperative to emphasize that there is nothing wrong with deforestation as long it is managed properly and effectively. Rain forests and their watersheds support the livelihoods of many. Therefore, their protection and conservation is of paramount importance. Enforcement of conservation of currently protected regions and areas previously administered under a 'gunpoint conservation' regime by the guerrillas will be fundamental. Hence, this chapter indirectly advocates for an appropriate conservation strategy when peace fully arrives in Colombia. In the past, the zones protected by the state assisted in reducing settlements and illegal drug activity. However, this might not be enough for the future (See Dávalos, 2001).

Chapter 5

5 Climate variability and theft in Colombia

Summary

The objective of this chapter is to estimate the causal impact of the most recent extreme weather event (EWE) in Colombia ('La Niña' between 2010-2011), labelled as the 'winter wave' by the local media, on persons, houses, business and car theft rates in municipalities subject to the treatment of this EWE. Using a novel annual municipal panel dataset (2007-2012, inclusive), and measuring the affected areas according to the number of houses damaged and destroyed, this study relies on a Difference-in-Difference (D-i-D) model to show that the concurrent year of the winter wave brought a decrease in theft rates, especially, theft from persons. This may be perhaps attributable to the emergence of pro-social behaviour in the municipalities most affected. We also find an increase in theft from houses possibly linked to a 'survival mechanism', rather than one that one that seeks reward like the type the Becker (1968) model of crime and punishment. In addition, the D-i-D estimates also reveal that the presence of conflict, in general, discourages theft perhaps due to the establishment of coercive institutions by illegal armed groups.

Keywords: Natural Disasters, Environmental Economics, Violence, Crime, Weather, Climate Variability, and Climate Change.

5.1 Introduction

The number of Extreme Weather Events (EWE) in Colombia increased from 58.3 to 332.7 between 1965-1975 and 2005-2015.[80] Each decade is warmer than the previous one[81], and although it is not right to say that EWEs are caused by climate change, the magnitude, frequency and the durations of EWEs are influenced by the emergence of a warmer atmosphere (WMO, 2011).

Countries are not affected equitably when affecting by EWEs. Developing countries, which contribute little to worldwide greenhouse gases, continue to bear a larger share of the costs related to greater climate variability. For example, in the developing world the weather shocks often push households below the poverty line. Usually, poor rural families lack formal insurance mechanisms and access to financial markets, so are required to either dispose of their productive assets, reducing household consumption, and/or decide not to send their children to school. This offers a strategy to offset the fall in income, rendering them even less able to recover in the long run. To worsen the situation, some of the urban poor families are often found on the periphery of rural zones prone to natural disasters like landslides or avalanches (See Hsiang et al., 2011).

The most recent major EWEs in Latin America comprised floods in Argentina (2007, 2012), two hurricanes in Mexico (2009), a tropical storm (2010) in Venezuela, and floods in Colombia (2010-2011) (See Garlati, 2013). In particular, between 1965 and 2015, Colombia faced 121 EWEs, placing it globally among the top three countries most exposed to climate variability after Brazil and Mexico (both, with 191 EWEs) in Latin America.

The main objective of this chapter is to estimate the causal impact of the most recent EWE in Colombia, the 'La Niña' episode of 2010-2011, on municipal-level theft rates. In particular, the seasonal occurrence of 'La Niña' and 'El Niño' climatic events alter the likelihood of distinctive climate patterns around the globe. Both are opposite phases of

[80] These calculations are based on data from the Centre for Research on the Epidemiology of Disasters (CRED), Université Catholique de Louvain (UCL) in Brussels -http://www.emdat.be -. Natural EWEs include climatological (drought, wildfire), hydrological (flood, landslide), and meteorological (extreme temperature, storm) events.
[81] The years 2010, 2005 and 1998 ranked as the warmest years on record.

what is known as the El Niño-Southern Oscillation (ENSO) cycle. La Niña is associated with a cooling of the Pacific tropical waters below normal temperatures, which causes heavy precipitation. On the other hand, El Niño relates to a band of warm seawater causing extreme droughts. The regions bordering the Pacific coasts of Colombia, Ecuador and Peru, which are highly dependent on agriculture and fishing, are particularly vulnerable.

During 2010-2011 La Niña hit Colombia extremely hard. It was a unique climate anomaly. It came along with intense rainfalls and floods higher than those observed historically. It caused approximately USD $7.8 billion losses related to the destruction of infrastructure, flooding of agricultural lands, and the payment of governmental subsidies. In addition, it left 3.68 million people affected, 467 people dead, 577 injured, 41 missing, half-a-million damaged homes with over 15,000 homes destroyed (CEPAL, 2012).

La Niña episode 2010-2011 was so strong that the local media in Colombia referred to it as 'the winter wave' ('La ola invernal' in Spanish). Under the winter wave aftermath two contrasting hypotheses emerge on what could have been the direction of the theft rates of the affected municipalities. On the one hand, the magnitude of the disaster forced some people to subsist by whatever means necessary; living with friends and family, or temporally on the streets in improvised shelters. Theft rates, therefore, have had the potential to increase because of the desperate living conditions of the victims.[82] On the other hand, theft rates may have decreased due to an increase in solidarity and pro-social behaviour in the communities affected – an occurrence frequently observed after a natural disaster episode. [83]

Historians have suggested the correlation between climatic disturbances triggered by the ENSO cycle, such as droughts, famines, floods, temperature extremes, and thecollapse of ancient civilizations.[84] In recent years, Hsiang et. al (2011), using data from 1950 to 2004,

[82] The winter wave may have exacerbated some of the factors that eventually lead to poverty, and, in turn, to violence, crime and conflict.
[83] For example, Rodriguez *et al.* (2006) found in the aftermath of Hurricane Katrina pro-social behaviour, including both physical and emotional support, was by far the primary response to this event by the people of New Orleans in Louisiana State.
[84] See Brian Fagan's book "*Floods, Famines and Emperors:* El Niño and the Fate of Civilizations (1999)".

find that the ENSO cycle may have had a role in explaining about one-fifth of civil conflicts since 1950.

In addition, Rojas *et al.* (2014) highlight straightforward negative correlations between a country's agricultural production (using the FAO's Agriculture Stress Index), and the occurrence of the ENSO (measured with the Oceanic Niño 'ONI' and the Southern Oscillation 'SOI' Indexes). In particular, the authors mention that the ENSO affects agriculture negatively causing extreme drought conditions, particularly during el Niño.

A sub-theme of the research in this chapter is to explore the impact of conflict on municipal-level theft rates so that we can situate this analysis within a context broadly similar to that governing the research presented in the previous chapters. In particular, the negative consequences of conflict on economic growth, development and poverty is a well-stablished fact (see, for example, Collier (1999); Hoeffler and Reynal-Querol (2003); and Justino (2012)[85]). However, the role of conflict on criminality and, in particular on theft, along with the inherent security implications on the state authority and the rule of law, remains a subject to be explored in more detail. In particular, limited data have constrained the ability to accurately measure the scope of conflict on theft in fragile developing contexts (De Boer and Bosetti, 2015).

In order to estimate the causal impact of 'the winter wave' on theft rates, this chapter relies on a Difference-in-Difference (D-i-D) estimator. A municipal panel dataset is constructed for the years 2007 and 2012 (subject to the availability of theft data) to assess specifically theft rates in the municipalities affected during a pre-treatment and a post-treatment period (i.e., before and after La Niña 2010-2011 episode). Colombian legislation states that a theft[86] belongs to the property crime category. What determines the degree of theft charges that an accused could face is the type and value of the property stolen. The outcome variable used in our analysis relates to the overall theft rate per 1,000 inhabitants expressed in terms of crimes against persons, houses, business, and cars. In

[85] Regarding the involvement of the poor in armed conflicts, Justino's (2012) paper offers five well-documented drivers: i) violence as a means to try to improve a social position, taking advantage of the opportunities of conflict; ii) joining militias to get access to basic needs and ensure the protection of families and livelihoods; iii) socio-emotional motivations such as a sense of injustice and unfairness and, thus, a feeling of revenge; iv) participation in conflicts through coercion, abduction and fear; and v) individual non-participation becomes costly, thus, participation occurs in spite of the risk to better manage the conflict.
[86] *Theft* is the act of intentionally depriving someone of his or her *property*.

addition, the sum of total thefts per 1,000 of the population is also used as an outcome measure.

An examination of the impact of EWEs on theft is apposite. Given evidence of increased theft behaviour after natural disasters, policy makers will be able to plan *ex ante* the implementation of safety net systems to prevent and mitigate the adverse consequences of the EWE in terms of increased criminal activity. Prompt government action in the aftermath of natural disasters is key to curtailing disaster losses. For example, anecdotal evidence suggests that the promotion of formal or informal insurance for households, and the establishment of community-safety-based systems assists in coping with, and mitigating, the impacts of natural shocks (see, for example, Wetherley, 2014).

The contribution of this study is that it provides empirical evidence on the causal impact of a natural disaster on the theft rates, a matter on which there is no research in Colombia to date. The number of houses damaged and destroyed by the EWE associated with the passing of the winter is used to construct three-exposure thresholds that differentiate the municipalities belonging to the treatment from the control groups. Employing different sets of treatment and comparison groups ensures that the overall analysis is not driven by the characteristics of a certain group of affected municipalities. Finally, a D-i-D estimator is used in conjunction with an appropriate identification strategy.

The remainder of the chapter is structured as follows. The next section briefly reviews the literature regarding the climate variability-natural disasters-crime relationship. The following sections provide respectively the contextual background to the 'winter wave' 2010-2011, the empirical strategy, and the data (including the descriptive statistics), the empirical results, and then some concluding remarks.

5.2 Literature review

The economic theory of crime popularized by Becker (1968) and Ehrlich (1973) has demonstrated that an individual engages in criminal actions if the net marginal returns from illegal activities exceed the net marginal benefit from legal activities. Consequently, appropriate legislation and enforcement decrease violence and crime rates, including theft, as criminals anticipate a greater cost in perpetrating illegal acts.

The seminal works of Becker (1968) and Ehrlich (1973) led to a wave of empirical research examining the socioeconomic determinants of crime, including economic disadvantage and social disorganization factors. In particular, rational choice has been implicated as the main driver of criminal behaviour. Individuals are rational and engage in either legal or illegal behaviour according to the relative returns from each activity conditional on the degree of deterrence. Thus, the role of income, inequality, and labour market conditions on determining property crime rates has been deeply studied.

First, in the literature the effect of income on crime is often considered ambiguous. On the one hand, the family income could be taken as proxy for the availability of illegal opportunities reflected in a bigger set of lucrative targets for the potential criminals; and on the other, it also could be associated with the availability of more remunerative legal jobs in the economy that deter entrance into criminal activity.

For example, Reilly and Witt (1996), using data from 42 Police-Force Areas (PFA) over 12 years (1980-1991) in the UK, and employing fixed effects regressions, find that per capita household income exerted a strong negative influence on the recorded rates of burglary and theft. Nonetheless, the authors notice that the inclusion of the unemployment rate in the regressions often rendered the income coefficient insignificant suggesting that the income variable may act as a proxy for the effects of unemployment. In any case, these authors also report that the growth in unemployment is seen to impact positively burglary and theft activity over the time period considered.[87]

[87] The authors preferred estimation suggest that 1% rise in unemployment raises burglary and theft by 0.17% and 0.12%, on average and ceteris paribus, respectively.

Doyle et. al (1999) employing a 48-contiguous state panel dataset for the US for the years 1984-1997, and running fixed-effects and GMM models, find evidence that the level of wages has a substantial negative effect on property and violent crime as explained by a reduction in the opportunity cost of crime. In particular, the authors report that a 10% increase in wages reduces property crime by 5.8%, on average and *ceteris paribus.*

In contrast, Han et al. (2013) , using data from PFAs covering the period 1992–2008 for the UK, and adopting a fixed effect dynamic GMM estimation methodology, find that real earnings exert a positive and statistically significant effect on property crime. In particular, the authors suggest that higher earnings imply greater opportunities for potential criminals.

Entorf and Spengler (2000) use static and dynamic panel models with data at Laenders (state) level covering the period 1975 and 1996 for Germany. The authors show that absolute income, as measured by GDP per capita, turns out to be a measure of illegal rather than legal income opportunities (i.e., higher income is associated with higher crime rates).

Second, one shared hypothesis among studies is that relative privation, as measured by income inequality, resulting even in feelings of antipathy and or even rage, leads to crime as well. Thus, for example, Han et al. (2013) also include in their regressions the Gini coefficient as a measure of income inequality. They find that the Gini coefficient has a positive and significant effect on burglary and theft.

Kelly (2000), however, using data taken from the 1991 FBI Uniform Crime Reports for 829 metropolitan counties in the US, and employing Poisson regressions shows that income inequality has no impact on property crime, but it does on violent crimes, with an elasticity above 0.5. Kelly (2000) goes further and also indicates that poverty is one of the strongest and stable predictors of property crime, with an elasticity of 0.3.

Third, there are also studies which show that unemployment has positive impacts on crime, but the magnitude of this effect may be relatively small. The reason is that unemployment encourages criminality, but people who engage in crime are also part of the legitimate labour force, and derive income from legitimate jobs (See Machin and

Meghir, 2004). For example, Entorf and Spengler (2000) find that unemployment yields small, often insignificant, and ambiguous signs in their crime regressions models for Germany.

Pratt and Cullen (2005) perform a meta-analysis synthesizing the results from over 214 studies of crime rates dated between 1960 and 1999, which contained 509 statistical models that produced a total of 1,984 size effect estimates for the US. They find that the unemployment rate and the length of unemployment variables are important predictors of crime rates.

Han et al. (2013), in contrast to Reilly and Witt (1996), show that higher unemployment leads to a “lower” level of burglary and fraud and forgery in the UK. The authors argue that the unemployment rate captures the net effect of two opposite situations; while higher unemployment motivates potential criminals, it also reduces the opportunities available for them.

The percentage of young people in the population is also included in crime models, as they are considered the most likely socio-demographic age group to engage in criminality given their low-risk aversion. In fact, it is often found that the likelihood of committing crime typically increases with age until the late teens and then it starts to decline. For example, Grogger (1998) using individual level data in the US from the National Longitudinal Survey of Youth, and employing probit and GMM models, showed that a fall in the real wage played an important role in determining youth crime during the 1970s and 1980s. According to the author, a 10% increase in the wage lead to a 1.8 percentage point reduction in the juvenile crime participation rate, on average and *ceteris paribus*. Pratt and Cullen (2005) found that the proportion of young people to be only a moderate predictor of the crime rate.

There are also other social disorganization factors that affect crime such as the rate of urbanization, family structure, racial composition or even nationality. For example, Hooghe et al. (2011) analysed the geographical distribution of crime rates in the 598 Belgian municipalities, covering the period 2001-2006 and using spatial regression techniques to demonstrate that crime rates tend to be concentrated in the urban regions.

In particular, there is a strong and consistent effect of population density on crime rates, and this holds for both property and for violent crime.

Comanor and Phillips (2002), using data from the US National Longitudinal Survey of Youth (NLSY) over the period from 1979 to 1980, employed probit models to reveal that parental roles that influence the behaviour of their children. In particular, according to the authors' regressions, the most critical family structure factor affecting the prospect that a male's youth will face the criminal justice system is the absence of a father in the home.

Pratt and Cullen (2005) provide evidence for the US indicating that some racial compositions exhibit higher levels of involvement in crimes, in part due to a labour market phenomenon. For example, blacks typically earn less than whites, and also are segregated from certain high paying jobs. Finally, Entorf and Spengler (2000), in their study for Germany, show that areas with a higher percentage of foreigners experienced more property crime rates.

Lastly, most these studies presented reveal that deterrence variables (including imprisonment, detection rates, police force levels) act as powerful influences in reducing crimes (both violent and property crime). The more successful are the police in detecting crime the lower the crime rate (Pratt and Cullen, 2005).

The analysis of Becker (1968) and Ehrlich (1973) hinges on the existence of social control, which may be weakened during a time of crisis. The simultaneity of climate variability and a natural disaster is neither a necessary nor a sufficient condition for a crime to occur, but it may increase its likelihood, holding other factors (such as the state capacity of law enforcement and/or the emergence of conflicts) constant.[88] In particular, understanding the mechanisms that drives the climate-crime relationship remains a major lacuna in the literature (Hsiang *et al*., 2013).

The existing research for the developed world tends to explain the temperature-crime positive gradient through a "psychological" channel relating heat to crime. Particularly

[88] For example, Buhaug (2010) argues that climate variability is a poor predictor of violence and conflicts. In its place, structural conditions, such as poverty, inequality, and a weak institutional framework are the major drivers.

violent crimes such as assault, murder, rape, and domestic violence, tend to increase at higher temperatures. Possible explanations draw on theories in which external conditions that facilitate social interactions directly affect human judgment in ways that cause heightened aggression and a loss of control[89] (see, for example, Blakeslee and Fishman, 2015; and Ranson, 2014). On the other hand, the studies for the developing world often correlate rainfall fluctuations with crime through an 'income [90] and poverty'[91] channel. This is because in that context of agricultural production, wages, and employment are more affected by rainfall due to the larger share of agriculture in such economies (see, for example, Dell et al., 2014).[92]

This chapter integrates two strands of the existing literature: one that concerns the climate variability-crime relationship, and another about a specific natural disaster-crime relationship. On the first theme, the literature differentiates two types of criminal outcomes due to climate variability: i) "*interpersonal"* referring to violence and crime between individuals, such as theft, murder, rape, and domestic violence (See, for example, Ranson; 2014[93]); and ii) "inter-conflicts", incorporating the emergence of social conflict and/or riots (See, for example, Hidalgo et al.; 2010[94]). In particular, Burke *et al* (2015) synthesized the increasing econometric literature concerning the links between climate, crime, and conflicts into a meta-analysis. Based on data from 55 studies and 45 datasets from around the world with a periodicity spanning 10,000 years BC to the present. They show that each standard deviation change in climate towards warmer temperatures and

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89 These situations are more frequent when individuals drink alcohol in hot conditions, since it enters the blood stream more rapidly.
90 There is a large body of literature that uses weather shocks as instruments for income. In turn, income reductions are associated with crime and conflict emergence. For example, the seminal paper by Miguel et al. (2004) uses rainfall variation as an instrumental variable to illustrate that economic growth is strongly negatively related to civil conflict in Africa. Panel estimation for 41 African countries during 1981–1999 demonstrate that a negative growth shock of five percentage points increases the likelihood of conflict by one-half the following year. In addition, La Ferrara and Harari (2014) also report that over the period 1997-2011, the link between weather and conflicts in sub-Saharan Africa are primarily driven by climate shocks during the growing season of the main crop in a given region.
91 Justino (2012) provides an extensive review showing the strong empirical association between poverty and violence, crime and conflicts.
92 This paper provides a literature review that examines how temperature, precipitation, and windstorms influence economic outcomes including agricultural output, industrial output, labour productivity, energy demand, health, conflict, and economic growth, among other things.
93 In line with Ranson (2014), for the case of United States there is a nonlinear effect of temperature on property crimes and a linear effect of temperature on violent crimes, such as murder.
94 Using a municipal level dataset of 5,299 land invasions from 1988 to 2004 in Brazil, Hidalgo *et al*. (2010) show that adverse economic shocks, instrumented by rainfall, cause the rural poor to invade and occupy large landholdings.

extreme precipitation increase the frequency of *interpersona*l violence by 4% and *inter-conflict* violence by 14%.

Focusing exclusively on the climate-theft outcomes (*interpersonal)* Blakeslee and Fishman (2015), using a crime and climate yearly panel dataset at the district level from India (1971-2000 inclusive), show that crime increases with elevated heat and droughts[95] which independently also reduce agricultural output. The effects are larger and more uniform for property crimes than for violent crimes. Droughts lead to a 4.5% increase in property crimes (2.3% increase in violent crimes), elevated temperatures lead to a 4.5% increase in property crimes (2.7% increase in violent crimes).

Similarly, Iyer & Topalova (2014) shed light on the mechanisms underlying the rainfall-crime relationship using a four-decade annual panel dataset (1971-2000) at the district level from India. Fixed effects estimation, controlling for the inclusion of weather and trade shocks, reveal that the income channel is the primary mechanism behind the emergence of a negative rainfall-crime relationship.[96] In particular, a one standard deviation increase in the log of rainfall is associated with a reduction of violent interpersonal crimes (4.2% decline), property crimes (2.2% decline) and economic crimes (3.8% decline).

Mehlum *et al.* (2006), using instrumental variables, estimated the causal effect of high grain (rye) prices on crime rates in 19th century Bavaria. The main innovation lies in using the lagged rainfall as a source of exogenous variation in the rye prices (which are a proxy of the cost of living in 19th century Bavaria given that rye was the main staple). According to the first-stage regression, the lagged rainfall variable had a positive effect on the rye price[97], and, in the second-stage estimation, the estimated rye price had a positive effect on property crime. Specifically, a one standard deviation increase in the estimated rye price was found to increase property crime by 8%, on average and *ceteris paribus.*

95 The authors defined the climate shocks as rainfall/temperatures of one standard deviation above the mean at the district level.

96 The authors suggest that an additional source of exogenous income shocks for households in rural India (completely independent of the amount of rainfall) was the trade liberalization process.

97 Excessive rainfall reduces rye yields by interfering with the sowing season for winter grains and by destroying the harvest.

On the second subject, which covers the literature about a specific natural disaster-crime relationship, Wetherley (2014) assessed the impact of typhoons on crime rates using an annual panel dataset (1990-2008 inclusive) covering 13 regions of the Philippines. The fixed effects estimation, using lagged weather-related explanatory variables such as precipitation, temperature and wind speed, reveal that the theft rates decreased during the immediate year of intense precipitation. However, the theft rates increased during the year following high wind speeds. In particular, an increase of one centimetre of rainfall is estimated to yield a decrease in thefts of 0.365 per 100,000 inhabitants, which is suggestive of pro-social behaviour immediately following a storm.

In contrast, Roy (2010) investigates how the crime rates respond to several kinds of natural disasters (e.g., hydrological, climatological, meteorological and geophysical) using an annual panel dataset for 227 districts between 1971 and 2006 from India. The size of the natural disaster is captured by intensity and frequency measures along with the number of disaster related deaths per district. The fixed effect regression estimates reveal that property crimes increase by 0.203-0.832 [98] per 100,000 people following high magnitude events. Other noteworthy results reported revealed that a higher pre-disaster newspaper circulation reduces crime rates. In particular, large disasters attract a lot of media attention in local newspapers, which perhaps suggest greater *ex-post* government aid for recovery.

In contrast, Leitner *et al*. (2011) assessed the impact of the massive population displacement following Hurricane Katrina in the US state of Louisiana on parish[99] crime rates using time series models (ARIMA) based on data from January 2000 through to June 2006. The results showed that the crime rates remained unchanged following the Hurricane for the majority of the parishes that received evacuees from the impacted areas. The authors explain that after the storm, the crime rates fell drastically in some parishes due to the arrival of National Guard troops.

There are also studies that focus on the impact of an "exogenous shock", not necessarily a natural disaster, on criminal activity. One of the best examples of an "exogenous shock"

[98] The focus was armed robbery and burglary, respectively.
[99] The name parish goes back to colonial Louisiana. There are sixty-four parishes in the state.

is terrorism. In particular, Draca et al. (2011) study the crime-police relationship before and after a terror attack using an instrumental variable approach. In particular, the terror attacks in London during July 2005 resulted in a large redeployment of police officers to central London boroughs as compared to the outer London areas. The authors report that during the time period when police presence was high, crime rates fell significantly in central relative to outer London. They estimate an elasticity of crime with respect to police of approximately −0.3 to −0.4, so that a 10 percent increase in police activity reduces crime by around 3 to 4 percent.

Finally, for the case of Colombia there is no research regarding both types of relationship (i.e., climate variability-crime and/or specific natural disaster-crime relationships). There is only one study worthy of mention here for Colombia which explores a link between climate and conflict. Specifically, Acevedo (2015), using a municipality panel dataset from 2004 to 2010 estimates the causal effect of a weather-induced agricultural shock on labour market conditions and on forced displacement. The author finds that each additional millimetre of rain is positively associated with an increase in the coca crop yields. This translates into a higher demand for rural workers, but the rural wage level remains unchanged. With respect to the conflict consequences, the author finds that an additional millimetre of precipitation above the municipality average decreases forced displacement by 1.22% in areas suitable for coca crop production. This result may be attributable to an increase in coca production and the coercion enforced by illegal armed coca-profiting groups.

As noted above, a small body of research suggests that crime is influenced by changes in climate. However, no paper has focused directly on Colombia, and only a small number have explored the behaviour of the common categories of property crime in a systematic way (See, for example, Mejia et al. 2014, Sánchez et al. 2003; Sánchez and Núñez, 2001). To address this gap in the literature, this chapter estimates the impact of the most recent Extreme Weather Event in Colombia, "La Niña" between 2010-2011 on the theft rates per inhabitant across categories related to persons, houses, businesses, and cars.

5.3 The 'winter wave' event 2010- 2011

El Niño and La Niña, meaning respectively the *little boy* and the *little girl* in Spanish, are periodic weather patterns resulting from the interactions between the ocean surface and the trade winds that often blow from east to west over the tropical Pacific Ocean. Both are opposite phases of the El Niño-Southern Oscillation (ENSO) cycle. El Niño and La Niña episodes typically occur every three to five years. The changes in ocean temperatures normally reveal their presence. Under El Niño conditions, the trade winds reverse direction, blowing from west to east. The warm waters migrate across the tropical Pacific towards Peru, and the waters turn cold in Asia. Typically, during a period of El Niño, Colombia experiences drier-than-average seasons.

Conversely, under La Niña conditions, colder than normal waters start to develop in the eastern equatorial Pacific as the trade winds intensify from the east (America) to the west (Asia). Strong high pressure builds over the eastern equatorial Pacific while low pressure follows the warm waters towards Asia. During a period of La Niña, Colombia experiences extreme rainy seasons.

El Niño typically lasts nine to twelve months, and La Niña endures for between one to three years. Both tend to develop during March-June, reach a peak of intensity between December and April, and then weaken during May-July (CEPAL, 2012).

La Niña episode of 2010-11 was very much out of line with anything that had occurred before in terms of the frequency of natural disaster events in Colombia. Figure 5.3.1 graphically depicts the number of houses affected (damaged and destroyed) by "atmospheric" (such as winds, gales, storms, or wild fires) and "hydrological" (such as floods, droughts, or landslides) natural events. The "winter wave", which is mostly associated with an excess of hydrological natural events, is clearly an outlier.[100] During 2010 and 2011, La Niña left almost four million people affected and half-a-million damaged houses (CEPAL, 2012).

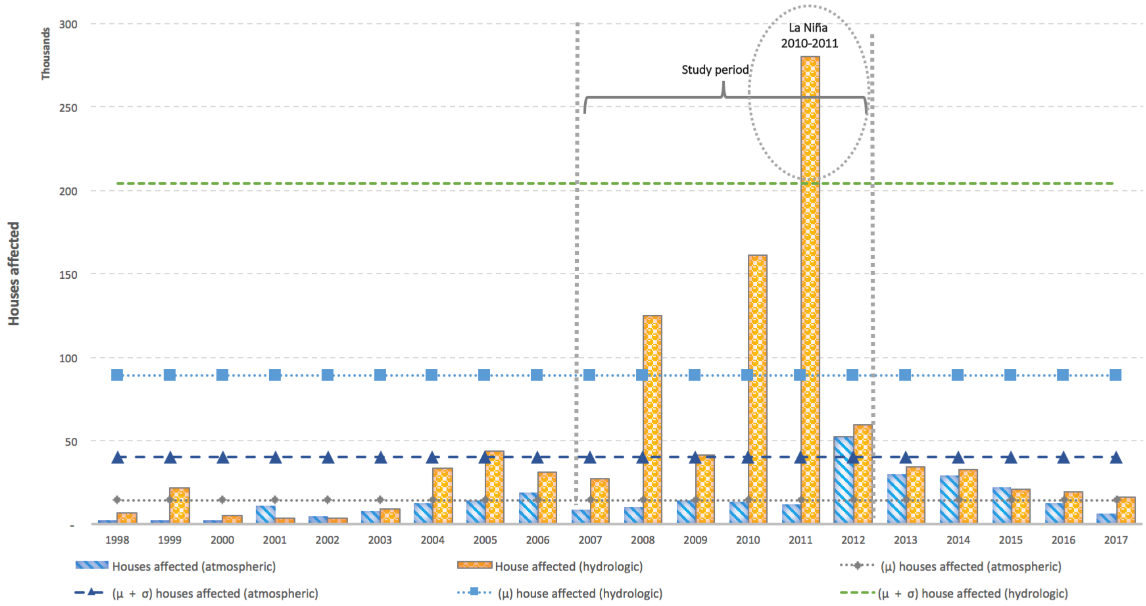
The study period (2007-2012) includes also the presence of El Niño 2009. However, the magnitude of that episode in terms of asset losses is minor when compared to the damage inflicted by La Niña 2010-2011 (CEPAL, 2012). The "El Niño" episodes are mostly

[100] During La Niña 2010-2011 episode the number of houses affected is above the mean by about one standard deviation as computed over the period 1998-2017.

associated with “atmospheric” events which are primarily caused by the warming of the Pacific waters and the increase in temperatures. In particular, during El Niño 2009 Colombia experienced some wild fires and water scarcity. Since wild fires[101] typically occur in remote and forested areas, and water scarcity effects are often mitigated given the prompt implementation of water management policies[102], it is not anticipated that there would be a link of this particular adverse climatic episode with the incidence of municipal theft rates. In fact, in 2009, the Government of Colombia protected the water reserves through increasing the generation of thermal energy (therefore, reducing the generation of hydroelectric energy). This increased its supply from 14% to 50% of the country's demand during that year (see World Bank, 2012).

[101] During El Niño 2009, approximately 1,878 forest fires were reported, which affected 83,270 hectares of forest and vegetation cover.
[102] During El Niño 2009.

Figure 5.3.1 Atmospheric and hydrological registered events 1998-2017

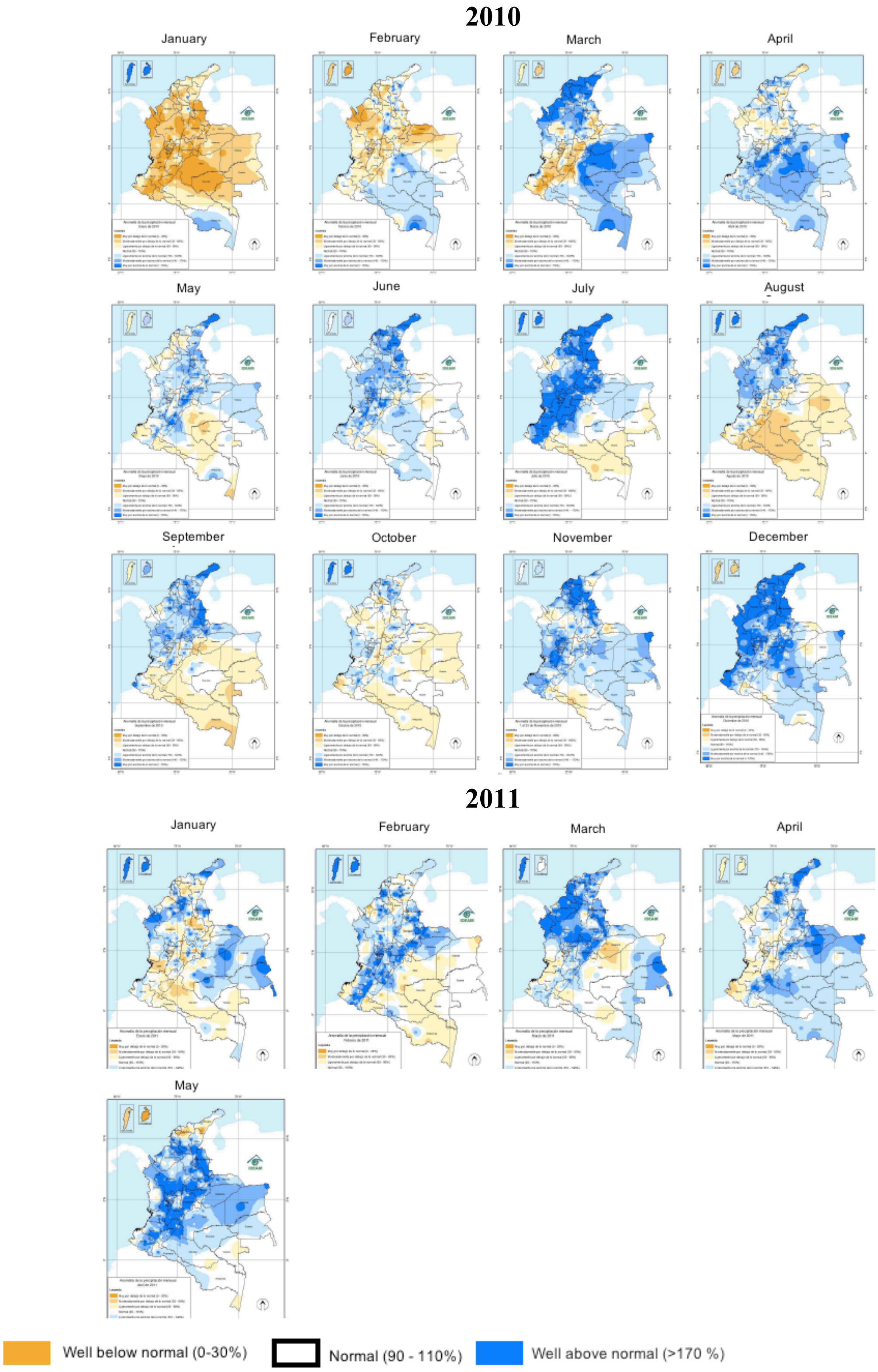


Source: author's calculations based on natural disaster categories established by the National Planning Department using data from the National Unit for Disaster Risk Management.

The Figure 5.3.2 taken from CEPAL (2012) graphically depicts the excess (or deficits) of rainfall relative to historical averages of each month in Colombia during La Niña episode 2010-2011 with darker blue colours. In early June 2010, La Niña initiated when the Pacific Ocean waters began to cool down with anomalous temperatures below –0.5°C. During September of the same year, the tropical Pacific water temperature dropped down to –1.5°C. La Niña episode was "strong"[103], in particular between July and August 2010, November and December 2010, and March and May 2011.

103 According to the US National Oceanic and Atmospheric Administration (NOAA), La Niña episode has reached the "strong" category only six times since 1950.

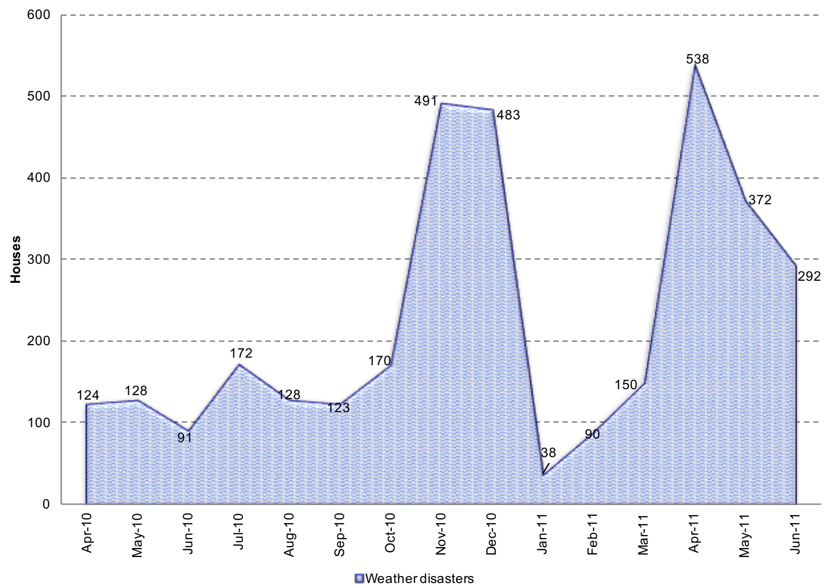
Figure 5.3.2 The monthly precipitation anomalies in Colombia 2010-2011



Note: maps show spatially excess (or deficits) rainfall relative to historical averages of each month.
Source: IDEAM, 2011

The excess of rainfall, well above historical averages, translated into an increase in the number of weather disasters such as rivers and water bodies over flooding, landslides and landmass movements. Consistent with Figure 5.3.3, based on statistics from the Colombian Government Disaster Management Unit, the number of weather disasters reached two major peaks between November (491) and December (483) 2010, and April (538) and May (372) 2011. Thus, in the period between September 2010 and May 2011, which covers the two major peaks, the official number of weather disasters registered was 2,219, which comprised 1,233 floods (55.6%), 778 landslides (35.1%), 174 gales and 24 avalanches, respectively. The other 10 remaining events were thunderstorms, hailstorms and tornadoes.

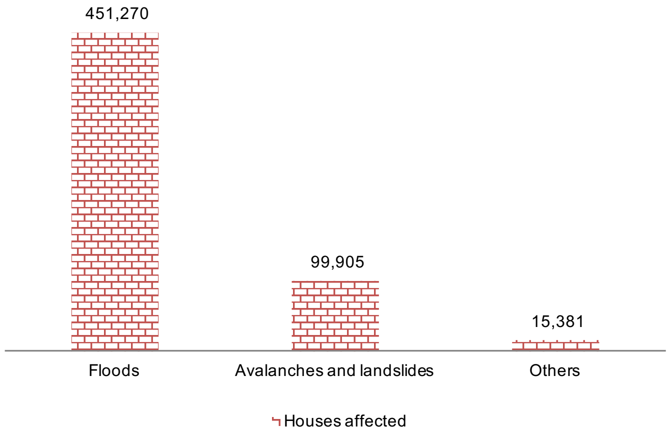
Figure 5.3.3 The "winter wave" 2010-2011



Note: Weather disasters (floods, avalanches and landslides, tornados, thunderstorm, wind, erosion and hail).
Source: author based on National Unit for Disaster Risk Management data.

One element common to all kinds of natural disasters relates to the "winter wave" in the municipalities impacted was a high degree of property damage rather than a high death toll (CEPAL, 2012). Figure 5.3.4 shows that around 451,270 (79.7%), 99,905 (17.6%) and 15,381 (2.7%) homes were affected by floods, avalanches and landslides, and others weather events such as tornados, thunderstorm, wind, erosion and hail.

Figure 5.3.4 Houses affected by type of natural disaster during the "winter wave" 2010-2011



Note: houses affected (damaged and destroyed) and others weather natural disasters (tornados, thunderstorm, wind, erosion and hail)
Source: author based on National Unit for Disaster Risk Management data.

Approximately 46.6%[104] of the country's area coverage experienced floods. Among the most shocking natural disaster tragedies, comparable to the floods caused by the Hurricane Katrina (2005) in New Orleans (US), was the rupture of the levees of the Dique channel (Canal del Dique), which connects the main Colombian river, El Magdalena, which historically has provided a vital trade route with the city of Cartagena, Colombia's major port in the Caribbean. Some branches of the El Magdalena River crested and flooded entire villages in the proximity of the river.

In addition, the landslides generated substantial infrastructure damages including houses, roads, and aqueducts. For example, in December 2010 a large landmass movement in the municipality of Gramalote, Northern Santander Department, negatively affected more than 4,000 people, leaving around 100 homes destroyed and 900 damaged. The government ordered a large-scale town evacuation. Another tragedy occurred in Bello, Antioquia Department, where a landslide killed 82 people, left 38 missing, and 10 injured, with 107 houses destroyed and 735 people without homes.

[104] Based on a representative sample that covered 66.3 % of continental national territory (IGAC-IDEAM-DANE).

In summary, the passing of the "winter wave" left 467 people dead, 577 injured, 41 missing, and 566,556 either damaged or completely destroyed homes.[105] The estimated cost of damages caused by the 'winter wave' was estimated to be USD 6.052 billion (CEPAL, 2012).

5.4 Empirical and identification strategy

The key research objective is to estimate the causal impact of the 'winter wave' on theft rates in the municipalities most affected by the extreme weather event. A standard D-i-D estimation procedure is employed using an annual panel dataset (2007-2012). The years are selected due to municipal-level data availability. The model is specified in Equation (5.1) as follows:

$$T_{i,t} = \alpha_i + \lambda_t + \beta(W_i * P_{i,2010}) + \gamma' X_{i,t} + \varepsilon_{i,t} \quad (5.1)$$

where $T_{i,t}$ is either the persons, houses, business and car theft rates per 1,000 of the population of municipality i in year t depending on the specification used. In addition, we also use as an outcome variable the aggregate of these four criminal categories per 1000 of inhabitants for municipality, including and also excluding car theft. W_i corresponds to the treatment indicator (a dummy variable for whether or not the municipality i has been affected by the "winter wave"). Since a panel data fixed effects estimator is employed W_i does not appear on its own. $P_{i,2010}$ is a dummy variable for the post 2010 period, therefore, the primary parameter of interest is β, which captures the average effect of the 'winter wave' on the different types of theft rates per inhabitant. It is assumed that the 'winter wave', like any other accidental or random climate event, caused a random allocation of the treatment and control groups similar to one yielded by a random experiment. In other words, the treated municipalities are presumed to be scattered randomly throughout the country.

Natural disasters typically set in motion a complex chain of events that can disrupt the local economy and, in extreme cases, the national economy. One element common to all

105 Statistics from the Colombian Government Disaster Management Unit (*Unidad Nacional para la Gestión del Riesgo de Desastres*, UNGRD Acronym in Spanish), May 31st 2011 cut-off date.

kinds of natural disasters related to the 'winter wave' in the municipalities impacted is a high degree of property damage rather than a high death toll. Hence, the number of houses affected per 1,000 inhabitants, defined as the sum of houses damaged and destroyed, regardless of the kind of the natural disaster, is used to construct the treatment dummy W_i (See, Figure 5.3.4).

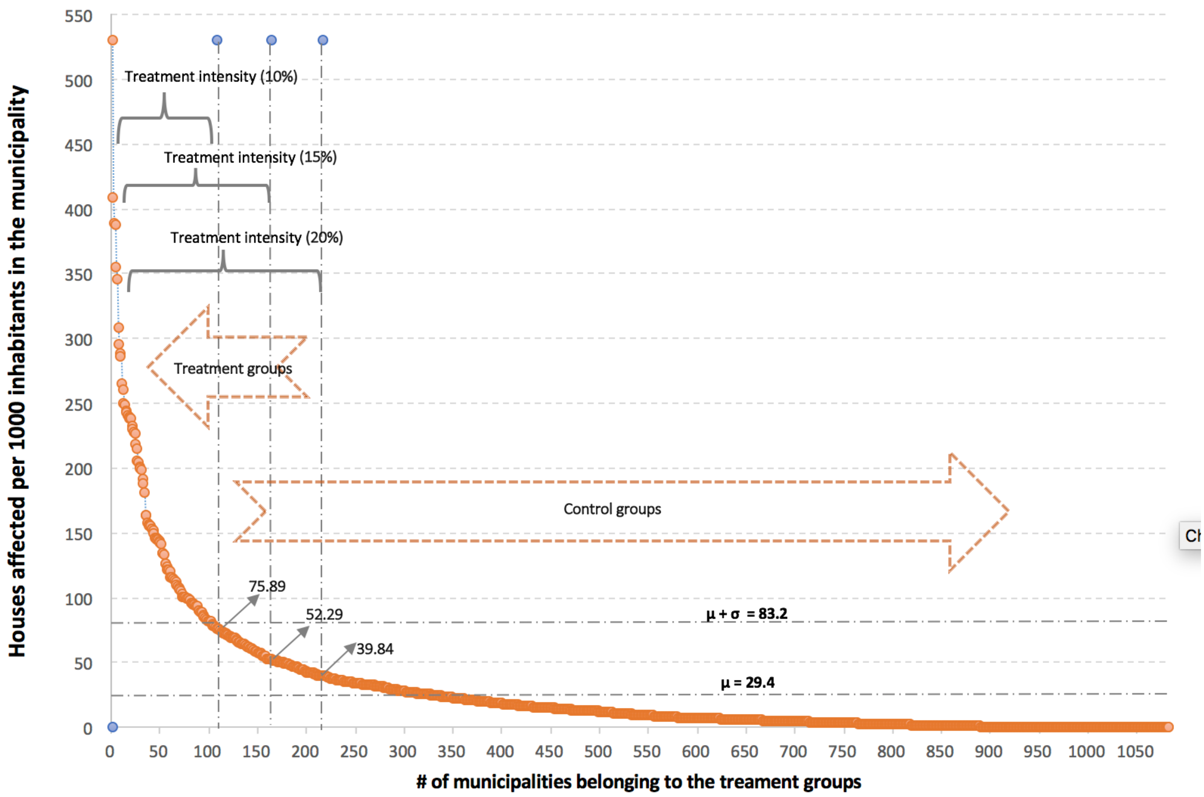
Three treatments groups for the D-i-D regression models are constructed based on the intensity of damage induced by the 'winter wave'. In particular, the municipal statistics on houses registered as affected per 1000 inhabitant due to the passing of the 'winter wave' were sorted from largest to smallest in number. We define the treatment groups in three different ways depending on the intensity of the damage to houses of the 'winter wave'. Specifically, if the municipality registered a number of houses affected by the 'winter wage' per 1,000 inhabitants in the top 10% of the distribution, then the municipality is in the treatment group and all other municipalities are in the control group. We relax this restriction by then re-defining the treatment group to include those municipalities that were in the top 15% of those affected by housing damage by the 'winter wave', with the remainder then consigned to the control group. Finally, we also use a 20% cut-off point as final way to delineate the treatment and control groups.

Bottom-line, consistent with this data sorting, a municipality belongs to the more intense to the less intense treatment group [Yes=1; No=0] if the number of houses registered as affected per 1000 inhabitant is in the top 10%; 15%; and 20% of the distribution, respectively. Therefore, we have three separately define treatment groups that range in the intensity of their exposure to the 'winter wave' with the 10% the most intensively affected.

The decision on how the cut-off points are defined is not random. The treatment intensity cuts-off points (i.e., 10%, 15% and 20%) capture adequately the level of destruction associated with the passing of the 'winter wave'.

According to these cut-off points, the municipalities included in the treatments groups at least experienced 39.8 houses registered as affected per 1,000 inhabitants, with a maximum of 529.9, a figure slightly above the mean (29.4), but way below the mean plus one standard deviation (83.2). Hence, the cut-off points used approximately capture a treatment effect and this is conveyed in the Figure 5.4.1 below. Indeed, the 20% cut-off point is "conservative" in nature in the sense that it allows the inclusion of municipalities that weren't severely affected in the treatment group. The cut-off points 10% and 15% are more precise in capturing the degree of asset destruction due to the 'winter wave'.

Figure 5.4.1 Houses registered as affected per 1000 inhabitant at municipal level sorted from largest to smallest in number.



Source: author based on natural disaster categories established by the National Planning Department using data from the National Unit for Disaster Risk Management.

Additionally, the cut-off points defined ensures a reasonable number of municipalities in the treatment groups. Thus, the 10%, 15% and 20% cut-off points restrict to 109, 163 and 217 municipalities included in the three treatment groups, respectively. A 5% cut-off point is not used as it would comprise a small number of treated municipalities (55), which would reduce the empirical power of the analysis (Table 5.4.1).

Table 5.4.1 The treatments groups for the D-i-D regression models constructed based on the intensity of damage induced by the 'winter wave'.

Treatment intensity	# Municipalities	Houses affected per 1000 inhabitants		
		Mean	Min	Max
10%	55	219.75	126.81	529.88
	54	97.08	75.89	126.07
15%	54	63.74	52.29	75.53
20%	54	45.91	39.84	52.21
30%	54	35.18	32.21	39.61
	54	28.36	25.43	32.17
40%	55	22.77	20.18	25.36
	54	17.85	15.82	20.15
50%	54	14.22	12.84	15.78
	54	11.24	9.78	12.81
60%	54	8.35	7.42	9.75
	54	6.67	5.98	7.39
70%	54	5.26	4.48	5.97
	55	3.83	3.26	4.48
80%	54	2.64	2.05	3.25
	54	1.61	1.17	2.02
100%	54	0.80	0.54	1.16
	162	0.07	0.00	0.53

Source: author based on natural disaster categories established by the National Planning Department using data from the National Unit for Disaster Risk Management.

The key research question of this chapter is to correlate the destruction associated with this natural disaster with theft. Therefore, setting a set of more lenient cut-off points is not consistent with the chapter's empirical objective. Furthermore, it would likely entail the construction of treatment groups that are less accurate in terms of exposure to treatment, and at the same time, smaller control groups which will reduce the empirical power of the analysis. For example, a 90% cut-off point as the treatment involves subjecting 867 municipalities to a fake 'treatment' since many would not necessarily be affected by the 'winter wave'. The corollary of this is that remainder of the municipalities would be consigned to an unrealistically small control group and would generate very little empirical power (Table 5.4.1).

Overall, although it is possible to amend these thresholds at the margin, we do not believe such changes would make a difference to the substantive finding in this chapter (See Figure 5.4.1). Further, the use of a radical threshold like 90% for treatment would make little sense in the current context given what has been depicted in the above figure where the effects of the weather event is fairly flat. Furthermore, the sample size of municipalities in the control group would shrink about 108 or less which not provide an adequate control group for our analysis.

On the other hand, in order to ensure clean control groups for each one of the treatment groups defined above, the number of houses registered as affected per 1,000 inhabitants is regarded also in conjunction with some available statistics concerning the number of people who declared that they were affected per inhabitant at the municipality level by the weather event. It is worth noting that the passing of the 'winter wage' left mainly property damage, thus, the number of people affected per inhabitant is only employed as a complementary indicator for improving the quality of the control groups. [106] In particular, both variables were again sorted from the largest to smallest number. A municipality is taken to belong to the more intense or to the less intense control group [Yes=1; No=0] if the number of houses and people registered as affected per 1000 inhabitant does not belong to the top 10%; 15%; and 20% of the distribution, respectively.

This data organization implies that for each treatment of intensity there is a particular sample size that guarantees a clear split between treatment and control groups. In addition, the existence of missing values in the dataset relate to the type of theft used in the regressions will also play a role in defining the final samples sizes. In any case, the use of a different sets of treatment and comparison groups ensures that the overall analysis is not driven by the characteristics of a certain group of municipalities affected.

The vector $X_{i,t}$ represents the municipal characteristics likely to affect the theft rates per inhabitant. In particular, the equation controls for the log of income tax revenue per inhabitant, the percentage of urban population [0-100], the log of density (ratio of population to area (Km2)) and the gross enrolment ratio (primary and secondary) [0-100].

In addition, Colombia has experienced high levels of crime, forced displacement, kidnappings, and corruption during a conflict which persisted for more than a half

[106] The use of the number of people affected per inhabitant alone is not recommended. It may be subject to measurement error, since the local governmental authorities usually offer a monetary donation for disaster relief. In any case, when the number of people affected per inhabitant was employed alone as an input to construct a treatment dummy, no impact on the theft rates was detected. In contrast, the statistics regarding the number of houses registered as affected per inhabitant are not only more suitable, covering more municipalities, but also accurate and easily verifiable by the local authorities, for example, using aerial imaging.

century. Therefore, the inclusion of the presence of conflict (illegal armed groups such as FARC and ELN) [Yes=1; No=0] as an explanatory control variable for theft at the municipality level is necessary. First, illegal armed groups are frequently conformed by potential criminals which can affect local theft rates. Second, illegal armed groups often deteriorate the presence of the state through intimidation, annihilation or expulsion, which in turn can affect local theft rates due to the establishment of coercive institutions. Guerrillas are habitually discouraged to commit crimes against property since it isn't as profitable as narcotraffic. In other words, illegal armed groups may provide a theft-free environment for coca growers in order to ensure a high level of drug production. As a corollary, guerrillas don't necessarily have the criminal networks established to sell the possible items to be stolen affecting theft rates. Therefore, the country is an exceptional laboratory for researchers interested in studying the relationship between conflict and theft (See Sánchez et al., 2003a).

The inclusion of municipality fixed effects (α_i) controls for any municipality-specific characteristics assumed fixed over time. The time fixed effects (λ_t) control for aggregate time trends in the theft rates per inhabitant, capturing, for example, annual shifts in departmental security policies.[107]

In Equation (5.2) the "year lags[108]" are included to capture whether the treatment effect dissipates over time, stays constant, or even increases. These are constructed by testing the statistical significance of the estimates corresponding to the dummy variables for the years 2011 and 2012, and interacting them with the treatment indicator (W_i) measuring the year-by-year effect after the 'winter wave' event. This leads to the specification of the following equation:

$$T_{i,t} = \alpha_i + \lambda_t + \sum_{t=2011}^{2012} \rho'(W_i * P_{i,t}) + \gamma' X_{i,t} + \xi_{i,t} \tag{5.2}$$

[107] The model in Equation (5.1) was also estimated excluding the time fixed effects (λ_t). These estimations reveal that the magnitudes and levels of significance of the coefficients (β) associated with the treatment indicator (W_i) is not considerably affected.
[108] The literature generally refers to as "leads" and as "lags" to the interactions of the treatment indicator with the "pre-treatment" and "post-treatment" time dummies, respectively.

where ρ' is a vector capturing the effects of the winter wave in year 1 (2011) and year 2 (2012).

A questionable assumption embedded in the estimation of Equation (5.1) is that, in the absence of the treatment, $T_{i,t}$ is evolving naturally over time in the same way as in the treated and non-treated groups. This is the "parallel trends" assumption. In fact, the potential change in theft rates in both groups of municipalities could be different due to intrinsic factors not necessarily related to the 'winter wave'. For example, in a hypothetical case, the municipalities most affected could be implementing better theft prevention polices, which in turn renders the common trends assumption less reasonable. This example illustrates that the parallel trend assumption is usually implausible if the treatment selection is correlated with some characteristics affecting the dynamics of the outcome variable.

In order to test the presence of parallel trends between treatment and comparison groups, trend (time dummies) and treatment interactions with the periods are included, essentially not limiting the 'winter wave' to just 2010. Thus, in Equation (5.3), three "year leads" are included.

$$T_{i,t} = \alpha_i + \lambda_t + \sum_{t=2008}^{2010} \phi'(W_i * P_{i,t}) + \sum_{t=2011}^{2012} \rho'(W_i * P_{i,t}) + \gamma' X_{i,t} + \zeta_{i,t} \tag{5.3}$$

Here, implicitly we are creating "placebo" treatments in all years. If the assumption of parallel trends holds for the treated and comparison groups for the period before 'winter wave', the estimates corresponding to the interaction of the treatment group with the 'year leads' should be statistically insignificant. In other words, the null hypothesis of similar trends is $\phi' = 0$. Note that the 2007 pre-treatment interaction is not included to avoid the dummy variable trap.

Finally, accordingly to Bertrand et al. (2004), D-i-D estimation, particularly those over an extended period, may yield biased standard errors due to the presence of serial correlation. Thus, supplementary estimation is conducted ignoring the time series information. The data before and after the winter wave periods are averaged across two periods and a panel of length two is estimated as a quasi-robustness test. Finally, in all estimation the standard errors are clustered at the municipality level. Thus, they are expected to be robust to the presence of both autocorrelation and heteroskedasticity.

5.5 Data and descriptive statistics

The panel dataset consists of yearly municipal observations from 2007 to 2012 (inclusive). The summary statistics reported for the treatment and control groups are given in Table 5.5.1 and Table 5.5.2 respectively. This contains the means, standard deviations, and the number of observations for the three treatment intensities defined in the Empirical and identification strategy section 5.4 above. The treatment (control) sample sizes contract (expands) when increasing the intensity of damage criterion from 20% to 10% exposure, respectively. The summary statistics for the full sample dataset, which merges treatment and control group observations, are presented in Table 5.5.3. The full sample size decreases from 20% to 10% exposure, due to a reduction in the availability of data points for the treatment groups as again defined in the Empirical and identification strategy section.

Table 5.5.1 Summary statistics -treatment sample-

Variable	Statistic	Treatment intensity		
		20%	15%	10%
Theft from persons per 1000 inhabitant	Mean	0.24	0.22	0.22
	Sd	0.38	0.08	0.36
	N	1257	941	612
Theft from houses per 1000 inhabitant	Mean	0.13	0.12	0.11
	Sd	0.27	0.25	0.23
	N	1233	917	600
Theft from business per 1000 inhabitant	Mean	0.1	0.08	0.08
	Sd	0.17	0.16	0.16
	N	1208	892	593
Theft from persons, houses and business per 1000 inhabitant	Mean	0.49	0.46	0.44
	Sd	0.7	0.68	0.63
	N	1137	821	534
Theft of cars per 1000 inhabitant	Mean	0.05	0.04	0.04
	Sd	0.09	0.08	0.08
	N	742	527	288
Theft to persons, houses, business and cars per 1000 inhabitant	Mean	0.64	0.61	0.65
	Sd	0.81	0.81	0.77
	N	712	497	270
Houses damage treatment group [Yes=1; No=0]	Mean	1	1	1
	Sd	0	0	0
	N	1298	982	653
Post 2010 [Yes=1; No=0]	Mean	0.5	0.5	0.5
	Sd	0.5	0.5	0.5
	N	1298	982	653
Post 2010 [Yes=1; No=0]*Treatment[Yes=1; No=0]	Mean	0.5	0.5	0.5
	Sd	0.5	0.5	0.5
	N	1298	982	653
Log income tax revenue per inhabitant	Mean	10.62	10.51	10.38
	Sd	1.03	1.04	1.07
	N	1298	982	653
Percentage of urban population [0-100]	Mean	36.67	36.59	35.84
	Sd	21.55	22.15	20.6
	N	1298	982	653
Log population to area (Km2) density	Mean	9.23	9.26	9.18
	Sd	0.82	0.86	0.77
	N	1298	982	653
Gross enrolment ratio, primary and secondary [0-100]	Mean	3.53	3.52	3.51
	Sd	0.98	0.93	0.92
	N	1298	982	653
Presence of conflict [Yes=1; No=0]	Mean	0.29	0.29	0.29
	Sd	0.45	0.45	0.45
	N	1298	982	653

Note: SD: Standard Deviation; and N: observations.

Table 5.5.2 Summary statistics –control sample-

Variable	Statistic	Treatment intensity		
		20%	15%	10%
Theft from persons per 1000 inhabitant	Mean	0.51	0.5	0.48
	Sd	0.8	0.78	0.77
	N	4319	4623	4898
Theft from houses per 1000 inhabitant	Mean	0.25	0.25	0.24
	Sd	0.4	0.39	0.39
	N	4280	4572	4841
Theft from business per 1000 inhabitant	Mean	0.18	0.17	0.17
	Sd	0.27	0.27	0.27
	N	4231	4535	4780
Theft from persons, houses and business per 1000 inhabitant	Mean	0.96	0.94	0.92
	Sd	1.29	1.26	1.25
	N	4179	4471	4710
Theft of cars per 1000 inhabitant	Mean	0.06	0.06	0.06
	Sd	0.11	0.11	0.11
	N	3519	3710	3907
Theft to persons, houses, business and cars per 1000 inhabitant	Mean	1.12	1.10	1.07
	Sd	1.39	1.37	1.35
	N	3455	3646	3837
Houses damage treatment group [Yes=1; No=0]	Mean	0	0	0
	Sd	0	0	0
	N	4355	4659	4934
Post 2010 [Yes=1; No=0]	Mean	0.5	0.5	0.5
	Sd	0.5	0.5	0.5
	N	4355	4659	4934
Post 2010 [Yes=1; No=0]*Treatment[Yes=1; No=0]	Mean	0	0	0
	Sd	0	0	0
	N	4355	4659	4934
Log income tax revenue per inhabitant	Mean	11.19	11.17	11.15
	Sd	0.89	0.9	0.9
	N	4355	4659	4934
Percentage of urban population [0-100]	Mean	45.78	45.07	44.54
	Sd	24.35	24.06	24.18
	N	4355	4659	4934
Log population to area (Km2) density	Mean	3.93	3.89	3.87
	Sd	1.36	1.35	1.34
	N	4355	4659	4934
Gross enrolment ratio, primary and secondary [0-100]	Mean	80.12	80.19	80.34
	Sd	15.22	15.5	15.38
	N	4355	4659	4934
Presence of conflict [Yes=1; No=0]	Mean	0.41	0.4	0.4
	Sd	0.49	0.49	0.49
	N	4355	4659	4934

Note: SD: Standard Deviation; and N: observations.

Table 5.5.3 Summary statistics -full sample-

Variable	Statistic	Treatment intensity		
		20%	**15%**	**10%**
Theft from persons per 1000 inhabitant	Mean	0.45	0.45	0.45
	Sd	0.74	0.74	0.74
	N	5576	5564	5510
Theft from houses per 1000 inhabitant	Mean	0.22	0.22	0.23
	Sd	0.38	0.38	0.38
	N	5513	5489	5441
Theft from business per 1000 inhabitant	Mean	0.16	0.16	0.16
	Sd	0.26	0.26	0.26
	N	5439	5427	5373
Theft from persons, houses and business per 1000 inhabitant	Mean	0.86	0.86	0.87
	Sd	1.2	1.2	1.21
	N	5316	5292	5244
Theft of cars per 1000 inhabitant	Mean	0.06	0.06	0.06
	Sd	0.11	0.11	0.11
	N	4261	4237	4195
Theft to persons, houses, business and cars per 1000 inhabitant	Mean	1.04	1.04	1.05
	Sd	1.32	1.32	1.33
	N	4167	4143	4107
Houses damage treatment group [Yes=1; No=0]	Mean	0.23	0.17	0.12
	Sd	0.42	0.38	0.32
	N	5653	5641	5587
Post 2010 [Yes=1; No=0]	Mean	0.5	0.5	0.5
	Sd	0.5	0.5	0.5
	N	5653	5641	5587
Post 2010 [Yes=1; No=0]*Treatment[Yes=1; No=0]	Mean	0.11	0.09	0.06
	Sd	0.32	0.28	0.23
	N	5653	5641	5587
Log income tax revenue per inhabitant	Mean	11.06	11.06	11.06
	Sd	0.96	0.96	0.96
	N	5653	5641	5587
Percentage of urban population [0-100]	Mean	43.69	43.59	43.53
	Sd	24.04	23.96	23.95
	N	5653	5641	5587
Log population to area (Km2) density	Mean	3.84	3.83	3.83
	Sd	1.3	1.3	1.3
	N	5653	5641	5587
Gross enrolment ratio, primary and secondary [0-100]	Mean	80.91	81.03	80.98
	Sd	16.22	16.22	16.14
	N	5653	5641	5587
Presence of conflict [Yes=1; No=0]	Mean	0.38	0.38	0.38
	Sd	0.49	0.49	0.49
	N	5653	5641	5587

Note: SD: Standard Deviation; and N: observations.

This study treats as the outcome variables the persons, houses, business, and car theft rates (and the sum) per 1000 inhabitants for all municipalities. Theft is the act of taking any valuable item from another person without proper consent and with the intention of never returning it. According to the Colombian penal code, theft belongs broadly to the property crime category.[109] What determines the degree of theft charges that an accused could face is the type and the value of the property stolen. In addition, charges will be interpreted as 'aggravated' when the act of theft involved the threat of force or direct violent behaviour. In some cases, the perpetrator's final intention will also play a role in defining the scale and magnitude of the charges.

The information regarding theft activity in Colombia is obtained from the statistical Information System of Delinquency Statistics of the National Police of Colombia (SIEDCO, correspond to the Spanish acronym). Individuals who have been the subject of theft often visit their local police departments and provide details, such as what property was stolen, when it was stolen, and how it was stolen. Thus, the theft statistics used here are mainly the reports for stolen property as filed by the victims and recorded by the police.

In the SIEDCO data, the availability of municipal theft data points varies accordingly to the type of theft. In particular, the lack of municipal data points increases from persons to houses, businesses and car theft respectively. This explains why each regression has its own sample size determined not only by the treatment intensities but also by the type of theft category. It is likely that the distinction between urban and rural municipalities is part of the explanation as to why there are more available data points for some types of theft than others. First, some type of thefts are more an urban than a rural phenomenon, such as is the case of car thefts. Second, large urban municipalities have more organized police departments with the resources to record a higher number of thefts. In order to control for such factors, the regression models include the municipal percentage of the urban population.

The effort here to model separately each type of theft represents a novel approach to try and identify the impact of the 'winter wave' on different theft rates in the municipalities

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[109] In Spanish "Delitos contra el patrimonio económico".

affected. However, the use of car theft data is particularly worrisome. Approximately 72% (4,494) of all car thefts are reported in three main metropolitan areas, Bogotá, Cali and Valle de Aburra (Medellin). Therefore, the use of this particular category raises questions as the incidence reflects what is happening in the main cities of the country. In addition, car theft is distinct from the other types of acquisitive theft in the sense that it is usually conducted as part of a highly organised criminal activity. This should be borne in mind in interpreting the results.

The official municipal data regarding the number of houses and people per 1,000 inhabitants registered as affected due to the passing of the winter[110] are obtained from the National Unit for Disaster Risk Management (UNGRD, based on the Spanish acronym). The UNGRD, which acts as the coordinator of the National System for Disaster Prevention and Attention (SNPA, corresponding to the Spanish acronym), consolidates the emergency reports submitted by the Local Committees for Emergencies and Disasters Prevention and Attention (CLOPAD, using the Spanish acronym) and the Regional Committees for Emergencies and Disasters Prevention and Attention (CREPA, using the Spanish acronym) at the city and departmental levels, respectively. When a weather disaster occurs the CLOPADs and the CREPADs, composed of public servants from the mayor and governor offices, the Secretariats of Agriculture, Finance, Health and Environment, and members of the Colombian Red Cross, Civil Defence and the Fire Department, coordinate the disaster response and the data collection at the site of event. The disaster data collection often serves two purposes: i) design a proper assistance to the immediate needs generated by the disaster; ii) inform policy decisions to help reduce disaster risks and build resilience.

On the other hand, the information regarding the presence of conflict at the municipality level was obtained via a yearly municipal-level dataset constructed by CEDE (Centro de Estudios sobre Desarrollo Económico, Universidad de los Andes, Bogotá), which contains information on the attacks perpetrated by the guerrillas.

The data on the income tax revenue per inhabitant, the percentage of urban population [0-100], the log of density (ratio of population to area (Km2)), the gross enrolment ratio

[110] Available from April 2010 to June 2011.

(primary and secondary) [0-100], was provided by the National Administrative Department of Statistics (DANE, according to its Spanish acronym), the Ministry of Education, and the National Planning Department (DNP, according to its Spanish acronym).

5.6 An overview of the theft rates before and after the 'winter wave'

A comparison of the theft rate trends split between the affected municipalities and non-affected ones, and, before and after the 'winter wave', can provide a portrait of the impact this extreme weather event on criminal activity. First, a visual inspection of the municipal theft rates reveals that the theft rates from the treated municipalities are higher than those of the control group (on average) as shown in Figure 5.6.1, Figure 5.6.2 and Figure 5.6.3. Second, when increasing the intensity of damage criterion, from the top 20% to 10% exposure, respectively, it is likely that the 'parallel trend' assumption test may hold for all theft categories excluding car theft and theft from business. And, third, after 2010, for most of the theft categories the treatment group is growing at slower rate than the control group, which means that perhaps the 'winter wave' may have brought a reduction in criminal activity in the municipalities affected.

Figure 5.6.1 Theft rates treatment and control groups of municipalities - 20% treatment intensity-

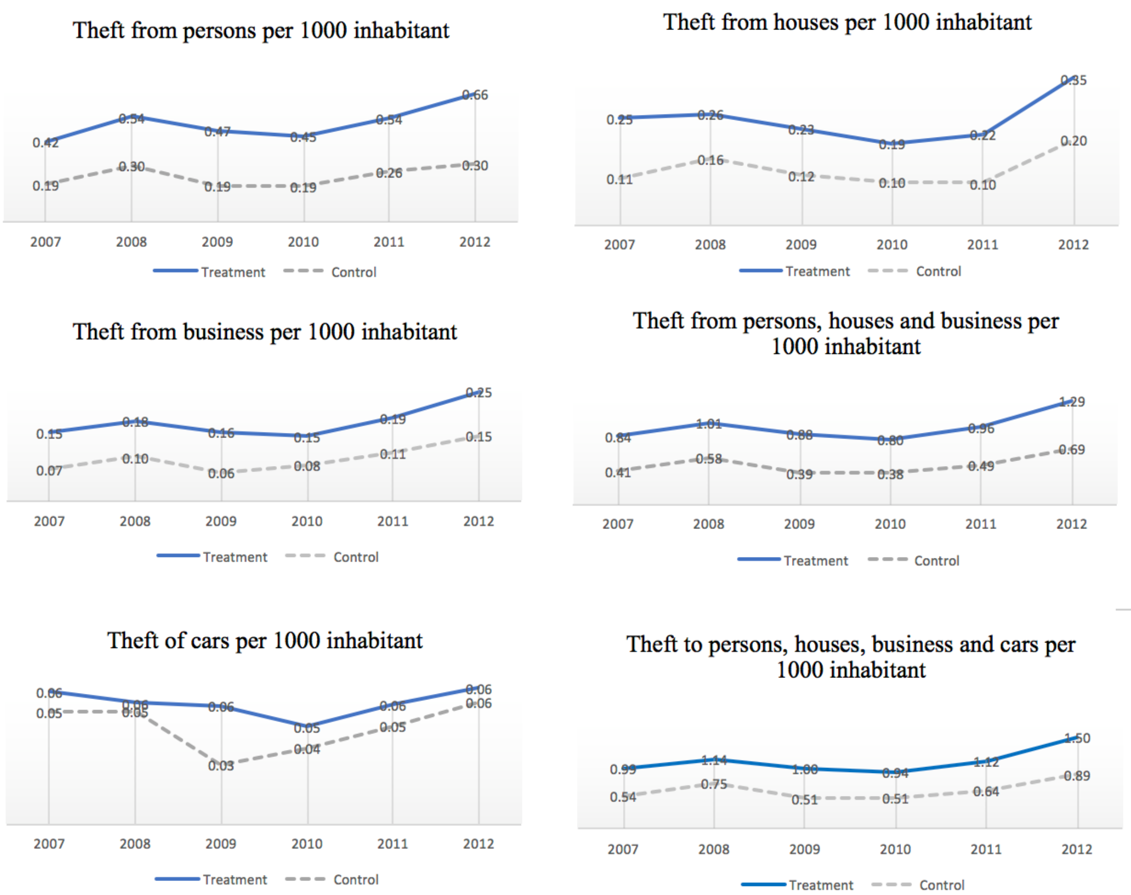

Figure 5.6.2 Theft rates treatment and control groups of municipalities - 15% treatment intensity-

Figure 5.6.3 Theft rates treatment and control groups of municipalities - 10% treatment intensity-

Beyond visual comparisons of the theft rate trends, a preliminary estimation using the D-i-D method can be conducted using the descriptive statistics. All that is necessary is to measure theft outcomes in the treatment group and control groups both before and after the 'winter wave'. In particular, the impact is computed as difference of the following two differences:

$$DiD\ impact = \left(\mathrm{T}_{i \in treatment}^{Post} - \mathrm{T}_{i \in treatment}^{Pre}\right) - \left(\mathrm{T}_{i \in control}^{Post} - \mathrm{T}_{i \in control}^{Pre}\right) \qquad (5.4)$$

Note that the municipality i is observed before and after the weather event. In addition, the D-i-D method implicitly controls for both, the observed and unobserved time-invariant characteristics given that when the difference in theft outcomes is computed, the effect of the characteristics that do not change over time cancel out. In particular, Table 5.6.1 disentangles the components of the D-i-D method using the panel dataset constructed. The table rows contain the mean theft outcomes for the treatment and control groups before and after the 'winter wave'.

Table 5.6.1 Theft outcomes pre and post the 'winter wave'

Outcome variables	Pre & Post 'winter wave'	Statistic	Winter Wave treatment intensity					
			20%		15%		10%	
			Treatment	Control	Treatment	Control	Treatment	Control
Theft from persons per 1000 inhabitant	Pre	mean	0.23	0.48	0.21	0.46	0.19	0.45
		SD	0.39	0.76	0.39	0.75	0.32	0.74
		N	628	2154	471	2305	306	2443
	Post	mean	0.25	0.55	0.24	0.53	0.24	0.51
		SD	0.38	0.84	0.39	0.82	0.39	0.81
		N	629	2165	470	2318	306	2455
Theft from houses per 1000 inhabitant	Pre	mean	0.13	0.25	0.11	0.24	0.09	0.24
		SD	0.28	0.39	0.26	0.38	0.24	0.38
		N	616	2136	459	2281	300	2416
	Post	mean	0.13	0.25	0.12	0.25	0.13	0.24
		SD	0.26	0.41	0.25	0.4	0.22	0.4
		N	617	2144	458	2291	300	2425
Theft from business per 1000 inhabitant	Pre	mean	0.08	0.16	0.07	0.16	0.07	0.16
		SD	0.14	0.24	0.14	0.24	0.13	0.23
		N	603	2111	446	2262	296	2385
	Post	mean	0.11	0.19	0.1	0.19	0.1	0.19
		SD	0.2	0.3	0.18	0.3	0.18	0.29
		N	605	2120	446	2273	297	2395
Theft from persons, houses and business per 1000 inhabitant	Pre	mean	0.46	0.91	0.43	0.88	0.37	0.87
		SD	0.7	1.21	0.7	1.19	0.59	1.18
		N	568	2086	411	2231	267	2351
	Post	mean	0.52	1.02	0.48	0.99	0.5	0.96
		SD	0.69	1.36	0.67	1.33	0.67	1.31
		N	569	2093	410	2240	267	2359
Theft of cars per 1000 inhabitant	Pre	mean	0.04	0.06	0.04	0.06	0.03	0.06
		SD	0.09	0.11	0.07	0.11	0.07	0.11
		N	371	1756	264	1851	144	1950
	Post	mean	0.05	0.06	0.04	0.06	0.04	0.06
		SD	0.09	0.12	0.09	0.12	0.08	0.11
		N	371	1763	263	1859	144	1957
Theft to persons, houses, business and cars per 1000 inhabitant	Pre	mean	0.6	1.0	0.58	1.0	0.56	1.0
		SD	0.82	1.3	0.84	1.28	0.75	1.27
		N	356	1725	249	1820	135	1916
	Post	mean	0.68	1.19	0.65	1.17	0.73	1.14
		SD	0.8	1.47	0.77	1.45	0.78	1.43
		N	356	1730	248	1826	135	1921

Note: SD: Standard Deviation; and N: observations.

The impact estimates computed using the formula in Equation (5.4) are reported in Table 5.6.1. These preliminary estimates are calculated assuming that there are not differential time varying factors between the two groups, other than the weather event, that is likely to influence theft rate behaviour over time. Furthermore, it is assumed that the treatment and comparison groups would have equal trends in outcomes in the absence of treatment. Since both assumptions are very strong, these D-i-D impact estimates may be invalid. However, they retain the ability to reveal the direction in which the theft rates will follow after the 'winter wave' event. Hence, it is likely that the D-i-D regression models will disclose a negative impact effect of the 'winter-wave' on the theft rates at the municipality level. For example, theft from persons, and the aggregate of the criminal categories, excluding and including car theft. It is unlike to detect and impact on car theft. In contrast, it is likely to detect an increase of theft rates, especially from houses and the aggregates, when the treatment intensity is high (i.e., 10% exposure). Finally, the D-i-D impact regression coefficients magnitudes more or less should be similar to these ones.

Table 5.6.2 Preliminary DiD impact estimates

Outcomes	Winter Wave treatment intensity		
	20%	**15%**	**10%**
Theft from persons per 1000 inhabitant	-0.05	-0.04	-0.01
Theft from houses per 1000 inhabitant	0.00	0.00	0.04
Theft from business per 1000 inhabitant	0.00	0.00	0.00
Theft from persons, houses and business per 1000 inhabitant	-0.05	-0.06	0.04
Theft of cars per 1000 inhabitant	0.01	0.00	0.01
Theft to persons, houses, business and cars per 1000 inhabitant	-0.07	-0.07	0.04

5.7 Empirical results

The mechanics and the explanations underlying the impact effects are likely to be different according to the type of theft considered. In particular, in the Becker (1968) model of crime and punishment, which is based on a ‘rational choice’ approach, criminal behaviour can be understood as if people choose crime by using the principles of cost-benefit analysis. Thus, thieves are highly motivated by the value of the reward they could obtain from the property stolen. In contrast, the higher the probability of arrest and punishment, the more certain is crime deterrence. However, real life does not preclude the possibility of people acting irrationally (i.e., choosing actions inconsistent with their expected preferences). In fact, people may pursue a course of action entirely inconsistent with their utility function because of false consciousness, survival motivation, habit, national culture, the rise of an emotional state, or even a sudden change in context.

Thus, often when a disaster strikes, there is a collapse of social control and poor people suffer the most.[111] Usually, people affected resort to theft as a 'safety net'. In such circumstances, the acquisitive motivation behind such behaviour is a 'survival mechanism', rather than one that seeks reward like in the Becker (1968) model of crime and punishment.

On the other hand, in the aftermath of a natural disaster often the social control fails, but the state of the organised criminal networks is unaffected. In fact, this sudden change of context creates new opportunities for organised crime. Thus, automobile theft, being a highly organised criminal activity, has the potential to thrive. In other words, the low risk and minimum penalties associated with apprehension in such circumstances, and the substantial difference between the potential gains from theft and the associated costs of apprehension, render car theft a profitable activity in the municipalities most affected, thus, providing support for the Becker's (1968) model of crime and punishment.

The main regression results for the D-i-D models are reported in Table 5.7.1. The dependent variable is either the theft rates per 1,000 of the population from either persons, houses, business or cars. The aggregates of these four criminal categories per 1,000 of the municipal population, including and also excluding car theft, are also employed as a dependent variable. Finally, panels A, B, and C distinguish between the three treatment intensities based on the exposure to 'winter wave' as outlined in the Empirical and identification strategy in section 5.4. We now turn to a review of these estimates.

[111] Poor people are more likely to live in fragile housing in vulnerable areas and frequently work in sectors highly susceptible to EWEs (like agriculture).

Table 5.7.1 D-i-D estimation of criminal activity rates (2007-2012)

Panel A: 10% treatment intensity

T_(i,t)	Persons	Houses	Business	Total	Cars	Total (+ cars)
Post 2010 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.014	0.025	-0.0046	0.011	0.0085	0.017
	(0.026)	(0.021)	(0.012)	(0.049)	(0.007)	(0.084)
Log income tax revenue per inhab	0.034**	0.030***	0.016*	0.091***	-0.0077	0.11**
	(0.014)	(0.011)	(0.010)	(0.030)	(0.006)	(0.048)
Percentage of urban population [0-100]	0.0067	0.00028	0.0076	0.015	0.0011	0.022
	(0.011)	(0.008)	(0.006)	(0.022)	(0.002)	(0.027)
Log population to area (Km2) density	-0.26	-0.44*	-0.23	-1.02*	0.0039	-1.34*
	(0.310)	(0.230)	(0.180)	(0.600)	(0.071)	(0.780)
Gross enrolment ratio, primary and secondary [0-100]	0.00059	-0.00026	0.00026	0.00019	-0.00023	-0.00057
	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.003)
Presence of conflict [Yes=1; No=0]	-0.051***	-0.025**	-0.015**	-0.092***	0.0013	-0.086**
	(0.017)	(0.011)	(0.007)	(0.030)	(0.004)	(0.036)
Observations	5510	5441	5373	5244	4195	4107
R-Squared (within)	0.0461	0.0379	0.0403	0.0647	0.00741	0.0754
F-stat	15.37	12.92	12.26	20.76	2.431	17.53

Panel B: 15% treatment intensity

T_(i,t)	Persons	Houses	Business	Total	Cars	Total (+ cars)
Post 2010 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.047*	0.00037	-0.014	-0.067	0.011	-0.084
	(0.027)	(0.020)	(0.011)	(0.050)	(0.008)	(0.075)
Log income tax revenue per inhab	0.035**	0.029**	0.017*	0.090***	-0.0085	0.11**
	(0.014)	(0.011)	(0.010)	(0.030)	(0.006)	(0.048)
Percentage of urban population [0-100]	0.0059	-0.0000014	0.0074	0.013	0.0011	0.02
	(0.011)	(0.008)	(0.006)	(0.022)	(0.002)	(0.027)
Log population to area (Km2) density	-0.29	-0.44*	-0.24	-1.07*	0.00086	-1.47*
	(0.310)	(0.230)	(0.180)	(0.600)	(0.069)	(0.780)
Gross enrolment ratio, primary and secondary [0-100]	0.00046	-0.00028	0.00015	0.00006	-0.00023	-0.00067
	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.003)
Presence of conflict [Yes=1; No=0]	-0.050***	-0.025**	-0.014*	-0.092***	0.0017	-0.086**
	(0.016)	(0.011)	(0.007)	(0.029)	(0.004)	(0.036)
Observations	5564	5489	5427	5292	4237	4143
R-Squared (within)	0.0464	0.0373	0.0402	0.0646	0.00808	0.0756
F-stat	15.46	12.72	12.13	20.7	2.55	17.48

Panel C: 20% treatment intensity

T_(i,t)	Persons	Houses	Business	Total	Cars	Total (+ cars)
Post 2010 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.052**	-0.0025	0.0033	-0.057	0.0043	-0.081
	(0.024)	(0.018)	(0.011)	(0.044)	(0.007)	(0.062)
Log income tax revenue per inhab	0.037**	0.029***	0.019*	0.092***	-0.0083	0.10**
	(0.015)	(0.011)	(0.010)	(0.030)	(0.006)	(0.047)
Percentage of urban population [0-100]	0.0039	0.00037	0.0064	0.0095	0.00087	0.019
	(0.011)	(0.008)	(0.006)	(0.022)	(0.002)	(0.027)
Log population to area (Km2) density	-0.27	-0.42*	-0.2	-1.01*	-0.002	-1.42*
	(0.310)	(0.230)	(0.180)	(0.600)	(0.068)	(0.770)
Gross enrolment ratio, primary and secondary [0-100]	0.00034	-0.00029	0.00012	-0.000084	-0.0002	-0.00085
	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.003)
Presence of conflict [Yes=1; No=0]	-0.049***	-0.024**	-0.014*	-0.090***	0.0016	-0.085**
	(0.017)	(0.011)	(0.007)	(0.029)	(0.004)	(0.035)
Observations	5576	5513	5439	5316	4261	4167
R-Squared (within)	0.0463	0.037	0.041	0.0643	0.0079	0.0756
F-stat	15.18	12.68	12.74	20.74	2.585	17.38

All panel regressions control for year fixed effects.
Standard errors in parentheses -adjusted for clusters in municipality-.
Treatment dummy does not appear due to fixed effects panel data estimation.
* $p < .10$, ** $p < .05$, *** $p < .01$

The coefficients associated with the primary variable of interest (Post 2010 [Yes=1; No=0]*Treatment [Yes=1; No=0]) captures the impact of the 'winter wave' on the various theft rates. In the circumstances when the treatment intensity is very high (i.e., 10% exposure), the estimation results reveal a negative effect of the 'winter-wave' on the theft rates from persons. This is found to be statistically significant at the 5% and 10% levels. As the treatment groups become larger and we focus down on a weaker exposure to the 'winter wave' overall (i.e., 15% and 20% exposure), the estimated impact of the 'winter wave' on theft from houses becomes better determined.

The magnitudes of the estimated causal effects can be interpreted as follows: i) a municipality in the top 15% treatment group most affected by the 'winter wave' exhibits a reduction of 4.7 theft from persons per 100,000 of the population, which represents a 10.4% decrease with respect to the mean (0.45), on average and *ceteris paribus* (Table 5.7.1, Panel B) ; and ii) a municipality in the top 20% treatment group affected by the 'winter wave' exhibited a reduction of 5.2 thefts from persons per 100,000 of the population, representing a 11.5% decrease with respect to the mean (0.45), on average and *ceteris paribus* (Table 5.7.1, Panel C).

The results confirm that the winter wave led to a decrease of theft from persons. Overall these results signal a pro-social community response to the 'winter wave', which led to a reduction in criminal activity. Often when a disaster strikes social barriers fall and people come together to survive and get through the hard times as a community, rather than turning on each other.

Most of the newspapers and media in Colombia captured how La Niña 2010-2011 fostered compassion and unity among the Colombians that discouraged theft in the municipalities affected by this natural disaster. For example, Grupo Aval Acciones y Valores S.A, the largest financial conglomerate in Colombia and one of the leading banking groups in Central America, with over USD 236.5 trillions in total assets and 468.0 trillion in assets under management, donated COP 15.000 million (equivalent to circa USD. 4.8 million) to the people affected[112]; popular bands of well-known Colombian artists throw a benefit concert increasing the donations[113]; and also, Mario

112 https://www.dinero.com/pais/articulo/grupo-aval-dona-15000-millones-para-damnificados/109158
113 https://www.eltiempo.com/archivo/documento/MAM-4314123

Hernandez, an emblematic entrepreneur of the fashion industry in Colombia, openly called for action asking the solidarity of the people to donate in the "Colombia Humanitaria" fund, a governmental imitative to offset the damages caused by the 'winter wave' [114].

Other donations were received and administered by private NGO's. For example, Teletón, the largest NGO that works in favor of children, youth and adults with physical or motor disabilities in the country, gather and invested more than COP 3.000 million (equivalent to USD 940.000)[115] in the territories affected. The Red Cross distributed more than 232 tons of aid[116], and most of the commercial banks initiated social campaigns for receiving donations[117].

In some municipalities the victims of this natural disaster gathered around "communal cooking pots" ("Ollas comunitarias", in Spanish). This pro-social initiative consisted in providing a shared lunch; indeed, all affected neighbours of some municipalities cooked and shared cups of soups[118].

In fact, in many one would anticipate hijacking, rioting, and looting in the wake of a natural disaster. However, there are also cases where altruism, cooperative behaviour, and solidarity among those adversely affected flourish. For example, there are well-documented cases of pro-social behaviour backed up with police reinforcements following a tsunami in Southeast Asia (December 2004), Hurricane Katrina[119] (2005),

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114 https://www.eltiempo.com/archivo/documento/MAM-4297321

115 https://www.elespectador.com/noticias/nacional/teleton-ha-recaudado-3000-millones-hasta-el-momento-articulo-241195

116 http://caracol.com.co/programa/2010/12/06/audios/1291645500_395713.html

117 http://www.elcolombiano.com/historico/solidaridad_para_ayudar_a_los_damnificados_por_el_invierno-LDEC_112393
http://www.elcolombiano.com/antioquia/ayudas-para-damnificados-por-tragedia-invernal-en-mocoa-putumayo-AA6255626

118 http://www.vanguardia.com/historico/84054-un-mute-solidario-por-los-damnificados-del-invierno
https://www.elheraldo.co/local/ollas-comunitarias-mas-que-una-solucion-alimentaria-para-los-damnificados

119 Many survivors invited victims to stay in their home temporarily, hotels housed displaced families, and even local doctors and nurses created improvised clinics in shelters.

and even during the terrorist attacks in London[120] (July 7, 2005) and New York City[121] (September 11, 2001).

While the empirical evidence previously shown supports the notion of pro-social behavior, it may not be the only explanation that reduced theft rates in the municipalities affected by the ‘winter wave’. On the one hand, the disruption to infrastructure reduced the ability of criminals and opportunists to engage in theft. During the ‘winter wave’ episode there were reports from at least 13 departments that faced a major damage in one of their primary roads that link them with other departments. These damages included 7 major bridges structures weakened, which needed immediate reinforcement or even re-building. The cost of damages caused to primary roads and bridges was estimated about circa USD 689 million. In addition, the destruction in secondary and tertiary roads accounted for 7% and 30% of their total length, respectively (CEPAL, 2012). Bottom-line, these damages were significant, and turned into a barrier for transporting criminal’s loots.

On the other hand, another reason of theft reduction is people relocation. The abandonment of settled areas with more destruction gives support to the hypothesis that there was also a reduction in the lucrative targets set for the potential criminals after this natural disaster. For examples, the settlements of Gramalote[122], Campo de la Cruz[123], Manatí[124], and El Arenal[125] ended covered by water, hence, leaving most of their inhabitants homeless. The media named them, the ghost towns (“Pueblos fantasmas”, in Spanish), since most of their infrastructure was devastated, therefore, their inhabitants left (including the potential criminals).

Another key finding that informs a sub-theme of our research, and links back to the earlier chapters, is that the presence of conflict impacts negatively on all theft rates, except the car theft category. All estimated regression models yield statistically significant and

[120] The attacks resulted in a large deployment of police officers to central London. During this time, crime fell significantly in central relative to outer London (See, for example, Draca et al.; 2011).
[121] There was 40% to 60% drop in the homicide rate in New York City after September 11, 2001.
[122] https://www.elespectador.com/impreso/articuloimpreso-241366-gramalote-un-pueblo-fantasma
[123] http://caracol.com.co/radio/2011/01/20/regional/1295517000_413848.html
[124] https://www.elespectador.com/noticias/nacional/municipio-de-manati-atlantico-totalmente-bajo-el-agua-articulo-306043
[125] http://www.eluniversal.com.co/cartagena/bol%C3%ADvar/arenal-bajo-el-agua-0

negative coefficients associated with presence of conflict dummy at the municipality level.[126] The theft reductions vary from 1.5 to 9.2 per 100,000 of the population, on average and *ceteris paribus*, depending on the specification and the theft category used. A dominant explanation of why the consolidation of some guerrilla fronts has been stronger in some municipalities than in others is related to weak state presence, especially in remote rural areas, where there is no effective provision of basic public goods such as sanitation, electricity, education or health.[127] Consequently, in those municipalities the provision of justice and the protection of fundamental legal rights have been neglected by the state. In the absence of a state presence, the illegal armed groups fill the vacuum, take advantage of the situation and provide 'justice and protection' through the establishment of coercive institutions which successfully deter thefts (or other types of crime). However, this happens only in areas where the guerrilla groups have territorial interests they control. For example, in coca production areas controlled by the guerrillas there are known to be few acquisitive criminal acts. Guerrillas protects coca farmers from theft to provide the security within which they can grow and harvest their illegal crops (see, for example, Sánchez and Chacón, 2005; and Acevedo, 2015).

The connection between low income and a high theft rate[128] is a research subject that has animated many social scientists in the past. Low and unstable income along with a high frequency of unemployment is usually positively correlated with acquisitive criminality. The log of the income tax revenue per inhabitant, which mirrors heterogeneity in the

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[126] Omitting the presence of conflict as an explanatory variable could potentially lead to biased and inconsistent coefficient estimates, though this is ultimately an empirical question. In any case, as an illustrative exercise, in Table 8.3.2 found in the Appendix 8.3 shows the D-i-D estimation of criminal activity rates (2007-2012) without controlling for the presence of conflict. The main results persist. The estimated impact of the 'winter wave' on theft remain negative and becomes better determined on a weaker exposure overall (i.e., 15% and 20% exposure). The magnitudes of the estimates of the 'winter wave' casual effects also remain similar. Table A, B, and C, also in the Appendix X, exhibit comparable estimates signs and sizes. The regression results including the year lags effects on theft, once again, one year after the "winter wave", show negative impacts concerning theft from persons, business and total thefts (excluding car theft). The D-i-D estimation results with all year lags and leads confirm a reduction of the theft rates, specially theft from persons, during the subsequent years of the "winter wave". These regressions also capture the positive effect on private houses during 2010, revealing that the 'winter wave' generated a mix of both pro-social behaviour and survival strategies.

[127] Sánchez and Chacón (2005) also point out the availability of economic resources and war economic interest as factors that also determine guerrilla groups' consolidation in some areas.

[128] In principle, following Becker's (1968) seminal paper, all other things being equal, an increase in the probability of being caught when committing a crime should deter the act of crime. Thus, in all of our empirical models, we also tried to include the number of criminal gangs and guerrilla members captured per 1,000 inhabitants as a proxy for policing efficiency and for the likelihood of getting caught. However, this estimated effect was not found to be well determined statistically in any of the specifications.

overall economic activities at the municipality level, is included in all the specifications. It yielded positive and a statistically significant effect in most cases. This finding could be taken to reflect the fact that higher incomes provide a greater opportunity set for thieves.

The percentage of the urban population and the log of the population density variables are included to assess the role of the city size and population density on crime, respectively. The percentage of the urban population yielded statistically insignificant estimates in all cases. This may be related to the fact that much of the cross-sectional variation in the urban population variable is absorbed within the income measure and the municipal fixed effects. On the other hand, the population density remains significant at 10% level regardless of the treatment intensity and exhibits a negative relationship with theft from houses, perhaps due to more effective policing in highly populated municipalities where the delivery of policing resources can exploit economies of scale.

The inclusion of the gross enrolment ratio (primary and secondary) may explain the role of education on theft. One can expect that individuals with higher levels of education are less likely to engage in theft activities given that, if apprehended, they would incur a large financial cost in terms of unusable and depreciated human capital (see, for example, Reilly and Witt 1996). However, for all the specifications based on the three different treatment intensities, there is no statistical relationship between the gross enrolment ratios (primary and secondary) and the theft rates. Once again, it is likely that much of the cross-sectional variation of this measure was absorbed within the municipal fixed effects.

The year lags effects of the 'winter wave' on thefts are reported in Table 5.7.2. The 2011 coefficient are small and statistically insignificant, nonetheless in 2012, one year after the natural disaster, the results reveal that there are some negative lag effects of the 'winter wave' on theft not only from persons, but also from businesses and total thefts but excluding car theft. The exact interpretation of the lag effects depends on the specifications (the treatment intensities and the type of theft), but they once again reveal that the post- 'winter wave' period was likely characterized by an increased degree of pro-social behaviour, therefore, a reduction in theft rates in the treatment groups. In particular, during 2012 theft reductions vary from 4.5 (from business) to 18 (total excluding car theft) per 100,000 of the municipality population, on average and *ceteris* *paribus.*

Table 5.7.2. is somehow telling half of the story; it is important to consider what would be the impact effect on theft when including also the year leads. The D-i-D estimation results, with all year lags and leads, are presented in Table 5.7.3.

Table 5.7.2 D-i-D estimations with year lags after the "winter wave"

Panel A: 10% treatment intensity

T_(i,t)	Persons	Houses	Business	Total	Cars	Total (+ cars)
Year 2011 [Yes=1; No=0] *Treatment [Yes=1; No=0]	-0.03	-0.014	-0.012	-0.051	0.0025	-0.071
	(0.028)	(0.016)	(0.015)	(0.046)	(0.010)	(0.064)
Year 2012 [Yes=1; No=0] *Treatment [Yes=1; No=0]	-0.10***	-0.034	-0.023	-0.15**	0.0047	-0.19**
	(0.035)	(0.030)	(0.018)	(0.069)	(0.011)	(0.097)
Log income tax revenue per inhabitant	0.034**	0.029***	0.016	0.090***	-0.0077	0.10**
	(0.014)	(0.011)	(0.010)	(0.030)	(0.006)	(0.048)
Percentage of urban population [0-100]	0.0066	0.00039	0.0076	0.015	0.0011	0.021
	(0.011)	(0.008)	(0.006)	(0.022)	(0.002)	(0.028)
Log population to area (Km2) density	-0.32	-0.48**	-0.24	-1.14*	0.0016	-1.50*
	(0.310)	(0.230)	(0.180)	(0.610)	(0.070)	(0.790)
Gross enrolment ratio, primary and secondary [0-100]	0.00041	-0.00035	0.00022	-0.000081	-0.00022	-0.00087
	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.003)
Presence of conflict [Yes=1; No=0]	-0.049***	-0.024**	-0.015**	-0.090***	0.0013	-0.084**
	(0.017)	(0.011)	(0.007)	(0.029)	(0.004)	(0.036)
Observations	5510	5441	5373	5244	4195	4107
R-Squared (within)	0.0478	0.0381	0.0407	0.0659	0.00728	0.0768
F-stat	14.29	11.94	11.01	19.35	2.131	16.16

Panel B: 15% treatment intensity

T_(i,t)	Persons	Houses	Business	Total	Cars	Total (+ cars)
Year 2011 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.011	-0.0061	-0.016	-0.035	0.007	-0.044
	(0.031)	(0.016)	(0.017)	(0.051)	(0.010)	(0.071)
Year 2012 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.11***	-0.032	-0.045**	-0.18**	0.0081	-0.20*
	(0.036)	(0.032)	(0.018)	(0.073)	(0.011)	(0.100)
Log income tax revenue per inhabitant	0.036**	0.029**	0.017*	0.090***	-0.0085	0.11**
	(0.014)	(0.011)	(0.010)	(0.030)	(0.006)	(0.048)
Percentage of urban population [0-100]	0.0061	0.00015	0.0075	0.013	0.0011	0.02
	(0.011)	(0.008)	(0.006)	(0.022)	(0.002)	(0.027)
Log population to area (Km2) density	-0.31	-0.45**	-0.25	-1.10*	-0.0021	-1.50*
	(0.310)	(0.230)	(0.180)	(0.600)	(0.069)	(0.780)
Gross enrolment ratio, primary and secondary [0-100]	0.00032	-0.00033	0.000095	-0.00013	-0.00023	-0.00075
	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.003)
Presence of conflict [Yes=1; No=0]	-0.049***	-0.024**	-0.014*	-0.091***	0.0018	-0.084**
	(0.016)	(0.011)	(0.007)	(0.029)	(0.004)	(0.036)
Observations	5564	5489	5427	5292	4237	4143
R-Squared (within)	0.0477	0.0376	0.0413	0.0657	0.00773	0.0764
F-stat	14.33	11.9	11.04	19.21	2.293	16.21

Panel C: 20% treatment intensity

T_(i,t)	Persons	Houses	Business	Total	Cars	Total (+ cars)
Year 2011 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.024	-0.0065	0.0014	-0.032	0.0015	-0.05
	(0.027)	(0.016)	(0.015)	(0.044)	(0.009)	(0.058)
Year 2012 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.11***	-0.036	-0.02	-0.16**	0.0053	-0.19**
	(0.033)	(0.028)	(0.018)	(0.066)	(0.010)	(0.090)
Log income tax revenue per inhabitant	0.037**	0.029**	0.019*	0.091***	-0.0083	0.10**
	(0.015)	(0.011)	(0.010)	(0.030)	(0.006)	(0.047)
Percentage of urban population [0-100]	0.0039	0.00036	0.0063	0.0095	0.00086	0.019
	(0.011)	(0.008)	(0.006)	(0.022)	(0.002)	(0.027)
Log population to area (Km2) density	-0.29	-0.44*	-0.22	-1.06*	-0.0028	-1.46*
	(0.310)	(0.230)	(0.180)	(0.600)	(0.068)	(0.780)
Gross enrolment ratio, primary and secondary [0-100]	0.00024	-0.00035	0.000085	-0.00024	-0.0002	-0.00096
	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.003)
Presence of conflict [Yes=1; No=0]	-0.048***	-0.023**	-0.014*	-0.088***	0.0016	-0.084**
	(0.017)	(0.011)	(0.007)	(0.029)	(0.004)	(0.035)
Observations	5576	5513	5439	5316	4261	4167
R-Squared (within)	0.0477	0.0375	0.0414	0.0655	0.00788	0.0766
F-stat	14.17	11.93	11.35	19.41	2.364	16.23

All panel regressions control for year fixed effects.
Standard errors in parentheses -adjusted for clusters in municipality-.
Treatment dummy does not appear due to fixed effects panel data estimation.
* $p < .10$, ** $p < .05$, *** $p < .01$

The D-i-D estimation results, with all year lags and leads, are presented in Table 5.7.3. The test for parallel trends between the treatment and comparison groups for the pre 'winter wave' period (2007-2010) is presented at the bottom of each intensity of treatment regression. The estimates suggest that we cannot reject the null of similar trends between the comparison and the treated groups for theft rates from persons, houses, business, and the aggregates (excluding and including car theft). However, as noticed previously, the treatment and control groups for the car theft category do not follow parallel trends. Hence, it is likely that D-i-D method yields biased estimates, which weaken any inferences drawn from the car theft regressions. One of the possible reasons why car theft does not pass the parallel trends test is because it occurs mostly in big cities (where it is a well-established enterprise), and such cities are not well represented in the control groups.[129]

It is confirmed that the subsequent years of the 'winter wave' exhibited a reduction of the theft rates, mainly in terms of theft from persons. However, in the specification where the treatment intensity is calibrated to be medium and low (i.e., 15% and 20% exposure), the estimation results reveal a positive effect of the 'winter-wave' on the theft rates from private houses during 2010. A municipality most severely affected by the 'winter wave' exhibits an increase of 4.1 theft from houses per 100,000 of the population, which represents a 18.6% increase with respect to the mean (0.22) on average and *ceteris paribus.* House thefts are very common in the aftermath of a natural disaster. Thieves steal from the damaged and destroyed houses, while residents are distracted by other matters or evacuated. However, the motivation behind house theft is a survival/coping mechanism. In summary, the aftermath of the 'winter wave' generated a mix of both pro-social behaviour and survival strategies that impacted theft rates against persons and houses.

Finally, the regression results based on averaging the data before and after the winter wave using a panel of length two are reported in Table 8.3.1 of the Appendix 8.3. The results remain broadly consistent with our key findings.

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[129] Big cities were also severely affected by the 'winter wave'. However, they are not in the treatment groups due to the ratio of houses affected and population is small. Nevertheless, nearby smaller cities are in the treatment groups.

Table 5.7.3 D-i-D estimation with year lags and leads after the "winter wave"

Panel A: 10% treatment intensity

T_(i,t)	Persons	Houses	Business	Total	Cars	Total (+ cars)
Year 2008 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.039	0.033	0.00077	-0.017	0.013	0.065
	(0.033)	(0.024)	(0.016)	(0.058)	(0.013)	(0.080)
Year 2009 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.074**	0.022	-0.015	-0.081	-0.018	-0.081
	(0.031)	(0.025)	(0.015)	(0.058)	(0.012)	(0.081)
Year 2010 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.058*	0.038	0.013	-0.031	0.0038	-0.044
	(0.031)	(0.024)	(0.015)	(0.060)	(0.013)	(0.087)
Year 2011 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.073*	0.0091	-0.012	-0.083	0.0022	-0.087
	(0.039)	(0.024)	(0.019)	(0.066)	(0.014)	(0.094)
Year 2012 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.14***	-0.011	-0.024	-0.18**	0.0043	-0.21*
	(0.042)	(0.036)	(0.021)	(0.084)	(0.016)	(0.120)
Log income tax revenue per inhabitant	0.034**	0.029***	0.015	0.090***	-0.0077	0.11**
	(0.014)	(0.011)	(0.010)	(0.030)	(0.006)	(0.048)
Percentage of urban population [0-100]	0.0067	0.00038	0.0076	0.015	0.0011	0.021
	(0.011)	(0.008)	(0.006)	(0.022)	(0.002)	(0.028)
Log population to area (Km2) density	-0.35	-0.47**	-0.24	-1.16*	-0.0012	-1.53*
	(0.310)	(0.230)	(0.180)	(0.610)	(0.069)	(0.800)
Gross enrolment ratio, primary and secondary [0-100]	0.00035	-0.00034	0.00021	-0.00016	-0.00025	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.003)
Presence of conflict [Yes=1; No=0]	-0.049***	-0.024**	-0.015**	-0.090***	0.0013	-0.084**
	(0.017)	(0.011)	(0.007)	(0.029)	(0.004)	(0.036)
Observations	5510	5441	5373	5244	4195	4107
R-Squared (within)	0.0484	0.0384	0.0411	0.0662	0.00909	0.0773
F-stat	11.87	9.577	9.657	15.93	2.721	13.69
F-test for Par. Trend	1.89	1.08	1.35	0.82	3.54	1.06
Prob > F	(0.13)	(0.36)	(0.26)	(0.48)	(0.01)	(0.37)

Panel B: 15% treatment intensity

T_(i,t)	Persons	Houses	Business	Total	Cars	Total (+ cars)
Year 2008 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.014	0.037	-0.0083	0.012	0.013	0.1
	(0.031)	(0.023)	(0.016)	(0.053)	(0.011)	(0.073)
Year 2009 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.051*	0.022	-0.024*	-0.06	-0.014	-0.04
	(0.028)	(0.025)	(0.014)	(0.051)	(0.009)	(0.069)
Year 2010 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.031	0.041*	0.0039	-0.0021	0.0049	0.0086
	(0.028)	(0.021)	(0.015)	(0.052)	(0.010)	(0.073)
Year 2011 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.034	0.018	-0.022	-0.047	0.0077	-0.028
	(0.038)	(0.023)	(0.020)	(0.064)	(0.012)	(0.090)
Year 2012 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.14***	-0.0086	-0.052***	-0.19**	0.0088	-0.19
	(0.040)	(0.037)	(0.020)	(0.082)	(0.013)	(0.120)
Log income tax revenue per inhabitant	0.036**	0.028**	0.018*	0.091***	-0.0084	0.11**
	(0.014)	(0.011)	(0.010)	(0.030)	(0.006)	(0.048)
Percentage of urban population [0-100]	0.0062	0.0000095	0.0075	0.013	0.0011	0.02
	(0.011)	(0.008)	(0.006)	(0.022)	(0.002)	(0.027)
Log population to area (Km2) density	-0.31	-0.45**	-0.25	-1.11*	-0.0042	-1.52*
	(0.310)	(0.230)	(0.180)	(0.600)	(0.069)	(0.780)
Gross enrolment ratio, primary and secondary [0-100]	0.00029	-0.00034	0.000076	-0.00019	-0.00026	-0.00088
	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.003)
Presence of conflict [Yes=1; No=0]	-0.049***	-0.024**	-0.013*	-0.090***	0.0018	-0.084**
	(0.016)	(0.011)	(0.007)	(0.029)	(0.004)	(0.036)
Observations	5564	5489	5427	5292	4237	4143
R-Squared (within)	0.0481	0.0382	0.0418	0.0659	0.00923	0.0769
F-stat	11.98	9.562	9.746	16	2.739	13.8
F-test for Par. Trend	1.15	1.80	1.71	0.85	3.01	1.22
Prob > F	(0.33)	(0.15)	(0.16)	(0.47)	(0.03)	(0.30)

Panel C: 20% treatment intensity						
T_(i,t)	Persons	Houses	Business	Total	Cars	Total (+ cars)
Year 2008 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.031	0.032	0.00029	-0.0082	0.0056	0.045
	(0.033)	(0.022)	(0.015)	(0.056)	(0.012)	(0.073)
Year 2009 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.069**	0.023	-0.011	-0.069	-0.019*	-0.053
	(0.030)	(0.024)	(0.014)	(0.056)	(0.012)	(0.076)
Year 2010 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.048	0.041*	0.016	-0.012	-0.00057	-0.0058
	(0.031)	(0.023)	(0.015)	(0.058)	(0.012)	(0.081)
Year 2011 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.061*	0.018	0.0027	-0.054	-0.0021	-0.054
	(0.037)	(0.023)	(0.018)	(0.063)	(0.013)	(0.087)
Year 2012 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.15***	-0.012	-0.019	-0.18**	0.0017	-0.19*
	(0.040)	(0.034)	(0.020)	(0.081)	(0.015)	(0.110)
Log income tax revenue per inhabitant	0.037**	0.029**	0.019*	0.091***	-0.0083	0.10**
	(0.015)	(0.011)	(0.010)	(0.030)	(0.006)	(0.047)
Percentage of urban population [0-100]	0.004	0.00036	0.0064	0.0094	0.00084	0.019
	(0.011)	(0.008)	(0.006)	(0.022)	(0.002)	(0.027)
Log population to area (Km2) density	-0.32	-0.43*	-0.21	-1.07*	-0.0062	-1.47*
	(0.310)	(0.230)	(0.180)	(0.600)	(0.068)	(0.780)
Gross enrolment ratio, primary and secondary [0-100]	0.00017	-0.00033	0.000074	-0.00031	-0.00023	-0.0011
	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.003)
Presence of conflict [Yes=1; No=0]	-0.048***	-0.023**	-0.014*	-0.088***	0.0016	-0.084**
	(0.017)	(0.011)	(0.007)	(0.029)	(0.004)	(0.035)
Observations	5576	5513	5439	5316	4261	4167
R-Squared (within)	0.048	0.038	0.042	0.066	0.009	0.077
F-stat	11.69	9.581	9.929	15.97	2.868	13.59
F-test for Par. Trend	1.73	1.29	1.30	0.84	2.96	0.64
Prob > F	(0.16)	(0.28)	(0.27)	(0.47)	(0.03)	(0.59)

All panel regressions control for year fixed effects.
Standard errors in parentheses -adjusted for clusters in municipality-.
Treatment dummy does not appear due to fixed effects panel data estimation.
* $p < .10$, ** $p < .05$, *** $p < .01$

5.8 Conclusions

During 2010-2011, as a result of the extraordinary and sustained increase in rainfall, Colombia faced one of the greatest natural disasters of its recent history, the ‘winter wave’. This affected more than 3.2 million people, left 467 people dead, 577 injured, at least 566,556 damaged or completely destroyed homes, and left damages 2,300 institutional buildings damaged. According to CEPAL (2012) losses amounted to about USD 6.052 billion.

This chapter has exploited a novel municipal panel dataset to determine whether the most recent EWE in Colombia, “La Niña” between 2007-2011, impacted theft activity in the municipalities affected. A Difference-in-Difference estimation procedure was used to show that the ‘winter wave’ induced a decrease in theft from persons. This finding is consistent with pro-social behaviour. Increased precipitation led to higher levels of flooding, landslides and washed away roads. Then, it created a situation where distress was evident and tended to increase compassion, cooperation and solidarity. Municipal members came together to help each other, giving a family a place to stay, helping clear a landslide or even rebuilding community houses together.

However, we also perceived a positive effect of the ‘winter-wave’ on the theft rates from private houses during 2010. When there is a collapse of social control we argue that the motivation behind theft from houses is likely best represented as a ‘survival mechanism’ rather than pecuniary reward, which conflicts with the Becker (1968) cost-benefit notion of acquisitive criminal behaviour. Crime rates could increase due to insufficient savings and lack of income, creating a desperate situation for vulnerable households.

On the other hand, the use of car theft data remains worrisome and some caveats are required. First, for interpretation purposes car theft rates could be interpreted within Becker's (1968) model of crime and punishment. Second, most of the car theft occurs in the main cities. Therefore, the use of this particular sample was questionable, as the sample may not accurately reflect the characteristics of the general population. This type of selection bias issue perhaps translated into different trends between treated and control groups of municipalities weakening the D-i-D estimation procedure for this category.

The conclusions drawn here have distinct policy implications, given climate patterns around the globe will continue to change due to the effect of greenhouse gases, such as carbon dioxide emissions from burning fossil fuels or deforestation. The need to develop instruments to mitigate criminality following an EWE is clear. Governmental planning and implementation of community-based safety net systems are fundamental to deal with disasters such as the ‘winter wave’ and will help ensure individuals do not need to resort to crime as a ‘safety net in such circumstances.

In fact, the Colombian government responded to the ‘winter wave’ with enthusiasm and support, gathering citizens and corporations around “Colombia Humanitaria” – a national public-private response and reconstruction pooled fund which managed to administered in cash and in-kind donations of around USD $83 million.The “Colombia Humanitaria” response delivered more than 39,503 tons of food, 4.283 infrastructure projects were executed, 66,601 homes where repaired and another 60,671 households were benefited with lease support, among many other achievements. However, the magnitude of the tragedy surpassed this disaster response. According to Dara (2012), some mismanagement and a deficient prioritisation limited Colombia Humanitaria’s performance, lowering the quality of the assistance provided. Good intentions and well-meant efforts are not always enough to build a working response system overnight. Hence, as a lesson learnt, disaster risk reduction and building local capacity should be a priority in the near future.

Finally, a sub-theme of this paper was to uncover the nexus between conflict presence and theft rates in Colombia. The empirical results reveal that the illegal armed groups have provided protection through the establishment of coercive institutions. This is particularly the case in the municipalities without a strong state presence, which in turn may have discouraged theft. This scenario is not necessarily optimal because the illegal armed groups, as any other criminal organization, have their own economic and political interests at the centre of their behaviour.

Chapter 6

6 Conclusions

This thesis contained three empirical essays around conflict, agricultural contracts, climate and environmental economics issues. In particular, the role of conflict on agribusiness contract durations, the civil war deforestation impacts, and the relationship of theft rates with the increasing presence of climate variability are all examined. Until now there were no previous studies exploring the research questions included in each one of these thesis chapters for the Colombian case. This makes this thesis unique, but naturally at the same time subject to limitations, and also opens new research avenues that will demand future work. The thesis's main findings, limitations and future work are discussed as follows:

Chapter 3 asked if the Colombian armed conflict has hampered the farmer capacity to sustain market linkages. In particular, some of the channels through which violence is allowed to affect agribusiness contract durations were examined. The primary finding of this chapter was that terrorism at the start of agribusiness contracts , appears to be the main cause of smallholder agribusiness contract failure. In addition, when the duration model allows violent incidents to vary over time, the armed conflict (i.e., the number of subversive actions) emerged as the main cause of agribusiness contract failure. Availability of rich data on agribusiness contracts and producer organization characteristics as obtained from archives of a public project whose goal is to establish commercial relationships between small producers and formal buyers (*Proyecto de Apoyo a Alianzas Productivas* – PAAP*,* in Spanish) facilitated this empirical analysis.

One limitation of the chapter was the absence of data regarding the reasons as to why the contract failed. With the current dataset, it is not possible to identify who is the actor that defaults from the original contract. Not only the producer organizations, but also the buyers may also be tempted to look for other providers.

In the context of linking farmers to markets, failure of the original contract is not necessarily something bad. Indeed, if the PAAP, linking farmers to a markets program, is effective, smallholder farmer beneficiaries at some point after its implementation may be able to link with buyers in more sophisticated supply value chains that offer better business growth opportunities. Therefore, a crucial research question raised by the findings of this chapter is which is the actor more prone to default? The producer organization or the buyer? A secondary question left unanswered is: what are the causes of failure? For example, future work could reveal the key explanatory variables constraining producer organizations to produce the agreed volume of products and/or meet a certain quality criteria; the buyer's inability to meet purchasing commitments; the changing market conditions (the business cycle); and/or the buyer's evolving business priorities.

The Chapter 4 examined the relationship between the Colombian armed conflict and its environmental impacts. In particular, using a unique annual municipality panel dataset (from 2004 to 2012) and an instrumental variable approach to control for possible endogeneity between forest cover and forced displacement, the primary finding of this chapter is that the armed conflict is a force of forest protection and growth. On the basis of the instruments used, the exogeneity assumption for the forced displacement variable is not rejected by a Hausman test, thus, the more appropriate method to make inferences is the OLS fixed effects (FE-OLS) model. The estimated effect suggests that an additional person displaced per 1,000 inhabitants increases the percent of forest covered by 0.0028 of a percentage point at the municipality level. The detected forestation effect is found to be negligible in magnitude when compared to other forestation drivers such as the average precipitations monthly, the distance to the department capital or a soils quality index. In any case, it is essential to highlight that the conflict imposed immense human pain and suffering that can't be compensated by such a small environmental forestation impact.

In addition, with the advent of peace in Colombia this chapter advocates for an appropriate conservation strategy since forest degradation often increases in post-war situations. The government will need to be ready to deploy conservation policies in areas currently under control of the guerrillas. In the past, the protected zones by the state helped in reducing settlements and illegal drug activity. However, this might not be enough for the future. Conservation enforcement of currently protected regions and areas previously under a "gunpoint conservation" regime by the guerrillas will be fundamental. Rain forests and their watersheds support the lives of many. Therefore, their protection and conservation is crucial. These findings spotlight a need for increased protection of Colombia's forests.

A major challenge for this chapter was getting the right estimates for the share of municipality area covered by the forest. Thus, an extension of this chapter could be an exploration of other forest cover estimates sources that may be useful not only to test the robustness of the econometric model results presented in the chapter, but also to include more municipalities enriching the sample representativeness. In addition, it would be desirable to examine in future work other factors that are difficult to measure that affect forest cover changes such as the conversion of forest areas into pastures, illegal logging and forest fires.

Chapter 5 estimates the impact of the most recent Extreme Weather Event in Colombia, "La Niña" on the theft rates in the municipalities affected between 2010-2011. Using a novel annual municipal panel dataset (2007-2012, inclusive), and measuring the affected areas according to the number of houses damaged and destroyed, this study relies on a Difference-in-Difference (D-i-D) model to show that the concurrent year of the winter wave brought a decrease in theft rates, in particular theft from persons. This could be perhaps attributable to the emergence of pro-social behaviour in the municipalities most affected. Together, we also find an increase in theft from houses possibly linked to a 'survival mechanism', rather than one that seeks pecuniary reward. In addition, the D-i-D estimates reveal that the presence of conflict, in general, discourages theft perhaps due to the establishment of coercive institutions by illegal armed groups.

The conclusions drawn by this chapter also have policy implications, as the climate patterns across the globe continue to change more rapidly due to the effect of greenhouse gases, such as carbon dioxide emissions from burning fossil fuels or deforestation. The need to develop pro-social behaviour instruments that have the potential to drastically decrease criminality following an EWE is increasing. For example, governmental planning and implementation of community-based safety net systems in the cities are fundamental to deal with a natural disaster such as the winter wave.

One of the major limitation of this chapter is the use of car theft. Most of car theft occurs in the main cities. Therefore, this particular sample reflect the characteristics of the general population, and doesn’t pass the parallel trends assumption. Although it is beyond the current scope of this chapter, future research for the case of Colombia could address the impact of a specific natural disaster, not only on property crime, but also on violent crimes. This would fit well with an existing literature that connects violent behaviour with weather conditions.

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8 Appendix

8.1 Appendix chapter 3

Table 8.1.1 Variable models definitions

Variable	Definition
Failure event	Dummy: 1 if the agribusiness contract fail; 0 otherwise
Average failure time	Average spell duration length of agribusiness contracts
Acts of terror, at start	Acts of terror including explosions, incendiaries or other type of terrorist acts
Subversive actions, at start	Subversive actions undertaken by the non-state armed actors such as guerrillas and paramilitaries including assaults to private property, attacks on entities or facilities, attacks on military headquarters, political attacks, roadblocks, ambushes, harassments, raids and car hijackings
Kidnappings per 100,000 inhab., at start	Kidnappings of civilians, political or members of the army per 100,000 inhabitants
Homicide rate per 100,000 inhab., at start	Homicides per 100,000 inhabitants
PO beneficiaries selected, at start (#)	Number of the PO beneficiaries exactly at the time when PAAP managers approved the agribusiness contracts
Avg. share of beneficiaries that work on the farm/UPA at start (0-100)	Average share of PO beneficiaries that work fulltime on the farm at the start of the agribusiness contract is computed
PA still at implementation stage	Dummy: 1 if POs remaining in the implementation stage of PAAP; 0 otherwise
Avg. distance to nearest wholesales food markets	Average distance to nearest wholesales food markets (kms) in the department
Crops	Dummy: 1= if the PO produce a crop product; 0 otherwise
Short growing cycle crop	Dummy: 1 if the PO produce a growing cycle crops (three to 12 months of maturity); 0 otherwise
Livestock	Dummy: 1 if the PO produce livestock; 0 otherwise
Fish	Dummy: 1 if the PO produce fish; 0 otherwise
Milk	Dummy: 1 if the PO produce milk; 0 otherwise
Other no crop product	Dummy: 1 if the PO produce beekeeping, silk thread and unrefined sugar cane; 0 otherwise

Table 8.1.2 Cox PH model estimates for commercial agreement failure (Violent incidents average 3 years before start)

VARIABLES	(1)	(2)
Acts of terror, avg. 3 years before start	0.066**	0.007
	(0.030)	(0.045)
Subversive actions, avg. 3 years before start	-0.029	0.094
	(0.127)	(0.120)
Kidnappings per 100,000 inhab, avg. 3 years before start	0.089	0.083
	(0.097)	(0.168)
Homicide rate per 100,000 inhab, avg. 3 years before start	-0.006	-0.004
	(0.004)	(0.003)
PO beneficiaries selected, at start (#)	-0.011***	-0.006
	(0.004)	(0.004)
Avg. share of beneficiaries that work on the farm, at start (0-100)	-0.006*	-0.001**
	(0.003)	(0.004)
PA still under implementation stage	0.925***	0.975***
	(0.226)	(0.229)
Average distance to nearest wholesales food markets	0.001	0.006*
	(0.001)	(0.004)
Short growing cycle crop	0.075	0.094
	(0.387)	(0.425)
Livestock	0.996***	1.185***
	(0.350)	(0.395)
Fish	0.372	1.04**
	(0.429)	(0.451)
Milk	-0.706*	-0.898**
	(0.391)	(0.419)
Other no crop product	-0.454	0.146
	(0.546)	(0.509)
Dummy Department (26)	No	Yes
Observations	434	434
Test of joint significance of departments (Prob>chi2)		0.002
Test of joint significance of type of product (Prob>chi2)	0.019	0.001
Model chi2	40.65	127.60
Df	13	39
Pseudo-Log(L)	-581.1	-556.4
AIC	1188	1191
N. of fails (without a business partner)	114	114

Robust standard errors in parentheses *** p<0,01, ** p<0,05, *p<0,1

Table 8.1.3 Contract durations statistics per semester

Semester	Contracts	Fail	Net Lost	Survivor Function	Std. Error	[95% Conf. Int.]	
1	434	17	0	0.9608	0.0093	0.9377	0.9755
2	417	23	0	0.9078	0.0139	0.8765	0.9315
3	394	12	122	0.8802	0.0156	0.8458	0.9073
4	260	8	19	0.8531	0.0178	0.8142	0.8844
5	233	9	63	0.8201	0.0202	0.7765	0.8561
6	161	9	35	0.7743	0.0242	0.7225	0.8176
7	117	7	14	0.728	0.0284	0.6677	0.7791
8	96	10	17	0.6521	0.0341	0.5809	0.7143
9	69	5	3	0.6049	0.0376	0.5270	0.6740
10	61	6	14	0.5454	0.041	0.4616	0.6216
11	41	3	6	0.5055	0.044	0.4164	0.5878
12	32	1	11	0.4897	0.0454	0.3982	0.5749
13	20	3	6	0.4162	0.0549	0.3081	0.5207
14	11	1	4	0.3784	0.0616	0.2594	0.4967
15	6	0	5	0.3784	0.0616	0.2594	0.4967
17	1	0	1	0.3784	0.0616	0.2594	0.4967

Table 8.1.4 Parametric accelerated failure time duration models

VARIABLES	Weibull AFT	Log-logistic AFT	Log-logistic AFT with I.G
Acts of terror, at start.	-0.053*	-0.050*	-0.050*
	(0.027)	(0.026)	(0.026)
Subversive actions, at start	0.099	0.109	0.109
	(0.066)	(0.070)	(0.070)
Kidnappings per 100,000 inhab, at start	0.007	0.010	0.010
	(0.019)	(0.024)	(0.024)
Homicide rate per 100,000 inhab, at start	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)
PO beneficiaries selected, at start (#)	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)
Avg. share of beneficiaries that work on the farm/UPA at start (0-100)	0.006**	0.005*	0.005*
	(0.002)	(0.003)	(0.003)
PA still under implementation stage	-0.511***	-0.537***	-0.537***
	(0.108)	(0.120)	(0.120)
Average distance to nearest wholesales food markets	-0.003*	-0.003	-0.003
	(0.002)	(0.002)	(0.002)
Short growing cycle crop	-0.021	0.083	0.083
	(0.222)	(0.270)	(0.270)
Livestock	-0.555**	-0.539*	-0.539*
	(0.225)	(0.297)	(0.297)
Fish	-0.709**	-0.671***	-0.671***
	(0.276)	(0.239)	(0.239)
Milk	0.430*	0.504**	0.504**
	(0.228)	(0.229)	(0.229)
Other no crop product	0.024	0.119	0.119
	(0.239)	(0.260)	(0.260)
Constant	1.937***	1.776***	1.776***
	(0.320)	(0.348)	(0.348)
Ln(alpha)	0.680***		
	(0.074)		
Ln(gamma)		-0.828***	-0.828***
		(0.080)	(0.080)
Ln(theta)			-13.582***
			(0.846)
Departments dummies (26)	Yes	Yes	Yes
Observations	434	434	434
Overall test (Prob>chi2) of product dummies	0.003	0.006	0.006
Overall test (Prob>chi2) of departmental dummies	0.024	0.002	0.002
Model chi-square	110.1	120.3	120.3
Df	39	39	39
Pseudo-Log(L)	-243.3	-244.8	-244.8
AIC	568.6	571.7	573.7
N. of fails (without a business partner)	114	114	114

Robust standard errors in parentheses *** p<0,01, ** p<0,05, *p<0,1

Table 8.1.5 Discrete time coefficients (cloglog regressions)

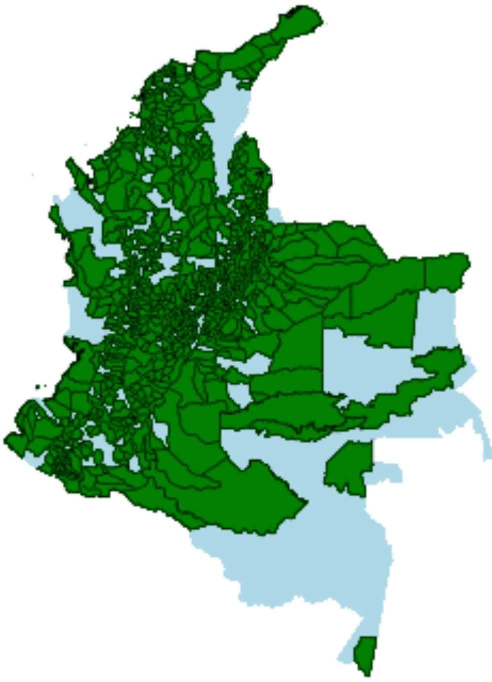
Variables	Baseline				
	Fully non-parametric	Log(t)	(t)	Quadratic	Cubic
Acts of terror	-0.043	-0.042	-0.044	-0.044	-0.045
	(0.037)	(0.037)	(0.037)	(0.038)	(0.037)
Subversive actions	0.226*	0.215*	0.226*	0.226*	0.221*
	(0.126)	(0.124)	(0.125)	(0.126)	(0.127)
Kidnappings per 100,000 inhab	0.010	0.011	0.011	0.011	0.008
	(0.019)	(0.017)	(0.018)	(0.018)	(0.019)
Killings per 100,000 inhab	0.002	0.001	0.001	0.001	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
PO beneficiaries selected, at start (#)	-0.006	-0.005	-0.005	-0.005	-0.006
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Avg. share of beneficiaries that work on the farm at start	-0.013***	-0.012**	-0.013***	-0.013***	-0.013***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
PA still under implementation stage	1.037***	0.817***	0.933***	0.934***	1.019***
	(0.245)	(0.219)	(0.235)	(0.232)	(0.239)
Avg. distance to nearest wholesales food markets in the department	0.006	0.006	0.006	0.006	0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Short growing cycle crop	0.077	0.087	0.091	0.091	0.074
	(0.512)	(0.514)	(0.518)	(0.518)	(0.517)
Livestock	1.329***	1.180**	1.255**	1.255**	1.304***
	(0.504)	(0.489)	(0.496)	(0.496)	(0.496)
Fish	1.364**	1.459**	1.432**	1.432**	1.334**
	(0.573)	(0.570)	(0.557)	(0.557)	(0.555)
Milk	-0.879**	-0.876**	-0.887**	-0.886**	-0.883**
	(0.437)	(0.433)	(0.432)	(0.435)	(0.434)
Other no crop product	0.240	0.199	0.246	0.246	0.240
	(0.597)	(0.600)	(0.598)	(0.595)	(0.590)
Ln(time=semester)		0.606***			
		(0.169)			
Time			0.179***	0.181	-0.390
			(0.038)	(0.113)	(0.283)
Time^2				-0.000	0.114**
				(0.009)	(0.055)
Time^3					-0.006**
					(0.003)
Constant		-3.150***	-3.222***	-3.225***	-2.516***
		(0.729)	(0.750)	(0.753)	(0.848)
Semesters dummy (14)	Yes	Yes	Yes	Yes	Yes
Departments dummy (26)	Yes	Yes	Yes	Yes	Yes
Observations	2,168	2,195	2,195	2,195	2,195
Log pseudolikelihood	-367.9	-380.1	-377.2	-377.2	-374.9

Table 8.1.6 Discrete time marginal effects (cloglog regressions)

Variables	Baseline				
	Fully non-parametric	Log(t)	(t)	Quadratic	Cubic
Acts of terror	-0.0012	-0.0013	-0.0013	-0.0013	-0.0013
	(0.0010)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Subversive actions	0.0063*	0.0065*	0.0067*	0.0067*	0.0064*
	(0.0035)	(0.0038)	(0.0037)	(0.0037)	(0.0036)
Kidnappings per 100,000 inhab	0.0003	0.0004	0.0003	0.0003	0.0002
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Killings per 100,000 inhab	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
PO beneficiaries selected, at start (#)	-0.0002	-0.0001	-0.0002	-0.0002	-0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Avg. share of beneficiaries that work on the farm at start	-0.0004***	-0.0004***	-0.0004***	-0.0004***	-0.0004***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
PA still under implementation stage	0.0334***	0.0277***	0.0314***	0.0314***	0.0341***
	(0.0087)	(0.0078)	(0.0084)	(0.0084)	(0.0088)
Avg. distance to nearest wholesales food markets in the department	0.0002*	0.0002	0.0002	0.0002*	0.0002*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Short growing cycle crop	0.0022	0.0027	0.0028	0.0028	0.0022
	(0.0153)	(0.0169)	(0.0166)	(0.0166)	(0.0161)
Livestock	0.0726	0.0647	0.0697	0.0697	0.0730
	(0.0463)	(0.0429)	(0.0451)	(0.0451)	(0.0462)
Fish	0.0753	0.0918	0.0866	0.0866	0.0752
	(0.0518)	(0.0594)	(0.0556)	(0.0556)	(0.0507)
Milk	-0.0184***	-0.0200***	-0.0196***	-0.0196***	-0.0192***
	(0.0070)	(0.0076)	(0.0073)	(0.0074)	(0.0072)
Other no crop product	0.0075	0.0066	0.0082	0.0081	0.0078
	(0.0207)	(0.0219)	(0.0221)	(0.0220)	(0.0213)
Ln(time=semester)		0.0185***			
		(0.0053)			
Time			0.0053***	0.0054	-0.0113
			(0.0011)	(0.0034)	(0.0083)
Time^2				-0.0000	0.0033**
				(0.0003)	(0.0016)
Time^3					-0.0002*
					(0.0001)
Constant					
Semesters dummy (14)	Yes	Yes	Yes	Yes	Yes
Departments dummy (26)	Yes	Yes	Yes	Yes	Yes
Observations	2,168	2,195	2,195	2,195	2,195
Log pseudolikelihood	-367.9	-380.1	-377.2	-377.2	-374.9

8.2 Appendix chapter 4

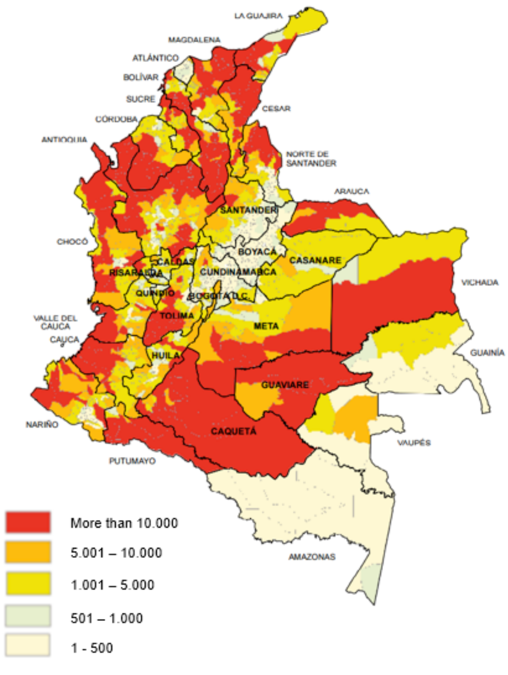
Figure 8.2.1 Final sample spatial distribution



: The municipality belongs to the sample.

Source: author

Figure 8.2.2 Forced displacement 2005-2014



Source: Centro Nacional de Memoria Histórica.

Table 8.2.1 Summary statistics of municipalities with missing values

Variable	Mean	SD	Min	Max
Share of municipality area with forest [0-100]	69.59	25.4	2.7	99.96
Forced displacement per 1000 inhabitants	13.43	31.19	0	490.33
Victims of massacres per 100,000 inhabitants (lagged one year)	0.67	6.09	0	100.64
Direct conflict kidnappings per 100.000 inhabitants (lagged one year)	0.98	7.15	0	215.32
Hectares of coca fumigated and manually eradicated (lagged one year)	98.37	533.78	0	11183.05
Percentage of the agricultural frontier with coca crops fumigates and manually eradicated (lagged one year)	0.12	0.78	0.00	24.34
Percentage of the municipal area with coca fumigated and manually eradicated (lagged one year)	0.13	0.78	0.00	23.49
Mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year)	0.17	0.37	0	1
Population	63887.63	483841.68	216	7571345
Log Population	9.39	1.16	5.38	15.84
Percentage of urban population [0-100]	41.76	23.78	3.43	99.79
Income tax revenue per inhabitants	84489.54	108837.26	0	1027696.81
Log income tax revenue per inhabitants	10.83	1.03	5.77	13.84

Variables statistics refer to a N that varies between 733 and 2334 observations for the rest of municipalities not included in the panel due to considerable presence of missing values in the period of our study 2004-2012.

Table 8.2.2 A Comparison of sample means for the included versus the excluded municipalities using t-test for difference of means

	t-test	p-value
Share of municipality area with forest [0-100]	-11.2	0.000
Forced displacement per 1000 inhabitants	-5.3	0.000
Victims of massacres per 100,000 inhabitants (lagged one year)	-1.8	0.069
Direct conflict kidnappings per 100.000 inhabitants (lagged one year)	0.4	0.689
Hectares of coca fumigated and manually eradicated (lagged one year)	3.2	0.002
Percentage of the agricultural frontier with coca crops fumigates and manually eradicated (lagged one year)	0.0005	0.99
Percentage of the municipal area with coca fumigated and manually eradicated (lagged one year)	-1.13	0.25
Mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year)	-1.1	0.251
Population	-5.2	0.000
Log Population	7.1	0.000
Percentage of urban population [0-100]	2.3	0.023
Income tax revenue per inhabitants	0.8	0.452
Log income tax revenue per inhabitant	4.1	0.000

Ho: diff = mean(x) - mean(y)=0.; Ha: diff != 0.

Table 8.2.3 Effect of lagged forced displacement rate on forest cover

Dependent variable: Share of municipality area with forest [0-100]	
	FE
Forced displacement per 1000 inhabitants (lagged one year)	0.0022**
	(0.0011)
Mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year)	-0.088*
	(0.052)
Log Population	-3.14***
	(0.49)
Percentage of urban population [0-100]	-0.047**
	(0.023)
Log income tax revenue per inhabitants	0.049*
	(0.029)
Year 2006	-0.19***
	(0.012)
Year 2007	-0.40***
	(0.023)
Year 2008	-0.59***
	(0.031)
Year 2009	-0.86***
	(0.041)
Year 2010	-1.02***
	(0.050)
Year 2011	-1.21***
	(0.059)
Year 2012	-1.44***
	(0.068)
Constant	90.7***
	(4.99)
Observations	6826
R-Squared	0.570
F-stat	108.6
Sigma	25.72
Sigma_e	0.503

Std. Err. (in parentheses) adjusted for clusters in municipality
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 8.2.4 Effect of the presence of coca crops on forest cover (FE-IV model)

Dependent variable: Share of municipality area with forest [0-100]

	FE-IV
Presence of coca crops [Yes=1; No=0]	-0.0030
	(1.17)
Mining (gold, silver, or platinum) [Yes=1; No=0] (lagged one year)	-0.094^{*}
	(0.051)
Log Population	-3.13^{***}
	(0.50)
Percentage of urban population [0-100]	-0.049^{**}
	(0.024)
Log income tax revenue per inhabitants	0.046
	(0.030)
Year 2006	-0.19^{***}
	(0.014)
Year 2007	-0.40^{***}
	(0.022)
Year 2008	-0.59^{***}
	(0.033)
Year 2009	-0.85^{***}
	(0.044)
Year 2010	-1.03^{***}
	(0.051)
Year 2011	-1.22^{***}
	(0.061)
Year 2012	-1.45^{***}
	(0.068)
Observations	6826
R-Squared	0.568
F-stat	107.5

Std. Err. (in parentheses) adjusted for clusters in municipality
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 8.2.5 Determinants of forest cover fixed effects (OLS model)

Dependent variable: Estimated municipal fixed effects	
	OLS
Municipality elevation (m)	0.0013^{*}
	(0.00073)
Avg. precipitation monthly (mm)	0.13^{***}
	(0.011)
Distance to the department capital (km)	0.030^{**}
	(0.015)
Soils quality index [1-8]	-3.53^{***}
	(0.70)
Constant	71.9^{***}
	(3.56)
Observations	848
R-Squared	0.237

Robust (heteroscedasticity correction) std. err. (in parentheses)
* $p < .10$, ** $p < .05$, *** $p < .01$

8.3 Appendix chapter 5

Table 8.3.1 DiD estimation pre and post averages -before and after the "winter wave"

T_(i,t)	Persons	Houses	Business	Total	Cars	Total (+ cars)
Panel A: 10% treatment intensity						
Post 2010 [Yes=1; No=0] *Treatment[Yes=1; No=0]	-0.0013	0.025	-0.00057	0.03	0.0093	0.046
	(0.026)	(0.021)	(0.012)	(0.049)	(0.007)	(0.083)
Log income tax revenue per inhab	0.070***	0.012	0.033***	0.13***	-0.01	0.23***
	(0.022)	(0.016)	(0.013)	(0.043)	(0.009)	(0.063)
Percentage of urban population [0-100]	0.023**	-0.00007	0.020***	0.040**	-0.00015	0.050**
	(0.010)	(0.007)	(0.005)	(0.019)	(0.002)	(0.023)
Log population to area (Km2) density	0.081	-0.41*	-0.18	-0.55	0.038	-0.73
	(0.310)	(0.220)	(0.180)	(0.590)	(0.072)	(0.730)
Gross enrolment ratio, primary and secondary [0-100]	-0.00036	0.001	0.00075	0.0012	-0.00052	0.00089
	(0.002)	(0.002)	(0.001)	(0.003)	(0.000)	(0.005)
Presence of conflict [Yes=1; No=0]	-0.062	-0.060**	-0.0027	-0.14*	-0.0015	-0.15*
	(0.039)	(0.029)	(0.017)	(0.071)	(0.012)	(0.088)
Observations	1842	1818	1796	1752	1402	1372
R-Squared (within)	0.0294	0.0121	0.039	0.0345	0.00676	0.0501
F-stat	5.79	2.784	6.463	7.195	0.826	8.205
Panel B: 15% treatment intensity						
T_(i,t)	Persons	Houses	Business	Total	Cars	Total (+ cars)
Post 2010 [Yes=1; No=0] *Treatment [Yes=1; No=0]	-0.032	0.0013	-0.0089	-0.044	0.012	-0.052
	(0.026)	(0.019)	(0.011)	(0.049)	(0.008)	(0.073)
Log income tax revenue per inhab	0.076***	0.014	0.036***	0.14***	-0.012	0.24***
	(0.023)	(0.016)	(0.013)	(0.044)	(0.009)	(0.064)
Percentage of urban population [0-100]	0.025**	0.00092	0.020***	0.043**	-0.00041	0.052**
	(0.010)	(0.007)	(0.005)	(0.018)	(0.002)	(0.023)
Log population to area (Km2) density	0.075	-0.40*	-0.18	-0.55	0.033	-0.79
	(0.310)	(0.220)	(0.180)	(0.590)	(0.072)	(0.720)
Gross enrolment ratio, primary and secondary [0-100]	-0.00052	0.00094	0.00066	0.00084	-0.00048	0.00066
	(0.002)	(0.002)	(0.001)	(0.003)	(0.000)	(0.005)
Presence of conflict [Yes=1; No=0]	-0.061	-0.057**	-0.0036	-0.13*	-0.0011	-0.16*
	(0.039)	(0.028)	(0.016)	(0.071)	(0.012)	(0.087)
Observations	1860	1834	1814	1768	1416	1384
R-Squared (within)	0.030	0.010	0.040	0.034	0.009	0.051
F-stat	5.64	2.18	6.35	6.56	0.91	8.23
Panel C: 20% treatment intensity						
T_(i,t)	Persons	Houses	Business	Total	Cars	Total (+ cars)
Post 2010 [Yes=1; No=0] *Treatment [Yes=1; No=0]	-0.031	-0.0019	0.0093	-0.027	0.005	-0.04
	(0.022)	(0.017)	(0.010)	(0.041)	(0.007)	(0.058)
Log income tax revenue per inhab	0.078***	0.016	0.034***	0.15***	-0.011	0.24***
	(0.023)	(0.016)	(0.013)	(0.044)	(0.009)	(0.064)
Percentage of urban population [0-100]	0.025**	0.0014	0.018***	0.041**	-0.00021	0.054**
	(0.010)	(0.007)	(0.005)	(0.019)	(0.002)	(0.022)
Log population to area (Km2) density	0.13	-0.37*	-0.14	-0.45	0.035	-0.71
	(0.310)	(0.220)	(0.180)	(0.590)	(0.071)	(0.720)
Gross enrolment ratio, primary and secondary [0-100]	-0.00051	0.00092	0.00064	0.00083	-0.00046	0.00061
	(0.002)	(0.002)	(0.001)	(0.003)	(0.000)	(0.005)
Presence of conflict [Yes=1; No=0]	-0.057	-0.056**	-0.0078	-0.13*	-0.0012	-0.16*
	(0.039)	(0.028)	(0.016)	(0.071)	(0.011)	(0.086)
Observations	1864	1842	1818	1776	1424	1392
R-Squared (within)	0.030	0.010	0.041	0.033	0.007	0.051
F-stat	5.38	2.13	7.31	6.45	0.69	8.29

All panel regressions control for year fixed effects.
Standard errors in parentheses -adjusted for clusters in municipality-.
Treatment dummy does not appear due to fixed effects panel data estimation.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 8.3.2 D-i-D estimation of criminal activity rates (2007-2012) without controlling for the presence of conflict

Panel A: 10% treatment intensity

T_(i,t)	Persons	Houses	Business	Total	Cars	Total (+ cars)
Post 2010 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.016	0.024	-0.0053	0.0084	0.0085	0.017
	(0.026)	(0.022)	(0.012)	(0.049)	(0.007)	(0.084)
Log income tax revenue per inhab	0.035**	0.030***	0.016*	0.091***	-0.0077	0.11**
	(0.014)	(0.011)	(0.010)	(0.030)	(0.006)	(0.048)
Percentage of urban population [0-100]	0.0074	0.00061	0.0078	0.016	0.0011	0.024
	(0.011)	(0.008)	(0.006)	(0.022)	(0.002)	(0.027)
Log population to area (Km2) density	-0.26	-0.44*	-0.23	-1.02*	0.0038	-1.34*
	(0.310)	(0.230)	(0.180)	(0.610)	(0.071)	(0.790)
Gross enrolment ratio, primary and secondary [0-100]	0.00066	-0.00021	0.00029	0.00037	-0.00023	-0.00042
	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.003)
Observations	5510	5441	5373	5244	4195	4107
R-Squared (within)	0.0442	0.037	0.0395	0.0626	0.00738	0.0739
F-stat	16.73	14.1	13.36	22.57	2.645	19.07

Panel B: 15% treatment intensity

T_(i,t)	Persons	Houses	Business	Total	Cars	Total (+ cars)
Post 2010 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.050*	-0.00086	-0.014	-0.071	0.011	-0.088
	(0.027)	(0.020)	(0.011)	(0.051)	(0.008)	(0.075)
Log income tax revenue per inhab	0.036**	0.029**	0.018*	0.091***	-0.0085	0.11**
	(0.014)	(0.011)	(0.010)	(0.030)	(0.006)	(0.048)
Percentage of urban population [0-100]	0.0065	0.00031	0.0075	0.014	0.0011	0.021
	(0.011)	(0.008)	(0.006)	(0.022)	(0.002)	(0.027)
Log population to area (Km2) density	-0.3	-0.44*	-0.24	-1.08*	0.00081	-1.47*
	(0.310)	(0.230)	(0.180)	(0.600)	(0.069)	(0.780)
Gross enrolment ratio, primary and secondary [0-100]	0.00053	-0.00023	0.00017	0.00024	-0.00023	-0.00052
	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.003)
Observations	5564	5489	5427	5292	4237	4143
R-Squared (within)	0.0444	0.0365	0.0395	0.0625	0.00803	0.0741
F-stat	16.83	13.89	13.24	22.49	2.766	19

Panel C: 20% treatment intensity

T_(i,t)	Persons	Houses	Business	Total	Cars	Total (+ cars)
Post 2010 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.054**	-0.0035	0.0028	-0.06	0.0043	-0.084
	(0.024)	(0.018)	(0.011)	(0.044)	(0.007)	(0.062)
Log income tax revenue per inhab	0.037**	0.029**	0.019*	0.092***	-0.0084	0.11**
	(0.015)	(0.011)	(0.010)	(0.030)	(0.006)	(0.048)
Percentage of urban population [0-100]	0.0046	0.00069	0.0065	0.011	0.00085	0.02
	(0.011)	(0.008)	(0.006)	(0.022)	(0.002)	(0.027)
Log population to area (Km2) density	-0.28	-0.42*	-0.2	-1.01*	-0.0021	-1.41*
	(0.310)	(0.230)	(0.180)	(0.600)	(0.068)	(0.780)
Gross enrolment ratio, primary and secondary [0-100]	0.00042	-0.00024	0.00015	0.000096	-0.0002	-0.0007
	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.003)
Observations	5576	5513	5439	5316	4261	4167
R-Squared (within)	0.0445	0.0362	0.0403	0.0624	0.00786	0.0741
F-stat	16.52	13.85	13.89	22.56	2.814	18.91

All panel regressions control for year fixed effects.
Standard errors in parentheses -adjusted for clusters in municipality-.
Treatment dummy does not appear due to fixed effects panel data estimation.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 8.3.3 D-i-D estimations with year lags after the 'winter wave' without controlling for the presence of conflict

Panel A: 10% treatment intensity						
T_(i,t)	Persons	Houses	Business	Total	Cars	Total (+ cars)
Year 2011 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.032	-0.015	-0.013	-0.053	0.0025	-0.071
	(0.028)	(0.016)	(0.015)	(0.046)	(0.010)	(0.063)
Year 2012 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.10***	-0.036	-0.024	-0.16**	0.0048	-0.20**
	(0.035)	(0.030)	(0.018)	(0.069)	(0.011)	(0.098)
Log income tax revenue per inhabitant	0.035**	0.029***	0.016*	0.090***	-0.0077	0.11**
	(0.014)	(0.011)	(0.010)	(0.030)	(0.006)	(0.048)
Percentage of urban population [0-100]	0.0073	0.00071	0.0077	0.016	0.0011	0.022
	(0.011)	(0.008)	(0.006)	(0.022)	(0.002)	(0.028)
Log population to area (Km2) density	-0.33	-0.48**	-0.25	-1.15*	0.0016	-1.50*
	(0.310)	(0.230)	(0.180)	(0.610)	(0.070)	(0.800)
Gross enrolment ratio, primary and secondary [0-100]	0.00048	-0.0003	0.00025	0.000089	-0.00023	-0.00073
	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.003)
Observations	5510	5441	5373	5244	4195	4107
R-Squared (within)	0.046	0.0372	0.04	0.064	0.00726	0.0753
F-stat	15.42	12.93	11.88	20.89	2.302	17.47
Panel B: 15% treatment intensity						
T_(i,t)	Persons	Houses	Business	Total	Cars	Total (+ cars)
Year 2011 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.014	-0.0072	-0.016	-0.038	0.0071	-0.046
	(0.031)	(0.016)	(0.017)	(0.051)	(0.010)	(0.070)
Year 2012 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.12***	-0.034	-0.046**	-0.19**	0.0082	-0.21**
	(0.037)	(0.032)	(0.018)	(0.073)	(0.011)	(0.100)
Log income tax revenue per inhabitant	0.036**	0.029**	0.018*	0.091***	-0.0085	0.11**
	(0.014)	(0.011)	(0.010)	(0.030)	(0.006)	(0.048)
Percentage of urban population [0-100]	0.0067	0.00046	0.0076	0.014	0.0011	0.021
	(0.011)	(0.008)	(0.006)	(0.022)	(0.002)	(0.027)
Log population to area (Km2) density	-0.31	-0.46**	-0.25	-1.11*	-0.0022	-1.50*
	(0.310)	(0.230)	(0.180)	(0.600)	(0.069)	(0.790)
Gross enrolment ratio, primary and secondary [0-100]	0.00039	-0.00029	0.00012	0.000037	-0.00023	-0.00061
	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.003)
Observations	5564	5489	5427	5292	4237	4143
R-Squared (within)	0.0459	0.0368	0.0407	0.0637	0.00767	0.0749
F-stat	15.48	12.88	11.94	20.73	2.465	17.52
Panel C: 20% treatment intensity						
T_(i,t)	Persons	Houses	Business	Total	Cars	Total (+ cars)
Year 2011 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.014	-0.0072	-0.016	-0.038	0.0071	-0.046
	(0.031)	(0.016)	(0.017)	(0.051)	(0.010)	(0.070)
Year 2012 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.12***	-0.034	-0.046**	-0.19**	0.0082	-0.21**
	(0.037)	(0.032)	(0.018)	(0.073)	(0.011)	(0.100)
Log income tax revenue per inhabitant	0.036**	0.029**	0.018*	0.091***	-0.0085	0.11**
	(0.014)	(0.011)	(0.010)	(0.030)	(0.006)	(0.048)
Percentage of urban population [0-100]	0.0067	0.00046	0.0076	0.014	0.0011	0.021
	(0.011)	(0.008)	(0.006)	(0.022)	(0.002)	(0.027)
Log population to area (Km2) density	-0.31	-0.46**	-0.25	-1.11*	-0.0022	-1.50*
	(0.310)	(0.230)	(0.180)	(0.600)	(0.069)	(0.790)
Gross enrolment ratio, primary and secondary [0-100]	0.00039	-0.00029	0.00012	0.000037	-0.00023	-0.00061
	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.003)
Observations	5564	5489	5427	5292	4237	4143
R-Squared (within)	0.0459	0.0368	0.0407	0.0637	0.00767	0.0749
F-stat	15.48	12.88	11.94	20.73	2.465	17.52

All panel regressions control for year fixed effects.
Standard errors in parentheses -adjusted for clusters in municipality-.
Treatment dummy does not appear due to fixed effects panel data estimation.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 8.3.4 D-i-D estimation with year lags and leads after the 'winter wave' without controlling for the presence of conflict

Panel A: 10% treatment intensity

T_(i,t)	Persons	Houses	Business	Total	Cars	Total (+ cars)
Year 2008 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.038	0.033	0.001	-0.015	0.013	0.066
	(0.034)	(0.024)	(0.016)	(0.058)	(0.013)	(0.081)
Year 2009 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.074**	0.022	-0.015	-0.082	-0.018	-0.081
	(0.031)	(0.025)	(0.015)	(0.058)	(0.012)	(0.082)
Year 2010 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.058*	0.038	0.014	-0.031	0.0038	-0.044
	(0.032)	(0.024)	(0.015)	(0.060)	(0.013)	(0.087)
Year 2011 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.075*	0.0082	-0.013	-0.085	0.0022	-0.086
	(0.039)	(0.024)	(0.019)	(0.066)	(0.014)	(0.094)
Year 2012 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.15***	-0.013	-0.025	-0.19**	0.0044	-0.21*
	(0.042)	(0.036)	(0.021)	(0.085)	(0.016)	(0.120)
Log income tax revenue per inhabitant	0.035**	0.029***	0.016	0.091***	-0.0077	0.11**
	(0.014)	(0.011)	(0.010)	(0.030)	(0.006)	(0.048)
Percentage of urban population [0-100]	0.0073	0.00069	0.0077	0.016	0.0011	0.022
	(0.011)	(0.008)	(0.006)	(0.022)	(0.002)	(0.028)
Log population to area (Km2) density	-0.35	-0.47**	-0.24	-1.17*	-0.0013	-1.53*
	(0.310)	(0.230)	(0.180)	(0.610)	(0.069)	(0.800)
Gross enrolment ratio, primary and secondary [0-100]	0.00042	-0.00029	0.00023	0.0000082	-0.00025	-0.00088
	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.003)
Observations	5510	5441	5373	5244	4195	4107
R-Squared (within)	0.0466	0.0376	0.0404	0.0642	0.00906	0.0759
F-stat	12.61	10.18	10.29	16.9	2.911	14.56
F-test for Par. Trend	1.87	1.09	1.37	0.83	3.54	1.06
Prob > F	(0.13)	(0.35)	(0.25)	(0.48)	(0.01)	(0.36)

Panel B: 15% treatment intensity

T_(i,t)	Persons	Houses	Business	Total	Cars	Total (+ cars)
Year 2008 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.012	0.038*	-0.0079	0.015	0.013	0.1
	(0.031)	(0.023)	(0.016)	(0.054)	(0.011)	(0.073)
Year 2009 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.051*	0.022	-0.025*	-0.06	-0.014	-0.04
	(0.028)	(0.025)	(0.014)	(0.051)	(0.009)	(0.069)
Year 2010 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.031	0.041*	0.0041	-0.0014	0.0049	0.0089
	(0.028)	(0.021)	(0.015)	(0.052)	(0.010)	(0.073)
Year 2011 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.036	0.017	-0.023	-0.049	0.0077	-0.029
	(0.038)	(0.023)	(0.020)	(0.064)	(0.012)	(0.090)
Year 2012 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.14***	-0.011	-0.053***	-0.20**	0.0089	-0.19
	(0.041)	(0.037)	(0.020)	(0.082)	(0.013)	(0.120)
Log income tax revenue per inhabitant	0.037***	0.028**	0.018*	0.092***	-0.0085	0.11**
	(0.014)	(0.011)	(0.010)	(0.030)	(0.006)	(0.048)
Percentage of urban population [0-100]	0.0068	0.00031	0.0076	0.014	0.0011	0.021
	(0.011)	(0.008)	(0.006)	(0.022)	(0.002)	(0.027)
Log population to area (Km2) density	-0.32	-0.45**	-0.25	-1.12*	-0.0043	-1.52*
	(0.310)	(0.230)	(0.180)	(0.610)	(0.069)	(0.790)
Gross enrolment ratio, primary and secondary [0-100]	0.00035	-0.00029	0.000097	-0.000028	-0.00026	-0.00074
	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.003)
Observations	5564	5489	5427	5292	4237	4143
R-Squared (within)	0.0462	0.0373	0.0412	0.0639	0.00917	0.0754
F-stat	12.72	10.17	10.41	16.98	2.92	14.69
F-test for Par. Trend	1.14	1.83	1.73	0.89	3.01	1.25
Prob > F	(0.33)	(0.14)	(0.16)	(0.45)	(0.03)	(0.29)

Panel C: 20% treatment intensity

T_(i,t)	Persons	Houses	Business	Total	Cars	Total (+ cars)
Year 2008 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.029	0.032	0.00066	-0.0055	0.0056	0.047
	(0.033)	(0.022)	(0.015)	(0.056)	(0.012)	(0.074)
Year 2009 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.069**	0.023	-0.011	-0.07	-0.019*	-0.052
	(0.030)	(0.024)	(0.014)	(0.056)	(0.012)	(0.076)
Year 2010 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.048	0.041*	0.016	-0.013	-0.00056	-0.0065
	(0.031)	(0.023)	(0.015)	(0.058)	(0.012)	(0.081)
Year 2011 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.063*	0.017	0.0023	-0.055	-0.0021	-0.055
	(0.037)	(0.023)	(0.018)	(0.063)	(0.013)	(0.087)
Year 2012 [Yes=1; No=0]*Treatment[Yes=1; No=0]	-0.15***	-0.014	-0.02	-0.19**	0.0018	-0.20*
	(0.041)	(0.035)	(0.020)	(0.081)	(0.015)	(0.120)
Log income tax revenue per inhabitant	0.037**	0.029**	0.019*	0.092***	-0.0084	0.11**
	(0.015)	(0.011)	(0.010)	(0.030)	(0.006)	(0.048)
Percentage of urban population [0-100]	0.0046	0.00068	0.0065	0.01	0.00082	0.019
	(0.011)	(0.008)	(0.006)	(0.022)	(0.002)	(0.027)
Log population to area (Km2) density	-0.32	-0.43*	-0.21	-1.08*	-0.0063	-1.47*
	(0.310)	(0.230)	(0.180)	(0.600)	(0.068)	(0.780)
Gross enrolment ratio, primary and secondary [0-100]	0.00024	-0.00028	0.000099	-0.00014	-0.00024	-0.0009
	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.003)
Observations	5576	5513	5439	5316	4261	4167
R-Squared (within)	0.047	0.037	0.041	0.064	0.009	0.075
F-stat	12.39	10.19	10.6	16.95	3.064	14.46
F-test for Par. Trend	1.71	1.31	1.31	0.86	2.96	0.65
Prob > F	(0.16)	(0.27)	(0.27)	(0.46)	(0.03)	(0.58)

All panel regressions control for year fixed effects.
Standard errors in parentheses -adjusted for clusters in municipality-.
Treatment dummy does not appear due to fixed effects panel data estimation.
* $p < .10$, ** $p < .05$, *** $p < .01$