Organised Crimes and Repeat Victimisation

Modelling victimisation patterns of extortion against Mexican businesses

by

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Figure 3.1: Photo by Alfredo Guerrero/Gobierno Federal, August 26, 2011, available at `https://www.flickr.com/photos/30118979@N03/6083852986/` licensed under a CC-BY-NC-SA 2.0 license. To view a copy of this license, visit `https://creativecommons.org/licenses/by-nc-sa/2.0/`

Figure 3.5: Map of areas of cartel influence is republished with the permission of Stratfor, a leading global geopolitical intelligence and advisory firm. Original available at `https://worldview.stratfor.com/article/mexican-drug-wars-scott-stewart-and-fred-burton-chapo-sinaloa-cjng`

I, *Patricio Rodrigo Estévez Soto*, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the work.

Signed _____

Date January 21, 2020

Abstract

Research consistently shows that crime concentrates on a few repeatedly victimised places and targets. However, such research has been mainly concerned with 'traditional' crimes against individuals and households and has paid little attention to the victimisation patterns of organised crimes. As such, it is not clear whether organised crimes exhibit concentration patterns consistent with repeat victimisation, nor whether the mechanisms that explain concentration in 'traditional' crimes also explain the concentration of organised crimes.

This thesis is concerned with the victimisation patterns of extortion against businesses, a quintessential organised crime activity. While the extortion phenomenon is often understood as an institutionalised practice of extra-legal territorial control exerted by organised criminal groups, this thesis approaches extortion predominantly from a situational perspective, focusing on the incidents that constitute the extortion phenomenon. Ultimately, the goal is to identify the incident-, victim-, and area-level characteristics that affect the patterns of extortion victimisation. To achieve this, it relies on secondary analysis of Mexico's National Commercial Victimisation Survey 2014, one of the largest business victimisation surveys in the world.

The thesis uses quantitative modelling to answer four research questions: is extortion concentrated beyond what is expected by chance? What could explain repeat extortion victimisation patterns? What are the predictors of compliance with extortion demands? And, do patterns and mechanisms of repeat victimisation vary according to the type of extortion suffered? The findings suggest that incident-, and victim-level measures are more relevant than area-level characteristics to understand extortion victimisation patterns. Furthermore, the findings suggest that event dependence is a stronger predictor of extortion concentration than risk heterogeneity. Lastly, the thesis discusses the implications of the findings for academia, crime statistics, and crime prevention policy.

Impact statement

This thesis focused on understanding the victimisation patterns of extortion against businesses. Specifically, the research examined the patterns of extortion among Mexican businesses to determine if incidents concentrated beyond the level that could be expected by chance, and to identify the incident-, business-, and area-level characteristics that could explain such concentration.

The research has important academic and practical implications. From the academic perspective, the research adds to the literature on crime concentration by examining a novel crime type (extortion) in a new context (Mexico). Additionally, the research contributes to the literature on organised crime by approaching a quintessential organised crime from the repeat victimisation perspective. The research also contributes to the quantitative criminology literature for its use of novel modelling frameworks, and the estimation of pseudo-longitudinal effects using cross-sectional data. Lastly, the research contributes significantly to the literature on crime and security in Mexico, as it represents the first systematic analysis of repeat victimisation and extortion in that country.

Practically, the research presented herein has implications for the measurement of extortion, as well as for its prevention. Regarding measurement, the research identified key areas of improvement for the measurement of extortion using victimisation surveys. Extortion is notoriously difficult to measure, thus improving the instruments used to measure its extent is crucial to understand (and hopefully tackle) the phenomenon. Regarding the prevention of extortion, the thesis identified several ways in which the findings can inform crime prevention practice, as well as the knowledge gaps to be addressed in future research which currently limit our ability to design tailored crime prevention strategies. The implications for crime prevention are of great importance, as extortion is the third most common crime against Mexican businesses, and appears to be a growing threat in other countries as well.

To bring the impact of this thesis into fruition, the research findings have been

disseminated in several ways. In academia, findings were presented at the 2016 Annual Meeting of the American Society of Criminology, the 2017 Environmental Criminology and Crime Analysis Symposium, and the 2nd General Conference of the Standing Group on Organised Crime of the European Consortium of Political Research in 2017. Furthermore, the first two chapters are currently being peer-reviewed for publication in two top-tier journals. Outside academia, the findings have been presented and discussed with policy practitioners in Mexico, the UK, and with an international experts' group concerned with countering organised crime in Africa. Furthermore, the research has also been discussed with journalists in leading global publications.

Going forward, I plan to continue the dissemination of the findings by publishing the remaining chapters in top-tier journals, as well as by engaging with practitioners and the wider public.

Funding delcaration

Acknowledgments

Dedicated to the 52 people who died in the extortion-related attack on the Casino Royale, August 25, 2011, Monterrey, Mexico.

In August 2011, 52 people were killed when a casino in northern Mexico was set ablaze for refusing to comply with extortion demands. At the time, widespread extortion was a relatively new phenomenon in Mexico, and there was not enough research on the matter. Convinced that the knowledge generated by academic research could help prevent similar tragedies from occurring again, I decided to pursue a PhD to study the patterns of extortion against Mexican businesses. Thus, this thesis has been a long time coming.

Though a PhD is a solitary endeavour, I have been privileged to enjoy the support of a great number of people from the moment I applied to UCL to my last days as a PhD student.

I would like to express my deepest appreciation to my PhD supervisors, Professor Nick Tilley and Professor Shane Johnson, for their initial interest in my research project, their steadfast guidance, and their immensely helpful feedback. It has been an absolute privilege to be your student.

I am indebted to the devoted public servants at Mexico's statistics agency, INEGI, that undertake the difficult but crucial task of measuring extortion against Mexican businesses. In particular, I am deeply thankful to Mario Palma, Oscar Jaimes and Edgar Vielma, for taking time out of their busy schedules to answer my questions regarding the national commercial victimisation survey, ENVE. Similarly, I am also very grateful to Dr Natalia Volkow and the wonderful staff at INEGI's data laboratory for facilitating access to the ENVE data.

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However, my most profound gratitude is to my wife, Melissa, who caught a boat to England with me. I will be forever grateful for your unfaltering support, your constant encouragement, and your boundless generosity. You make everything possible, and you make everything worthwhile, thank you.

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Chapter 1

Introduction

1.1 Main aims

This thesis is concerned with understanding the victimisation patterns of extortion against businesses. Specifically, the main aim is to examine patterns of extortion among Mexican businesses to determine if repeat victimisation occurs, and if it does, to identify the incident-, victim-, and area-level factors and mechanisms that could explain the concentration of extortion. In addition to enhancing our understanding of extortion, it is hoped that findings will prove useful to prevent extortion against businesses.

Repeat victimisation occurs when a person, household, business, object, or other target however defined suffers the same offence two or more times in a given time period (Grove & Farrell, 2010; Pease, 1998). The phenomenon of repeat victimisation accounts for one of the most consistent findings in victimisation research: that crime is unequally distributed among potential targets (for reviews, see Farrell & Pease, 1993; Farrell, Tseloni, & Pease, 2005; Pease, 1998; SooHyun, Martinez, Lee, & Eck, 2017; Tseloni & Pease, 2005). Such inequality is reflected in highly skewed distributions of criminal incidents, where small proportions of potential targets suffer disproportionate amounts of criminal incidents.

In a seminal study, Farrell and Pease (1993) noted that according to the 1982, 1988, and 1992 British Crime Surveys, repeat victims accounted for 14% to 20% of the population, yet suffered between 71% and 81% of all incidents. International evidence is consistent with these findings. Based on results from 17 countries originally reported by Farrell and Bouloukos (2001), Farrell and Pease (2011) estimate that around '40 per cent of crimes against individual people and against households are

repeats ... with variation by crime type and place' (p. 123). More recently, SooHyun et al. (2017) conducted a systematic review of victimisation studies and found strong support for repeat victimisation as a widespread phenomenon. In particular, they found that 5% of potential victims experience 60% of all victimisation incidents, with higher rates of concentration among businesses than households (p. 12).

Crime concentration is not a phenomenon exclusive to victims. Decades of research similarly indicate that small proportions of offenders (see Martinez, Lee, Eck, & SooHyun, 2017) and places (see Lee, Eck, SooHyun, & Martinez, 2017) tend to suffer disproportionate amounts of crime. In the case of places, the patterns of concentration have been so consistent that Weisburd (2015) has recently coined the term 'the law of crime concentration at place' to describe the phenomenon. In the limiting case of victims that are immovable (i.e. a house, a commercial property), repeat victimisation is an extreme case of concentration at place (Johnson, Bowers, & Hirschfield, 1997; Pease & Laycock, 1999)

Two mechanisms have been proposed to explain repeat victimisation (Farrell, Clark, Ellingworth, & Pease, 2005; Farrell, Phillips, & Pease, 1995; Johnson, 2008). The first, risk heterogeneity (*flags*), suggests that enduring differences between targets make some more attractive or vulnerable than others, attracting different offenders to the same targets (Pease, 1998; Sagovsky & Johnson, 2007). The second mechanism, event dependence (*boosts*), suggests that there is a dynamic component to victimisation risk, with one incident increasing the likelihood of a subsequent incident against the same target, in many cases by the same offender (Bernasco, 2008; Pease, 1998; Sagovsky & Johnson, 2007).

Insofar as both mechanisms speak to characteristics and the immediate conditions that make targets vulnerable or attractive—and hence influence offenders' choice of victim—repeat victimisation is closely linked to the family of theories known as environmental criminology (Wartell & Gallagher, 2012; Wortley & Mazerolle, 2011). In contrast with theories that seek to explain offenders' criminal dispositions (e.g. Akers & Jennings, 2015; Barnes, Boutwell, & Beaver, 2015; Britt & Rocque, 2015; McGee & Farrington, 2015), and those more concerned with the the social, cultural, and economic root causes of criminal behaviour (e.g. Agnew, 2015; Berg, Sevell, & Stewart, 2015; Kubrin & Wo, 2015; Messner & Rosenfeld, 2009; M. D. Schwartz & Brownstein, 2015), environmental criminology is predominantly concerned with the criminal events themselves and with the physical and social characteristics of the environments where they occur (see Andresen, 2014; Sidebottom & Wortley, 2015; Wortley & Mazerolle, 2011). At its core, environmental criminology understands

crime events as the product of criminal opportunities created when a motivated of-fender and a suitable target coincide in the absence of capable guardians (Cohen & Felson, 1979).

Thus, testing hypotheses informed in part by environmental criminology, the study of repeat victimisation tends to focus on identifying those specific target characteristics—and the conditions in their environments—that are associated with a higher risk of victimisation (e.g. Bowers, Johnson, & Pease, 2005; Daigle, Fisher, & Cullen, 2008; Farrell, Tseloni, & Pease, 2005; Osborn & Tseloni, 1998; Tseloni & Pease, 2004).

However, findings from repeat victimisation studies have important implications beyond expanding criminological theory, as they provide a rational—and effective (Grove, Farrell, Farrington, & Johnson, 2012)—basis to guide crime prevention ef-forts (Farrell, 1992, 1995; Farrell & Pease, 1993; Kleemans, 2001; Laycock, 2001). On the one hand, the concentration of a disproportionate amount of incidents on a small proportion of targets suggests that focusing crime prevention resources on repeat victims can potentially lead to disproportionate reductions in overall crime rates (Farrell & Pease, 2001). While on the other, identifying risk and protective factors associated with repeat victimisation can provide guidance to design more effective crime prevention interventions.

Most research on repeat victimisation has focused on 'traditional' crimes—such as burglary, robbery and assault—against individuals or households (e.g. Daigle et al., 2008; Johnson et al., 1997; Kleemans, 2001; Osborn & Tseloni, 1998; Tseloni, Osborn, Trickett, & Pease, 2002; Tseloni & Pease, 2003, 2004; Tseloni, Wittebrood, Farrell, & Pease, 2004; Young & Furman, 2007), and though fewer, studies have also examined traditional crimes against businesses or those that take place in non-residential settings (e.g. Bowers, Hirschfield, & Johnson, 1998; Burrows & Hopkins, 2005; Dugato, 2014; Gill, 1998; Hopkins & Tilley, 2001; Matthews, Pease, & Pease, 2001; Salmi, Kivivuori, & Lehti, 2013; van Dijk & Terlouw, 1996).

In contrast, the literature on repeat victimisation has paid little attention to organised crimes. This is partly because one of the most influential research pro-grammes on repeat victimisation was born out of the UK crime prevention field (Grove & Farrell, 2012; Laycock, 2001), and as such, it was mostly concerned with high-volume local crimes—which are the focus of neighbourhood police and crime prevention priorities (Farrell, Edmunds, Hobbs, & Laycock, 2000). Furthermore, many activities associated with organised crime—such as money laundering or drug trafficking, for example—do not generally have clearly defined targets suitable for

victimisation research (van Dijk, 2007a). Yet, while some organised crimes of a predatory nature do have clearer targets that are better suited to victimisation research—such as contract killings, modern slavery and extortion against businesses—there is scant quantitative research on their concentration patterns. Thus, it is not clear whether such organised crimes also concentrate on repeat victims, nor whether the mechanisms that explain concentration of 'traditional' crimes also explain the concentration of organised crimes.

Moreover, the bulk of the literature on organised crime has not been particularly concerned with repeat victimisation or concentration patterns. There are several reasons for this. The concept of 'organised crime' itself is contested (Kleemans, 2018, p. 872), and is often used to describe a variety of 'empirical manifestations' (von Lampe, 2016) rather than a clearly identified cohesive phenomenon. Such empirical manifestations of organised crime are seldom amenable to victimisation research: studies may focus on the characteristics of organised crime groups themselves, their exercise of extra-legal power, or on certain organised crime activities—the majority of which may not have clear victims (e.g. drug trafficking), or cannot be easily reduced to incidents to be tallied (e.g. money laundering). Consequently, repeat victimisation is not not usually considered relevant to most theoretical approaches to organised crime.

However, in recent times researchers have begun to focus on organised crimes from an environmental criminology perspective (see Bullock, Clarke, & Tilley, 2010b; Kleemans & Soudijn, 2017; Kleemans, Soudijn, & Weenink, 2012; van de Bunt & van der Schoot, 2003). The situational approach to organised crimes—so called for its emphasis on disrupting organised crime using situational crime prevention (see Clarke, 2011)—aims to identify the criminal opportunities that facilitate the commission of narrowly defined organised crime activities, with the aim of finding novel, and hopefully effective, 'pinch points' to prevent them (Bullock, Clarke, & Tilley, 2010a). Situational studies of organised crimes have mostly employed descriptive and qualitative approaches to unpack the 'crime scripts' involved in certain organised criminal activities, and have not explored repeat victimisation patterns. Studying repeat victimisation patterns is crucial to understanding the risk factors driving specific organised crimes, in addition to providing an objective measure to direct crime prevention efforts.

In this thesis, I attempt to fill this gap in the literature by studying repeat victimisation patterns of extortion against businesses, a quintessential organised crime (Paoli, 2014a; Tilley & Hopkins, 2008; von Lampe, 2005). In the organised crime lit-

erature, the extortion phenomenon is often understood as an institutionalised practice of extra-legal territorial control exerted by organised criminal groups (Elsenbroich, Anzola, & Gilbert, 2016; Varese, 2001, 2014). However, I argue that from a situational approach, the focus falls on the individual victimisation incidents that in aggregate may reflect such practices.

I chose extortion against businesses for three main reasons: one, unlike 'victimless' organised crimes, it is a predatory crime with discrete incidents suitable for victimisation research; two, there is better data availability when compared to other predatory organised crime incidents (e.g. kidnapping), as extortion is often captured by national and international commercial victimisation surveys (Mugellini, 2013c; van Dijk, 2008); and three, it is an archetypal organised crime (Tilley & Hopkins, 2008), thus the research contributes to the literature on the situational approach to organised crimes.

As stated earlier, the main aim is to determine if extortion exhibits patterns of repeat victimisation, and if so, to identify the factors and mechanisms that may explain them. To achieve this, I take a predominantly quantitative approach, employing advanced modelling techniques and drawing on data from Mexico's National Commercial Victimisation Survey (ENVE, INEGI, 2014c), one of the largest business victimisation surveys in the world.

1.2 Why extortion in Mexico?

Two main issues motivate the choice of researching extortion in Mexico. First, having lived through some of Mexico's darkest days of organised crime violence and seen first hand the havoc and pain it can wreck, I was interested in developing a research project with relevant policy implications. Mexico is currently suffering the highest level of violence since records began. In particular, extortion is the most common high-impact crime in the country (INEGI, 2014a), and has been linked to prominent cases of violence (e.g. Guerrero-Gutiérrez, 2011; Wilkinson, 2011) and political instability (e.g. Fisher, Taub, & Martínez, 2018). Nonetheless, the extortion phenomenon in Mexico is notoriously understudied. Thus, the aim is that by approaching extortion from the environmental criminology and situational perspective, the research presented in this thesis can contribute to understanding and reducing this crime.

Second, despite being plagued by criminal violence and organised crime, little research on Latin America can be found in the environmental criminology literature.

In particular, most research on repeat victimisation and crime concentration has focused on the US and Canada, a handful of European cities, and Oceania (e.g. Andresen, Curman, & Linning, 2016; Andresen, Linning, & Malleson, 2017; Curman, Andresen, & Brantingham, 2015; Farrell, Tseloni, & Pease, 2005; Johnson & Bowers, 2010; Lynch, Berbaum, & Planty, 1998; Perreault, Sauvé, & Burns, 2010; Sagovsky & Johnson, 2007; Tseloni et al., 2004). This scarcity brings into question whether the causal relationships envisioned by environmental criminology—and their implications for crime prevention—are generalisable to crimes in non-western settings (Sidebottom & Wortley, 2015).

Recently, there has been a welcome increase in studies focused on non-western countries, such as a special edition of *Crime Science* (Natarajan, 2016), as well as individual studies on Latin America (Chainey, Serrano, & Veneri, 2017; Jaitman & Ajzenman, 2016; Melo, Matias, & Andresen, 2015; Muggah, Aguirre, & Chainey, 2017), and other non-western settings (Kuo, Cuvelier, Sheu, & Zhao, 2012; Park, 2015; Sidebottom, 2012). Nonetheless, apart from the research presented in this thesis, there have been no systematic studies of repeat victimisation in Mexico.

1.3   Contributions to the literature

This thesis contributes to the literature in four ways. First, it adds to the environmental criminology and crime science literature in general, and to that relating to repeat victimisation in particular, by studying crime patterns of a non-traditional crime (extortion) in a new context (Mexico). As stated earlier, developing countries face some of the world's most serious crime problems, yet there is very little literature from the perspective of environmental criminology and crime science focused on these countries. Despite a recent increase in interest, many opportunities remain for researching crime in developing countries—and such research is sorely needed, given its crime prevention implications. Furthermore, by studying a non-traditional crime from the perspective of repeat victimisation, my research contributes to deciphering whether the mechanisms and risk factors behind repeat victimisation in traditional crimes are generalisable to other kinds of offending activities, hence refining our understanding of the phenomenon.

Second, it contributes to the literature on organised crime by approaching an activity traditionally associated with organised crime (extortion) from a new perspective. Thus, it expands the situational approach to organised crimes (see a compilation edited by Bullock et al., 2010b; and the special issue of *Trends in Organized*

Crime edited by Kleemans et al., 2012) by incorporating the repeat victimisation perspective. While the focus here is on extortion against businesses, the approach could also be usefully applied to the study of other organised crimes, notably kidnapping and human trafficking. Furthermore, by broadening the definition of victim to other types of targets and by breaking down complex organised crime activities into discrete steps required to execute them (i.e. developing their crime scripts), the analyses presented here could conceivably be applied to crime problems not usually suited for victimisation research, such as the concentration of drug trafficking at different ports of entry, or very concrete instances of financial system misuse for money laundering purposes.

Third, the research contributes to quantitative approaches to criminology. In particular a hurdle modelling framework is used to explicitly test whether the mechanisms driving the risk of becoming a victim of extortion are the same as those driving the number of extortion incidents suffered by victims (see Chapter 5). Another contribution in this field is the use of cross-sectional data to investigate the potential role of event dependence within the reference period observed (see Chapter 8).

Lastly, this research contributes to the literature on crime and public security in Mexico. Crime has long been neglected by academia in Mexico, though there has been a surge of research following the rise of violence in the country in the past decade (e.g. Corcoran, 2013; del Pilar Fuerte Celis, Lujan, & Ponce, 2018; Guerrero-Gutiérrez, 2011; Heinle, Ferreira, & Shirk, 2016; Huebert, 2019; Meneses-Reyes & Quintana-Navarrete, 2017; Osorio, 2015; Rios, 2012; Shirk & Wallman, 2015; Snyder & Durán-Martínez, 2009b; Vilalta, 2013; Vilalta & Muggah, 2016; Widner, Reyes-Loya, & Enomoto, 2011; Williams, 2009). However, much research focuses on broad definitions of crime, violence and 'insecurity' that have limited practical applications for crime prevention. While this research is important, there is a need for a more pragmatic approach to crime research, with clear implications for crime prevention, such as that used in environmental criminology and crime science. Hopefully the research presented in this thesis can provide an initial impetus for other researchers, and spur greater interest in Mexico from a crime science and environmental criminology perspective.

1.4 Summary of the thesis

The structure of this thesis is as follows. Chapter 2 sets the theoretical foundations underpinning this thesis. It begins with a review of the literature on organised crime,

with particular attention to the situational approach to organised crimes. Then, I discuss the literature on repeat victimisation and its theoretical underpinnings in environmental criminology. Lastly, the chapter discusses the literature on extortion and considers the challenges and limitations of approaching this crime from a repeat victimisation perspective. The chapter concludes with the specific research questions that will be addressed in the thesis.

Given that details of the Mexican context may be unfamiliar to readers outside Latin America, in Chapter 3 I provide an introduction to Mexico and present an overview of Mexican history. Then, I review the history of Mexican organised crime, to provide the background necessary to understand the extortion phenomenon in the country.

Chapter 4 describes the main data sources and research settings used in the thesis. It begins with a discussion of the methodological difficulties associated with measuring extortion, and introduces crime surveys as a suitable option for doing so. Then it provides a brief overview of the sources of Mexican crime statistics, followed by a more detailed discussion on the national commercial victimisation survey (ENVE), the main data source for extortion measurements used in this research. It concludes with a description of the research settings and workflow used to generate the analyses and results reported in the following chapters.

The empirical contributions of the thesis are contained in Chapters 5 to 8. Each study addresses specific questions to progressively tell the story of repeat extortion victimisation in Mexico, building on findings from preceding chapters. All studies contain an introduction outlining the specific problem and hypotheses to be tested, any relevant features of the data not previously mentioned, the analytical strategy to be employed, findings, and a discussion of the results and their limitations.

The first empirical study, Chapter 5, seeks to determine whether extortion victimisation is concentrated beyond what is expected by chance, and whether the risk factors that explain the likelihood of becoming a victim (prevalence) are the same as those that explain the number of incidents suffered by victims (concentration). It begins by comparing the distribution of extortion incidents to that expected assuming a random process. Then, considering the risk heterogeneity mechanism of repeat victimisation, analyses are conducted to test whether relevant business- and state-level variables are good predictors of extortion prevalence and concentration. This is achieved using a novel modelling technique, the multilevel negative binomial-logit hurdle model, which allows explicit testing of whether prevalence and concentration are fuelled by distinct mechanisms. The findings suggest that risk heterogeneity is

less relevant for concentration than for prevalence, which implies that event dependence may be a more relevant predictor of repeat victimisation.

The second study, Chapter 6, is concerned with the factors that affect compliance with extortion demands. Despite being a very widespread crime, compliance with extortion in Mexico is relatively rare. This contrasts with the perception of the country as being overrun by organised crime and extortion. The chapter first reviews the theoretical explanations for extortion compliance to identify suitable hypotheses. Then, these are tested using a multiple logistic regression framework with clustered standard errors. The findings suggest that incident-level characteristics are the main predictors of compliance with extortion, with business- and state-level variables playing a secondary role. In particular, the study suggests compliance probabilities vary substantively between in-person extortions and those that occur remotely via telephone or the internet, which indicates that further analyses should heed this distinction.

Chapter 7, builds on the findings from Chapters 5 and 6 and examines repeat victimisation patterns of extortion using the in-person/remote distinction. It follows the same methodological approach used in Chapter 5. The main findings suggest that remote and in-person extortion incidents are associated with different predictors, thus they are likely to be fuelled by different opportunity structures. This means that analyses and interventions focused on extortion should consider remote and in-person extortion as different offence classes.

Chapter 8 seeks to capture event-dependence by splitting extortion measurements into two time periods. It begins by analysing the time-course of repeat extortion victimisation to determine if the distribution of waiting times between repeat incidents is different from that expected by chance. Next, the effect of event-dependence is estimated using the hurdle modelling framework. Findings suggest that the timing of repeats clusters at a rate higher than chance for remote and in-person extortion. Furthermore, victims that suffered previous victimisation incidents were more likely to suffer extortion incidents at a later period, though important variations per extortion type were discovered.

Lastly, Chapter 9 offers the concluding remarks of the thesis. The chapter first recounts the aims and its objectives of the thesis. This is followed by an overview of the findings and their limitations. Then, I describe how the findings contribute to the literature, as well as to the prevention of extortion victimisation. The last section covers the limitations of the research and avenues for future research.

Chapter 2

Literature Review

This thesis juxtaposes two concepts not usually found together: repeat victimisation and organised crime. Thus, there are two routes for reviewing the literature of these seemingly disparate concepts. The first would be to focus initially on repeat victimisation, argue why this perspective can be applied to organised crime, and then move on to the organised crime literature. Alternatively, the second route reviews the organised crime literature first, identifies its shortcomings, suggests how the repeat victimisation perspective might address them, and then reviews the repeat victimisation literature. Both routes are appropriate. However, as 'organised crime' remains an ambiguous umbrella term referring to many different phenomena (Paoli, 2014a), I opted for the second option, as it allowed me to define sharply the dimension of organised crime that can be approached from the repeat victimisation perspective. Then, the chapter specifically looks at extortion and discusses the challenges and limitations of approaching this crime from a repeat victimisation perspective. The chapter concludes with the set of research questions that will be addressed.

2.1 Organised crime

Organised crime is a concept that is, at the same time, commonly used and almost impossible to define. It entered mainstream use around the 1950s and 1960s in the United States referring to a specific—and rather unique—type of criminal organisation: the Italian-American Mafia, *La Cosa Nostra* (von Lampe, 2016). This narrow definition, however, was contested from its inception, in part for its heavy reliance on ethnicity (Paoli & Vander Beken, 2014), though also because it neglected the fact that many of the illicit activities that were thought to be associated with organised

crime, were in fact committed by a wide, fragmented constellation of actors, instead
of hierarchical, Mafia-type organisations (Reuter, 1983). Attempts at arriving at an
'authoritative' definition of organised crime, either in academia (e.g. Abadinsky,
2017) or policy (e.g. UNODC, 2004), have been somewhat unsuccessful, 'given the
continuous stream of new definitions that are being proposed' (von Lampe, 2016,
p. 12).

The elusive meaning of 'organised crime' has received considerable attention from
scholars (e.g. Newburn, 2013; Paoli & Vander Beken, 2014; von Lampe, 2016),
and indeed one of the goals of research in this field is to define the phenomenon
itself (Kelly, 1986; von Lampe, 2009). Today, many scholars question the need for
an overarching definition (von Lampe, 2016, p. 12-14), and some have suggested
dropping the term altogether (e.g. Edwards & Levi, 2008). Instead, they argue, it
is more fruitful for research and policy, to focus on its empirical manifestations, as
'organised crime' itself is not an empirical, observable fact, but a social construct
instead (von Lampe, 2016, p. 11).

Echoing the initial controversy surrounding the term, Paoli and Vander Beken
(2014, p. 14) contend that:

> the understanding of organized crime has shifted back and forth between
> two rival notions: (1) a set of stable organizations illegal per se or whose
> members systematically engage in crime, and (2) a set of serious criminal
> activities mostly carried out for monetary gain.

von Lampe (2016), on the other hand, proposes a more conciliatory approach,
suggesting organised crime is an analytical framework accommodating three—not
necessarily conflicting, and sometimes interdependent—dimensions cataloguing a
range of diverse empirical manifestations: organised criminal activities, criminal
structures, and extra-legal governance (see Figure 2.1).

The first, organised criminal activities, acknowledges the fact that some crimes
are organised, in the sense that they require—or benefit from—some degree of or-
ganisation and cooperation by criminals (Edwards & Levi, 2008; Hagan, 2006; Levi,
1998b). Thus, the different empirical manifestations in this dimension include rel-
atively simple crimes such as kidnapping (e.g. Pires, Guerette, & Stubbert, 2014;
Stubbert, Pires, & Guerette, 2015), or more complex phenomena such as transna-
tional drug trafficking (e.g. UNODC, 2008, 2010b) or arms trafficking (e.g. Feinstein
& Holden, 2014). Given the wide range of criminal activities that can be labeled
as 'organised', von Lampe (2016) proposes classifying them under three categories:
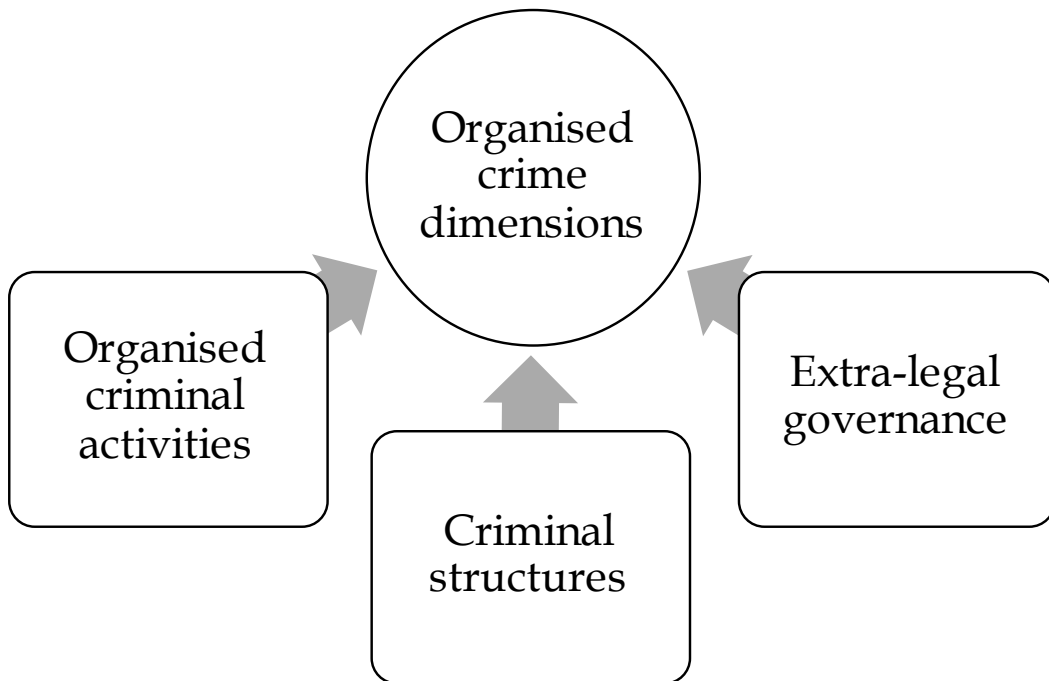
Figure 2.1: Von Lampe's (2016) basic dimensions of organised crime phenomena.

(i) crimes that involve markets where willing participants offer and acquire illegal goods (e.g. drugs) and services (e.g. contract killings); (ii) predatory crimes involving clearly defined victims (e.g. theft, modern slavery); and (iii) crimes deriving from the exercise of illegal power (e.g. enforcing of illegal contracts, regulating other criminals) (von Lampe, 2016, p. 31).

The second dimension, criminal structures, refers to the fact that some criminals cooperate with other criminals and effect such cooperation through a wide array of organisational forms (von Lampe, 2016, p. 32). These can vary from hierarchical mafia-type organisations (e.g. Albanese, 2014; Paoli, 2008; Varese, 2001), to flatter structures of gangs and other bands of criminals (e.g. Bjerregaard, 2008; Decker & Pyrooz, 2014; Densley, 2012; Garzón, 2008), to looser networks of offenders (e.g. Kenney, 2007; McIllwain, 1999; Morselli, 2009), and to more sporadic

market-based interactions (von Lampe, 2016, p. 32) between participants in criminal transactions (e.g. Becucci, 2008; Bezlov & Gounev, 2008; Reuter, 1983, 2014).

Lastly, the third dimension, extra-legal governance, refers to the exercise of power by criminals 'in a way that is more akin to governments and politics than to market-based or predatory crime' (von Lampe, 2016, p. 32). This reflects the fact that under certain conditions, individuals and groups can acquire roles traditionally reserved for the state, such as the provision of security and protection, regulatory functions, civil arbitration, criminal justice, contract enforcement, taxation, and—more broadly— the ordering of social interactions (e.g. Branović & Chojnacki, 2011; Gambetta, 1988; Koonings & Kruijt, 2004; Schelling, 1971; Skaperdas, 2001; Snyder & Durán-Martínez, 2009a; Sung, 2004).

Such extra-legal governance can be restricted to the *underworld*—a 'sphere of society where the state has no ambition to regulate behaviour other than to suppress it' (von Lampe, 2016, p. 32)—when some criminal individuals and groups exert power to regulate, tax, and broadly order, the behaviour of other criminals. However, particularly under conditions of weak (or absent) legitimate governance, this extra-legal influence can extend to the *upperworld*, where non-criminal activity takes place (von Lampe, 2016, p. 32). The extent of such influence can vary widely, including rigging lawful markets (e.g. Reuter, 1987), levying fees or 'taxes' on legitimate businesses (e.g. Chin, 2000), bribing or intimidating authorities (e.g. Morris, 2013), and downright capturing the state's political institutions (e.g. Bailey, 2012; Casas Zamora, 2013; Smilov, 2013).

Other dimensions are acknowledged, such as the social embeddedness of organised crime (von Lampe, 2016, p. 32), which recognises that organised criminal activities, criminal structures and extra-legal governance do not occur in a vacuum, but within a broader social environment (Van de Bunt, Siegel, & Zaitch, 2014, p. 321). However, precisely because a social and cultural context mediates all social interactions, this dimension can be better thought of as the backdrop to the empirical manifestations of organised crime.

With these dimensions, von Lampe (2016) sidesteps the need to articulate a specific definition of organised crime and instead proposes an analytical framework for the diverse phenomena labelled as such. Though not without critics (e.g. Sciandra, 2016), this framework serves its purpose insofar as it provides a tool to narrow down such an elusive concept, and thus focus the object of study—which is precisely the goal of this chapter. Given that this thesis is specifically concerned with the patterns of extortion against Mexican businesses, it is more precise to say that the focus is on

a specific type of organised criminal activity, rather than organised crime overall.[1] Thus, henceforth I will be consistent with this framework and specify the dimension of organised crime when referring to particular phenomena, and reserve 'organised crime' for situations that concern all of them.

2.1.1 Theoretical approaches to organised crime and their implications for its control

While there is a sizeable corpus of research on organised crime, much of it is mainly descriptive of specific phenomena, such as particular groups or activities (von Lampe, 2016, p. 45). Thus it is not always useful for developing theories that seek to explain specific expressions of organised criminal activity (Kleemans, 2013, p. 32). Furthermore, given the policy relevance of the subject, it is disappointing that much organised crime research is not geared towards practice (Kleemans, 2014, p. 57).

Researchers face serious obstacles to the study of organised crime phenomena— including unreliable data, impediments to accessing offenders and their activities, and serious risks to their well-being (von Lampe, 2016, p. 53). Such obstacles partly explain why organised crime research is underdeveloped. Furthermore, the fuzzy nature of the concept of organised crime itself hinders the development of theoretical explanations, as the diverse phenomena under the organised crime umbrella resist theoretical generalisations.

Mainstream criminological theories have not paid much attention to organised crime phenomena, and most are inadequate to explain them—nor do they aim to do so. While the case can be made that some mainstream criminological theories may explain, for example, why some marginalised individuals engage in organised crime (Newburn, 2013, p. 423), or why criminal groups emerge in areas with social disorganisation (Papachristos & Zhao, 2015, p. 170-171), they are not geared to accommodate the complexity of organised crime.

On the other hand, over the half-century since the organised crime concept has entered the public mainstream, a number of theoretical approaches have emerged to explain—if not the entirety of organised crime—some of its main dimensions (e.g. Kleemans, 2013; Slade, 2015; von Lampe, 2016). With respect to the practical implications for controlling organised crime, some approaches have been more successful than others. In the sections that follow, I discuss the six main theoretical

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[1]It could be argued that extortion is also an example of extra-legal governance, however this ambivalence will be addressed in Section 2.3.1.
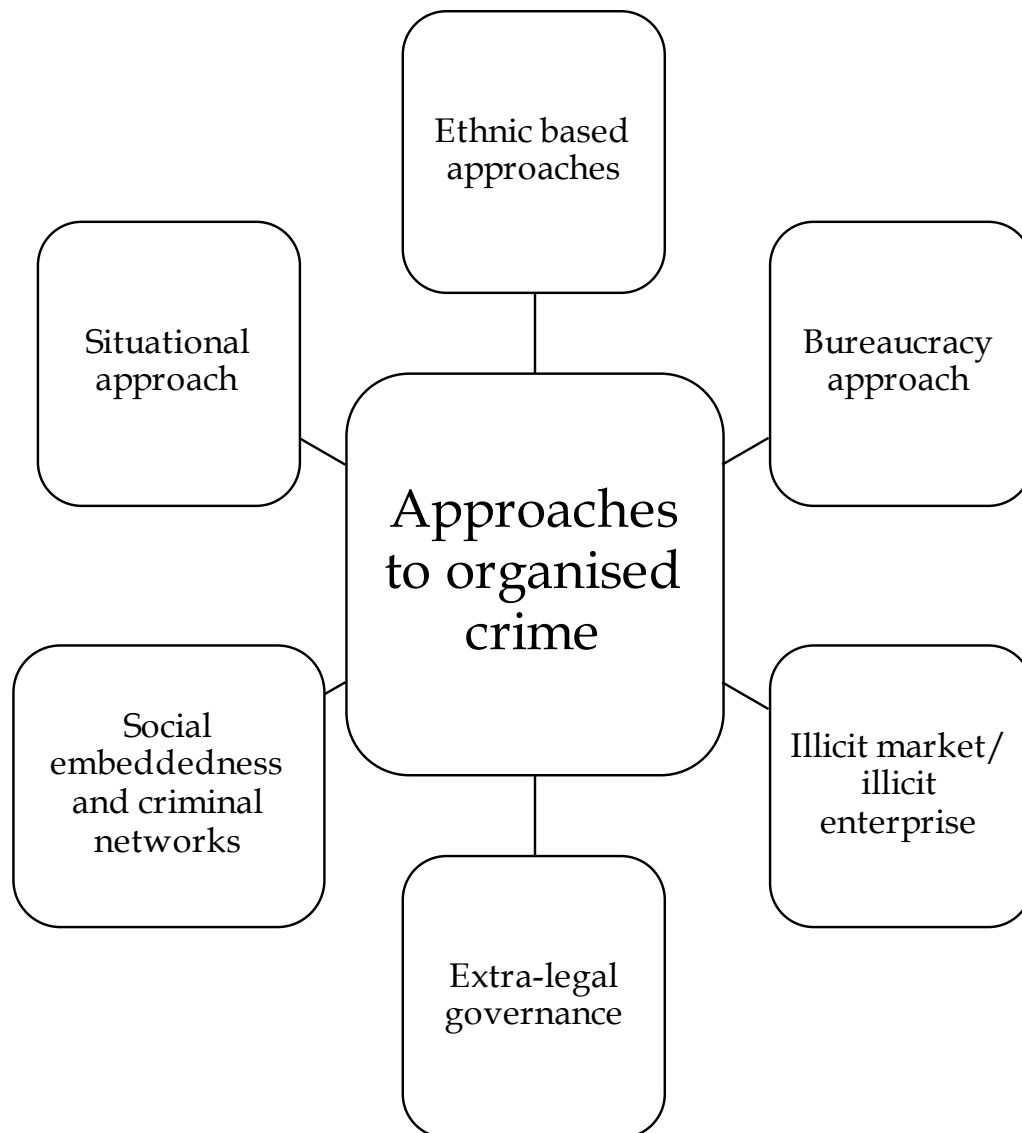
Figure 2.2: A summary of the main theoretical approaches to organised crime identified by Kleemans (2013).

approaches to organised crime identified by Kleemans (2013, see Figure 2.2), with particular attention to the situational approach.

2.1.1.1   Ethnic-based approaches

Ethnic-based approaches seek to explain why certain ethnic groups—especially as immigrant minorities—appear to be closely related to the emergence of organised

criminal groups. The first of these, the 'Alien Conspiracy Theory', was influenced by Cressey's (1969) observations suggesting that organised crime in the United States was largely and firmly under control of a vast and hierarchical organisation, the Italian-American Mafia (Kleemans, 2013, p. 33). The central idea of this theory, thus, was that organised crime did not emerge organically in American society, but was imported by Italian immigrants.

Though this model has been overwhelmingly rejected (e.g. Albini, 1988; Mastrofski & Potter, 1987; Potter, 1994; D. C. Smith, 1976), it has proven pervasive in shaping the public's perception of organised crime, with clear effects on policy to date (Woodiwiss & Hobbs, 2009). For example, consider the executive order recently issued by the President of the United States to tackle transnational criminal organisations, which alleges that these have 'spread throughout the Nation, threatening the safety of the United States and its citizens' (US President, 2017). While poor on details, the order echoes the alien-conspiracy theory when it claims that external organised crime groups have 'penetrated' the United States, and emphasises the role of 'foreign nationals who are members of such organizations' (US President, 2017).

The inadequacies of the alien-conspiracy model notwithstanding, other more plausible approaches have explored the relationship between ethnicity and organised crime; which is an empirical fact in some contexts (e.g. Paoli & Reuter, 2008). One of these approaches suggests that immigrants form organised crime groups with individuals sharing their ethnic identities to cope with assimilation difficulties, though as ethnic groups gradually integrate into their host communities they are replaced by other, recently arrived minorities in an 'ethnic succession' (Newburn, 2013, p. 423-424). Other researchers point to the increased opportunities for participating in organised criminal activities that come with ethnic kinship, such as a connection to drug-producing or drug-transit countries (Paoli & Reuter, 2008, p. 23-26), or the increased likelihood of social ties that facilitate connections and trust between co-offenders (Kleemans & de Poot, 2008; Kleemans & van de Bunt, 1999; Van de Bunt et al., 2014).

In any case, these new perspectives on the link between ethnicity and organised crime stress that (a) the relationship is not inherent to a particular ethnicity, (b) where there is a relationship, it does not involve the majority but only a small fraction of individuals belonging to a certain ethnic group, and (c) that connections between organised crime and ethnicity may not apply in all contexts (Morselli, Turcotte, & Tenti, 2011; Paoli & Reuter, 2008).

2.1.1.2   Bureaucracy approach

The bureaucracy approach was also heavily influenced by Cressey's (1969) observations on *La Cosa Nostra*. According to this approach 'organized crime is viewed as a distinct organization and equated with a specific organizational form' (Kleemans, 2013, p. 34). Thus, research in this area is particularly concerned with 'traditional' organised crime groups: mafias, drug cartels, syndicates, etc. There is much attention to their structure, codes of conduct, history, and to the individuals that command them (e.g. Brophy, 2008; Corcoran, 2013; Garzón, 2008; Kenney, 2007; Richards, 1999).

Like the alien-conspiracy theory, the bureaucracy approach has been particularly persistent in shaping popular perceptions, even though it has been routinely shown that it does not correspond to the vast majority of manifestations of organised crime (Albini, 1988; Mastrofski & Potter, 1987; Reuter, 1987; von Lampe, 2016). For example, Reuter's (1983) landmark study of organised crime in the United States found that illegal markets were not, as was then assumed, dominated by an all-powerful Italian mafia. Instead, they were better represented by a decentralised loose network of individuals held together by the invisible hand of the market.

Nonetheless, the bureaucracy approach has had important implications for policies designed to control organised crime groups. For example, the bureaucratic model is evident in policies that seek to disrupt groups by attempting to capture their leaders, the so-called 'kingpin' strategy (Calderon, Robles, Diaz-Cayeros, & Magaloni, 2015; Jones, 2013; Kenney, 2007). While removing leaders and key actors from criminal organisations can indeed weaken powerful groups (Richards, 1999; von Lampe, 2016), this seldom has a lasting impact on the overall level of organised criminal activities—particularly in the case of market-based crimes—as weakened groups are replaced by other criminal actors.

In some cases, such strategies can lead to dramatic increases in violence, as power vacuums created in the wake of arrests or the killing of powerful criminals can lead to conflicts between and within groups (Calderon et al., 2015; Dickenson, 2014; Jones, 2013; Rios, 2012).

2.1.1.3   Illicit enterprise/market approach

This approach suggests that organised crime is best understood from the perspective of economics and business, emphasising 'the—sometimes remarkable—similarities between illegal activities and legal activities' (Kleemans, 2013, p. 35). The funda-

mental argument is that the main driver of organised crime is financial profit, and thus criminals are presented as entrepreneurs responding to the demand for illicit or restricted goods and services.

Governments routinely prohibit or restrict access to certain products (e.g. drugs), or services (e.g. gambling) because they may pose a threat to consumers, society, or in some way contravene a country's laws or social mores. However, when demand for these items remains high, such restrictions tend to increase the price they fetch in a black or underground market. This attracts individuals and organisations to supply the market, claiming outsized profits.

The approach has proved very powerful in explaining the dynamics of market-based crimes (e.g. Bezlov & Gounev, 2008; Boekhout van Solinge, 2010; Killias, Isenring, Gilliéron, & Vuille, 2011; Kilmer, Caulkins, Bond, & Reuter, 2010; Rhodes, Johnston, Han, McMullen, & Hozik, 2000), and has further been extended to predatory and governance-type organised crimes by presenting them as the result of a market demand for violence and protection (e.g. Gambetta, 1988; Konrad & Skaperdas, 1998; Mehlum, Moene, & Torvik, 2001, 2002; Parakilas, 2012; Reuter, 1987; Varese, 2001). Furthermore, the approach has been used to explore how the conditions of specific illicit markets can explain the organisational nature and behaviour of criminal structures (e.g. Reuter, 1983; Wainwright, 2016). However, scholars that study criminal activities from this perspective, do note that economic factors in themselves are seldom enough to understand the entire organised crime phenomenon (e.g. Levitt & Venkatesh, 2000).

The illicit enterprise/market approach has also been very influential in shaping policies aimed at countering organised crime. It has been highly critical of supply-side interventions (e.g. the eradication of drug crops, drug seizures) for failing to noticeably disrupt organised criminal activities and structures (Mazerolle, Soole, & Rombouts, 2007; Rhodes et al., 2000; Zedillo & Wheeler, 2012). The approach assumes that as long as the demand for an illegal commodity is strong enough to raise its price above the costs imposed by prohibition and enforcement, any disruption to supply will be resolved by the market, raising prices further to attract new suppliers. In the case of high-level drug trafficking, this is evident in the 'balloon' effect (UN-ODC, 2011, p. 58), in which disrupting drug production in one location produces displacement to another one.

As a policy prescription, the approach stresses the importance of reducing the demand for illicit goods and services (Andersen & Farrell, 2002; Babor, 2012), or of disrupting market conditions that facilitate the emergence of black markets—such

as addressing inadequate regulation (J. A. Blum, Levi, Naylor, & Williams, 1999; Passas, 1999), or questioning the prohibition regime itself (Caulkins & Lee, 2012; Donohue, 2012; MacCoun & Reuter, 2001; Miron, 2012; Spapens, 2012; Wainwright, 2016; Wodak, 2014).

However these policy prescriptions have turned out to be difficult to implement. First, interventions aimed at reducing demand for illicit goods and services have generally failed to attract the same amount of public support than supply side approaches (MacCoun & Reuter, 2001, p. 32-38), and have somewhat modest effects (MacCoun & Reuter, 2001, p. 32-38; Reuter, 2010, p. 121). Second, improving regulations, especially harmonising cross-border asymmetries, is a slow and politically fraught process, and while it can have important effects in reducing certain black markets, it does not cover a wide range of organised crime phenomena. Lastly, though there is a constant debate on the case for legalising and/or decriminalising controlled goods and services (e.g. W. Huisman & Kleemans, 2014; Kilmer et al., 2010; MacCoun & Reuter, 2001; Reuter, 2012; Weatherburn, 2014), there is insufficient empirical evidence on the real-world effects of legalisation/decriminalisation on organised crime phenomena, and much uncertainty regarding potential unintended consequences (MacCoun & Reuter, 2001; Reuter, 2012).

Furthermore, regulation-based approaches are likely to be especially difficult to implement in countries with weak rule of law and inadequate regulatory frameworks, such as those in Latin America—which not coincidentally bear the lion's share of organised crime related violence associated with illicit markets. Lastly, while the global drug prohibition regime appears to be softening (Vicknasingam, Narayanan, Singh, & Chawarski, 2018), there are many controlled goods and services that are unlikely to be legalised or decriminalised—such as child pornography and modern slavery. Thus, as long as there is demand for these and other illicit goods and services, other approaches to counter organised crime will be required.

2.1.1.4 Extra-legal governance approach

If the illegal enterprise approach sees organised crime as a business, the extra-legal governance approach suggests that it is more akin to government (Kleemans, 2013; von Lampe, 2016). This approach is deeply influenced by Tilly's (1985) observations drawing parallels between the formation of the state and the rise of organised crime groups. Tilly's observations underlie the assumption that 'organized crime emerges out of the power vacuum that is created by the absence of state enforcement' (Skaperdas, 2001, p. 173). These vacuums may be geographical, or refer to

specific dimensions of social life. For example, Schelling (1971) suggested that such extra-legal power was mainly exerted through extortion of the underworld—by which he meant the predatory levying of 'taxes' on criminals—while Gambetta, in contrast, posited that such governance was the result of a demand for protection and regulation in an uncertain market (be it licit or illicit) (Gambetta, 1988, 1993).

The approach is rooted in economics and political economy; however the main aim is to understand the political functions of criminal structures (von Lampe, 2016, p. 47). Recently, the approach has been used to study and make sense of the emergence of organised crime in the developing world following situations of state failure (Mehlum et al., 2001; Sung, 2004), particularly in post-Soviet countries (Frye & Zhuravskaya, 2000; Varese, 2001; Volkov, 1999), and Latin America (Bailey, 2012; Kalyvas, 2015; Snyder & Durán-Martínez, 2009a, 2009b; Thoumi, 2007; Williams, 2009), and on a much smaller scale, to understand how criminal structures have come to control slums and similar marginalised areas in cities in the developing world (Felbab-Brown, 2011a; Koonings & Kruijt, 2004; Koonings, Veenstra, & Murillo S, 2007).

One common concern within the extra-legal governance approach is that, left unchecked, power-wielding criminal groups can become a threat to the existence of the state itself by challenging its legitimacy, corroding trust, and capturing state institutions through corruption and co-option. Thus, the fundamental policy implication of the perspective is that if states are to counter the many threats of organised crime, they need to recover control over any geographical or social dimensions lost to these groups.

One option is to directly confront organised crime using law enforcement and the military, as Colombia (Gutiérrez Sanín & Jaramillo, 2004; Mejía, 2012; Thoumi, 2014) and Mexico (Felbab-Brown, 2011b; Guerrero-Gutiérrez, 2011) did with ongoing 'wars' against powerful criminal organisations, or as the police did in Rio de Janeiro, 'pacifying' *favelas*—slums—controlled by organised crime groups to restore the rule of law (Felbab-Brown, 2011a). Additionally, and commonly presented as an indispensable complement to law enforcement, states embark on extensive state-building, institutional reform, and extend social policies to strengthen legitimate governance (Aguirre & Herrera, 2013; Brands, 2010; Felbab-Brown, 2011a; Herrera-Lasso, 2013; Olson, Shirk, & Selee, 2010), or rally civil society to reject organised crime influence in local and business communities (La Spina, 2014, p. 598-599; La Spina, 2008b).

There are, however, important practical drawbacks to these options. Confronting organised crime groups militarily—unavoidable as it may be in certain situations—

is costly and can provoke dramatic surges in violence (del Pilar Fuerte Celis et al., 2018; Rios, 2012). On the other hand, 'softer' state-building approaches are unlikely to provide short-term respite, nor may they be enough to break the grip of organised crime in communities where it is deeply entrenched (von Lampe, 2016, p. 396).

Furthermore, policies that boost legitimacy, strengthen institutions, and improve social conditions are important, not only to combat organised crime, but to increase development and human welfare more generally; however, the problems they are attempting to address (e.g. poverty, exclusion, unemployment, inequality, access to justice, trust in institutions, educational advancement, etc.) are not low-hanging fruit, but persistent issues that—to varying degrees—plague societies worldwide. Lastly, it is not guaranteed that development-focused policies would automatically reduce organised crime, as they could inadvertently facilitate it. For example, Kleemans (2007, p. 175-176) notes how the infrastructure for legal trade in The Netherlands—such as ports and airports—provides an excellent opportunity structure for organised crimes, especially transit crimes (see also Zaitch, 2003), while Bergman (2018, p. 109-142) shows how increased prosperity following democratisation in Latin America since the 1990s led to an explosion in illicit markets in everything from stolen and counterfeit consumer goods to illicit drugs, thus stimulating the growth of criminal entrepreneurs—both formally and informally organised.

2.1.1.5   Social embeddedness and criminal networks

This approach focuses on the social ties and interactions between co-operating offenders to understand organised crime (Kleemans, 2013, p. 37-38; von Lampe, 2016, p. 47-48). It argues that organised crime activities do not happen in a vacuum and, instead, are embedded in the social and structural ties that mediate interactions between people (Kleemans & van de Bunt, 1999; Van de Bunt et al., 2014). These ties can be dictated by family, ethnicity, community, geography and work, among other factors. Thus, the implication is that to understand the different dimensions of organised crime, it is crucial to understand the social relations upon which criminal networks are formed (Kleemans & van de Bunt, 1999).

One of the main contributions of this approach is to shed light on the empirical—rather than assumed—shapes of criminal organisations (McIllwain, 1999, p. 301; von Lampe, 2016, p. 48; Kenney, 2007, p. 233), and to highlight the different roles that offenders take within a criminal network (Farah, 2012; Malm & Bichler, 2011; Morselli, 2009). Furthermore, it has introduced highly technical methodologies for social network analysis to the study of organised crime (e.g. Morselli, 2009; Tayebi &

Glasser, 2011). This approach is limited by the fact that many interactions between offenders happen in private. Thus, many researchers rely on surveillance data, which might not necessarily reflect the 'true' interactions in a network (Kleemans, 2013, p. 41).

An important implication for practice, is that the approach helps explain the resilience of criminal networks to disruption by arresting or removing its members: 'if there are many connections between offenders, some offenders may be more important than others, yet nobody is really irreplaceable' (Kleemans, 2013, p. 40). However, the corollary is that if key individuals can be identified, removing them could prove highly disruptive to the network. Therefore, the approach has gained ground in research aiming to disrupt organised crime phenomena (Cockbain, Brayley, & Laycock, 2011; for a review see Bichler & Malm, 2015).

2.1.2 The situational approach to organised crimes

The situational approach to organised crimes aims to identify the opportunity structures that facilitate the commission of narrowly defined organised crime activities, with the aim of finding novel, and hopefully effective, 'pinch points' to prevent them (Bullock et al., 2010a).

Underpinning the situational approach is the assumption that organised crime is 'rational crime par excellence: it is highly planned and organized, directed and committed by older, more determined offenders, usually with strong economic motivations' (Cornish & Clarke, 2002, p. 41). While the assumption of rationality is central to how other approaches conceive organised crime, the distinction is that the situational approach aims to understand how organised crimes are carried out, rather than to question why they occur (Cornish & Clarke, 2002, p. 41). Thus, the focus is not on broader organised crime phenomena, but on narrowly defined organised criminal activities (for reviews, see Bullock et al., 2010b; Felson & Clarke, 2012; Kleemans et al., 2012; Levi & Maguire, 2004).

Furthermore, the situational approach is underpinned by the fact that many opportunity structures feeding organised crimes are directly or indirectly tied to legitimate activities and environments (Felson, 2006b). This insight reveals a particularly powerful avenue for prevention interventions, as identifying and regulating the legitimate sphere is conceivably easier to accomplish than attempting to regulate illicit activities that more often than not take place covertly.

The situational approach to organised crimes is based on situational crime prevention, an approach to 'ordinary' crime that aims to reduce specific crime problems

by focusing on the settings in which they take place, rather than on the offenders that commit them (Clarke, 2009, p. 259). At the core of situational crime prevention is the assumption that crime is a product of opportunity (Felson & Clarke, 1998). Crime opportunities emerge when a likely offender and a suitable target coincide in time and space in the absence of capable guardianship (Cohen & Felson, 1979, p. 589; Felson & Santos, 2010). Whether opportunities materialise as crimes depends on the interaction between offender motivation—however acquired—and situational characteristics that influence the decision to offend (such as those affecting effort required, perceived risks, potential rewards, as well as environmental precipitators that affect criminal disposition) (Cornish & Clarke, 1987, 2003; Wortley, 2012).

2.1.2.1   Theoretical underpinnings of situational crime prevention

Though it was independently developed, situational crime prevention is now closely associated with theories of environmental criminology: the rational choice perspective, the routine activity approach, and crime pattern theory. First, the rational choice perspective (Clarke & Cornish, 2011; Cornish & Clarke, 1985) considers that crimes are the product of a rational calculation by offenders, who weigh risks and rewards when confronted with a criminal opportunity. This rationality, however, is distinct from the perfect rationality traditionally presumed in mainstream economics,[2] and instead is bounded (Simon, 1955, 1990) by circumstance, experience, ability, available information and other cognitive biases.

Thus, rather than presenting crime as a one-off decision, the rational choice perspective considers that decisions to offend are crime- and situation-specific, meaning that offenders are affected by the specific characteristics of a particular criminal opportunity. Cornish and Clarke (1987) referred to the characteristics which render some opportunities differentially attractive to particular individuals or groups as *choice-structuring properties* (p. 935). Furthermore, the rational choice perspective deconstructs the crime event into a sequence of steps and logistical requirements (i.e. 'crime scripts'), each of which may be affected by choice-structuring properties and pose specific logistical requirements (e.g. certain tools and skills required to complete a step) (Clarke & Cornish, 2011; Cornish, 1994).

Situational crime prevention, thus, aims to identify those choice-structuring prop-

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[2]The perfect rationality assumption in classical economics has been widely challenged (e.g. Conlisk, 1996; Simon, 1955), which has led to the adoption of bounded rationality, bringing the sub-field of *behavioural economics* to the mainstream in recent times (Mullainathan & Thaler, 2000; Thaler, 2015).

erties and logistical requirements—both regarding the decision to offend and smaller decisions in the crime-commission process—that are easily disrupted in a way that renders the offence unattractive.

Second, the routine activity approach (Cohen & Felson, 1979; Felson, 2011; Felson & Cohen, 1980) introduced the trio of elements considered necessary for crime opportunities—a motivated offender, a suitable target, and the absence of a capable guardian.

However, one of the main contributions of the approach is to link concepts from human ecology to explain why crime opportunities are not evenly distributed, but occur in certain locations and at certain times involving specific offenders and targets (Felson & Cohen, 1980, p. 390). Such concentrations, Felson and Cohen (1980) argue, are determined by the rates at which offenders and targets converge in time and space absent capable guardians (p. 391). This rate, drawing on Hawley's (1950) observations on human ecology, is determined by the social and urban structures that organise the routine interactions people have with one another and their environments during their daily lives. Thus, these routine activities—e.g. family, work, school, leisure, transport, the use of technology—provide the opportunity structure for specific crimes.

From this premise, the routine activity approach goes on to explain how changes in a society's routine activities (e.g. increasing female participation in the workforce, the rise of the automobile, the ubiquity of mobile phones and the internet) can have dramatic effects on the opportunity structures for crime, and thus to changes in crime rates, even if there are no changes to offender motivations (Cohen & Felson, 1979; Farrell, Tilley, Tseloni, & Mailley, 2011; Leukfeldt & Yar, 2016; Tilley, Farrell, & Clarke, 2015). From a situational crime prevention perspective, the aim is to understand these opportunity structures and to identify the factors that may be manipulated to promote guardianship, deflect or deter offenders, and safeguard targets.

Third, crime pattern theory (Brantingham & Brantingham, 1993; Brantingham, Brantingham, & Taylor, 2005) is similar to the routine activity approach, in the sense that it is concerned with the non-random concentration of crime events at certain times and locations. However, while the routine activity approach is concerned with the social and urban structures dictating day-to-day activities, crime pattern theory explains how the urban backcloth shapes these routine activities within a city, as well as influencing offenders' criminal disposition or target suitability (Brantingham & Brantingham, 1993; Brantingham et al., 2005).

The first assumption is that as offenders travel to and from their routine activity spaces, they develop cognitive 'awareness spaces' where they are more likely to notice crime opportunities. Second, certain types of locations are likely to affect their willingness to commit a crime by providing more attractive targets or reducing guardianship. Brantingham and Brantingham (1995) term 'crime generators' locations that attract a large number of people for reasons unrelated to crime, but which increase the likelihood of exposing targets to offenders (e.g. shopping malls, transport hubs, festivals). On the other hand, 'crime attractors' are specific places that attract a high number of offenders due to well-known opportunities for crime (e.g. open-air drug markets, troublesome bars).

Awareness spaces, crime generators and crime attractors are constrained by the urban backcloth—streets, walkways, land use, public transport, etc. Thus, crime pattern theory is particularly concerned with the characteristics of this backcloth (complexity, structure, accessibility), as—from this perspective—they are crucial in determining urban crime patterns (e.g. Bernasco & Block, 2011; Brantingham & Brantingham, 1995; Kurland, Johnson, & Tilley, 2014). From a situational perspective, crime pattern theory helps narrow down the interaction between routine opportunity structures, choice-structuring properties and the physical and social environment where activity takes place (for a review, see Andresen & Kinney, 2012).

2.1.2.2   Applying a situational approach to organised crimes

Transplanting the insights of the situational approach to an organised crime context has proven challenging. As Kleemans, Soudijn, and Weenink (2010) note:

> Theoretically, situational crime prevention is applicable to all sorts of crime, including organised crime and terrorism. However, the problem with organised crime and terrorism is that these phenomena have to be scaled back to tangible events, offenders, and specific settings that can be studied. (p. 18-19)

As stated earlier, organised crime is a contested concept that can refer to a wide variety of different empirical phenomena. Thus, in order to scale the organised crime phenomenon to a dimension suitable for situational analysis, the first step is to narrowly define the specific phenomena under scrutiny.

The situational approach has mostly focused on two types of organised crime phenomena: specific activities associated with organised crime (henceforth 'organised

crimes') (e.g. Bullock et al., 2010b), and the organisation of such crimes (e.g. Edwards & Levi, 2008). These two phenomena roughly correspond to the first two dimensions of organised crime identified by von Lampe (2016): organised crime activities and criminal structures (see Figure 2.1), though in the latter the focus is on the organisational requirements of certain crimes and on the environmental and situational elements that facilitate the persistence of criminal cooperation, rather than on the nature and characteristics of the structures themselves.

Regarding organised crimes, the situational approach encounters additional complications. Organised crimes are considered to be more complex than non-organised crimes, insofar as 'their commission involves a complex interplay of criminal actors, equipment, locations and activities' (Cornish & Clarke, 2002, p. 42). Thus, they are not easily reduced to a criminal event—the main focus of situational analyses. Organised crimes do not necessarily have a clear beginning and end or an easily identified 'target' or victim, they do not always take place in a fixed point in space, and they are not always carried out in full by the same offender.

To address this complexity, the situational approach to organised crimes relies on the use of 'crime scripts' (Cornish, 1994; Kleemans & Soudijn, 2017; Leclerc, 2017; Leclerc & Wortley, 2013a). A crime script 'represents the complete sequence of actions adopted prior to, during, and following the commission of a particular crime' (Leclerc & Wortley, 2013b, p. 6). They are conceptual tools used to represent a somewhat continuous process in discrete steps. In the context of organised crimes, crime scripts are particularly helpful to unpack their complexity into dimensions suitable for situational analysis. As Cornish and Clarke (2002) note, organised crimes can be thought of as 'a string of interlinked offense scripts, each component script having its own stages, casts, locations and activities' tied together by a 'master script' (p. 50). Furthermore, Hancock and Laycock (2010, p. 175) suggest considering two additional processes when breaking down organised crimes: the criminal lifestyle, and the criminal groups or networks that participate in the script.

Once a complex organised crime is broken down into more manageable components, analysis can be directed at each constituent part. As one of the predominant goals of situational analysis is to identify suitable 'pinch points' to prevent or disrupt specific crimes, analyses tend to follow a loosely structured problem-solving methodology (Clarke, 2009, p. 265). In an ideal setting, Clarke (2009, p. 266) notes that situational interventions should be devised using a form of 'action research', through an iterative cycle of hypothesis development, solution identification, implementation of responses, and evaluation of results—a process similar to the SARA

model (consisting of scanning, analysis, response and assessment stages) proposed for problem-oriented policing by Eck and Spelman (1987).

However, the application of situational crime prevention to organised crimes has remained mostly a theoretical exercise (Kleemans & Soudijn, 2017, p. 395; von Lampe, 2016, p. 394)—though as von Lampe (2016) notes, some successful measures implemented to counter organised crimes have been retrospectively interpreted as falling within the scope of the situational approach, for example: money laundering regulations (von Lampe, 2016, p. 394), Amsterdam's administrative approach to organised crime[3] (Ayling, 2014; Nelen, 2010; Nelen & Huisman, 2008; van der Schoot, 2006, ch. 4), as well as specific intelligence-led policing projects aimed at disrupting organised crime groups (Kirby & Nailer, 2013).

Thus, situational studies of organised crimes have focused on identifying *potential* intervention points based on the various opportunity structures used in the commission of narrowly defined crimes (Bullock et al., 2010a, p. 8). These opportunity structures can refer to access to specialised tools, skills and settings, such as communication and information technologies for online wildlife trafficking (Lavorgna, 2014) and for crimes organised from prisons (van der Laan, 2012), abundant and accessible targets for poaching (Pires & Clarke, 2011; Pires & Guerette, 2014), equipment, materials and other logistical requirements necessary to manufacture illicit drugs (Chiu, Leclerc, & Townsley, 2011; Vijlbrief, 2012), suitable infrastructure to transport contraband cigarettes (von Lampe, 2010) and other illicit goods (Kleemans, 2007; Kleemans et al., 2010), and access to professional facilitators such as solicitors, bankers, accountants and notaries (Middleton & Levi, 2005; Soudijn, 2012; van Gestel, 2010), among other examples.

Nonetheless, opportunity structures can also be found in wider social conditions and arrangements, such as spaces dominated by criminal subcultures that subvert formal guardianship on members of outlaw motorcycle gangs (S. Huisman & Jansen, 2012), socioeconomic push and pull factors affecting victim vulnerability to human trafficking for sexual exploitation (Finckenauer & Chin, 2010; Savona, Giommoni, & Mancuso, 2014), corruptible officials in the illicit timber trade (Graycar & Felson, 2010), cross-national regulatory asymmetries regarding tobacco sales in cigarette smuggling (von Lampe, 2010), information asymmetries in real estate markets in

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[3]The administrative approach to organised crime is based on the fact that public services and facilities are usually needed to carry out certain organised criminal activities. Thus, instead or relying solely on law enforcement, the approach involves the strategic use administrative ordinances and procedures (e.g. reshaping procurement rules, permits, licensing) to alter the opportunity structures of certain organised crimes (Kleemans & Huisman, 2015; Nelen, 2010; Nelen & Huisman, 2008).

mortgage fraud (van Gestel, 2010), and opaque administrative processes in the infiltration of the public construction industry (Savona, 2010).

Additional situational analyses focusing on specific organised crimes can be found in Bullock et al. (2010b), van de Bunt and van der Schoot (2003), Leclerc and Wortley (2013a), and the special edition of *Trends in Organised Crime* edited by Kleemans et al. (2012).

On the other hand, regarding the organisation of crimes, the situational approach is concerned with two ideas: that 'different forms of crime *require* different levels of organisation' (Levi, 1998a, p. 436), and that criminal cooperation is a function of the physical and social environment.

The focus on organisational requirements stems from the inherent complexity of organised crimes. A key difference with studies that are concerned with the characteristics of organised crime structures is that the situational approach considers such structures to be 'emergent properties of the crime scripts' (Cornish & Clarke, 2002, p. 52), meaning that the characteristics of such criminal structures are expected to be determined by the logistical needs of a particular criminal activity being pursued. The analytical implications of this insight are that crime scripts need to incorporate such organisational ramifications when unpacking criminal activities—exemplified by the parallel processes outlined by Hancock and Laycock (2010, p. 175). The practical implications are that potential interventions can go beyond interrupting the procedural causal chain and also consider disrupting the organisational links sustaining criminal activities.

However, these insights are unlikely to be applicable to all organised crime phenomena, as 'it seems to be an oversimplification to assume that criminal organization is merely a response to the specific logistical needs of particular criminal endeavours' (von Lampe, 2011, p. 149). While this criticism is particularly salient in crimes related to the extra-legal governance dimension of organised crime (where it is assumed that criminal structures emerge in response to complex socio-political processes), it is likely that organising pressures envisioned by the situational approach are relevant to the fluid criminal structures that exist to support market-based organised crimes (e.g. illegal gambling). As Reuter (1983) notes, 'the "magic of the marketplace" may find its truest meaning in the distribution of illegal goods and services, where the visible hand of force is so frequently defeated by the invisible hand of market economics' (p. 187).

Regardless of whether criminal activity drives organisation, or criminal structures drive activities, studies that focus on the second idea—that criminal cooperation is a

function of the physical and social environment—are mostly concerned with understanding how offenders 'find the co-offenders necessary or helpful for any given set of offences' (Levi, 2008, p. 390). To understand this, Felson (2003) introduced 'offender convergence settings', which refer to places and times where offenders coincide and socialise, and thus set the stage for criminal cooperation (Agustina & Felson, 2015; Felson, 2006b).

Offender convergence settings were developed invoking Barkers' (1963) 'behaviour settings' as a unit of analysis (Agustina & Felson, 2015, p. 145), and set the stage to explain how the physical and social characteristics of particular places at particular times can facilitate the convergence of willing offenders and foster cooperation in criminal endeavours. As offender convergence settings depend on features of the environment, they help to explain why criminal cooperation can persist even when the particular offenders may vary (Felson, 2006b, p. 9).

While the routine activity approach and crime pattern theory were conceptualised to explain the convergence of likely offenders and suitable targets in places with poor guardianship, their insights on the relationship between the socio-urban environment with offender behaviour can also explain offender convergence settings (e.g. Agustina & Felson, 2015; Bichler, Christie-Merrall, & Sechrest, 2011; Bichler, Malm, & Christie-Merrall, 2012; Bichler, Malm, & Enriquez, 2014; Felson, 2006b, 2017), meaning that such settings need to be understood as products of offenders' daily activities (i.e., work, school, leisure) and as a function of the urban backcloth. Furthermore, recent research has expanded the applicability of offender convergence settings to 'virtual places' (e.g. internet forums) that appear to serve a similar function for certain cybercrimes (Soudijn & Zegers, 2012). The implication for practice is that offences that depend of criminal cooperation could be disrupted by improving place management (Eck, 2018) of relevant offender convergence settings.

As an alternative approach to understanding the determinants of criminal cooperation, Kleemans and de Poot (2008, p. 75) introduced the concept of 'social opportunity structures', which refer to 'social ties providing access to profitable criminal opportunities' (p. 75) and help explain involvement in organised crime activities. Social opportunity structures were born out of the social embeddedness approach to organised crime (see Section 2.1.1.5), insofar they reflect the important role that social relations play in organised crimes (Kleemans, 2013, p. 75). While social opportunity structures emphasise the importance of social ties—rather than environmental factors—the fact that they depend on fixed (e.g. family ties, ethnicity, nationality, occupations) and varying personal characteristics (e.g. work, acquaintances, roman-

tic partners, friendships) (Kleemans & de Poot, 2008; Kleemans & van de Bunt, 2008), provides a bridge to the situational approach.

After all, individual characteristics are also associated with routine activities, and social ties also have a spatiotemporal dimension affected by the urban backcloth. The implication for the situational approach is that crime script analyses can be combined with social network analysis (e.g. Bichler, Bush, & Malm, 2015; Bright & Delaney, 2013; Morselli & Roy, 2008) to better capture the complexity of organised crimes. The implication for practice is that the social opportunity structures, and the interface between social ties and the stages of criminal activities, provide additional intervention points to disrupt criminal activities.

2.1.2.3 Existing criticism of the situational approach to organised crimes

Existing criticism of the situational approach to organised crimes can be classified in two categories. The first questions the suitability of using a theoretical framework devised to understand 'ordinary' criminality in the context of more complex organised criminal activity. The second, on the other hand, is more concerned with whether the situational approach can live up to its promise of delivering effective crime prevention strategies to counter organised crime problems.

Regarding theoretical suitability, von Lampe (2011) notes that the situational approach appears to be well suited to some organised crimes, while other crimes require modifications to the model 'to the point where it is questionable whether the framework of Situational Crime Prevention can be meaningfully applied at all' (p. 157).

Among the main issues identified by von Lampe is that some organised crimes are too complex (temporally, spatially and logistically) to reduce to archetypal crime situations—represented by the crime triangle of offender, target and place (Hough & Tilley, 1998, p. 23). While the crime script depicts the crime commission process as a series of discrete steps that can be anchored to a particular point in time and space, von Lampe argues that this condition is not always met in organised crimes (p. 151). Furthermore, targets can vary across the crime script, and in many organised crimes—such as non-predatory crimes—it can difficult to establish what is the target of the criminal activity, if there is one at all (von Lampe, 2011, p.151-152). Lastly, von Lampe argues that the situational approach tends to focus too narrowly on the situational contingencies of the crime event—namely the elements of the crime triangle—and neglects that 'the anatomy and inner functioning of crime

situations. . . may well be contingent upon distinct social, economic and political conditions' (von Lampe, 2011, p. 158).

Von Lampe's emphasis on the complexities of organised crime activities and his contention that the situational approach may not be relevant to understand some criminal activities is warranted. Yet, this does not mean that the approach should be discarded when the activities under focus can be meaningfully understood from the situational perspective. However, the criticism does highlight the importance of tackling narrowly-defined organised crime phenomena.

On the other hand, as highlighted in the previous section, situational analyses of organised crimes need not be constrained by the crime triangle—also known as the 'problem analysis triangle' (Hough & Tilley, 1998, p. 23). The rational choice perspective, the routine activity approach, and crime pattern theory—as well as the social embeddedness approach—offer a rich set of insights that can help explain the environmental and social opportunity structures supporting organised criminal activities, well beyond the crime triangle.

Similarly, the situational approach does not deny the influence of wider social, economic, and political conditions on organised crime phenomena. Indeed, in an elaboration of the situational approach, Ekblom's (2003) conjunction of criminal opportunity (CCO) framework incorporates proximal and distal pre-conditions of crime events to the analysis, and, according to Levi and Maguire (2004), 'provides a means of addressing problems of reductionism in social structural accounts of organized crime' (p. 383). Nonetheless, the desire to accurately capture the complexity of organised crime phenomena across all its dimensions needs to balance the potential benefits of a more realistic portrayal of the phenomenon with the amount of effort required to achieve a comprehensive model, as the CCO framework is recognised to be very laborious (Levi & Maguire, 2004, p. 409). This is particularly relevant as the situational approach is characterised by the pursuit of 'good enough' theories to understand criminal phenomena (M. J. Smith & Clarke, 2012). Thus, situational analyses should strive to balance depth of understanding with applicability to crime prevention efforts.

On this note, the other type of criticism focuses on whether the interventions envisioned in situational analyses can deliver on their preventive potential. This scepticism stems from three key distinctions between organised and non-organised crimes. One, the situational model considers that some crime events come about spontaneously as offenders stumble upon criminal opportunities in the course of their daily, non-criminal activities (Andresen, 2014, p. 87). Whereas in the case

of organised crime, it is presumed that criminals are more purposive and actively seek and create crime opportunities by either adapting to changing conditions, or by manipulating such conditions as required (Ekblom, 2003, p. 252; von Lampe, 2011, p. 152-153; Edwards & Levi, 2008, p. 382; Kleemans & Soudijn, 2017, p. 397).

Two, organised crimes are judged to be more resilient to disruption than non-organised crimes. This resilience is in part explained by the fact that organised criminals are more resourceful (Ekblom, 2003, p. 250) and can adapt to changing circumstances as outlined above. In addition, as Kleemans and Soudijn (2017) note, the continuous interactions that constitute some organised crimes, coupled with the fact that such activities are embedded in their social and political context, challenges the idea that they can be easily interrupted (Kleemans & Soudijn, 2017, p. 398).

And three, some of the preventive mechanisms that are central to the situational approach—increasing guardianship and place management in particular—are likely to be less effective for organised crimes. This is because organised criminal activities sometimes also involve licit activities where disruption may be hard to justify legally (von Lampe, 2011, p. 152). Furthermore, given the ability to shape crime opportunities mentioned above, organised criminals may be able to render formal guardianship and management ineffectual using corruption, infiltration, or coercion (Kleemans & Soudijn, 2017, p. 397; Edwards & Levi, 2008, p. 375). Indeed, as Ekblom (2003, p. 255, 260) notes, 'preventers' can become 'promoters' of organised crimes when corruption is involved. Lastly, in territories where organised crime groups exercise extra-legal governance, it is highly unlikely that mechanisms of formal or informal control could be leveraged to counter organised crime (Edwards & Levi, 2008, p. 379-380; Kleemans & Soudijn, 2017, p. 397; von Lampe, 2011, p. 154).

The points discussed above need to be considered carefully when conducting situational analyses of organised crimes, as empirical studies suggest that displacement is indeed likely (e.g. Vijlbrief, 2012). Nonetheless, such displacement has costs that are disruptive to the complex chains of organised crimes. Thus, it is possible that situational interventions could lead to some net-benefits. Furthermore, adaptation is not unique to organised crime problems, as the situational approach generally acknowledges that crime prevention occurs within an 'arms race' (Ekblom, 2002, 2005; Lasky, Fisher, & Jacques, 2017), whereby interventions are faced with 'conscious opponents' (Sparrow, 2008). Thus, Ekblom (2003) recommends thinking through potential adaptations when developing possible intervention strategies. Nonetheless, as opportunity structures change—either as the result of offender adaptation

or social, technological, or regulatory changes—interventions will require constant monitoring and adjustment.

Lastly, extra-legal governance poses a distinct challenge to the situational approach, as this phenomenon tends to be rooted in social and political conditions that are unlikely to be remedied by situational interventions (Edwards & Levi, 2008, p. 380). Yet, the case can be made that even in areas with somewhat homogeneous social, economic and governance conditions, specific empirical manifestations of organised crime activities may exhibit patterns amenable to situational intervention. For example, De Souza and Miller (2012) found that the situational factors that explained the spatial concentration patterns of homicide in Brazilian favelas— irregular urban settlements characterised by extra-legal governance exerted by local gangs—were 'quite conventional, most having close parallels with those from existing literature, suggesting that the backcloth of the favela has much in common with other settings that environmental criminologists have studied' (De Souza & Miller, 2012, p. 801) (such as open-air drug markets, bars, alleys, and areas with poor natural surveillance). Thus, while criminal governance may explain why some areas see more crime than others, the situational characteristics of crimes within such areas may be amenable to intervention.

Thus, while much of this criticism is valid and should inform future situational analyses, it is not fatal to the approach. As Kleemans and Soudijn (2017) conclude, the situational approach 'can be a useful way to think about alternative options for disrupting criminal networks and making the execution of criminal activities more difficult' (p. 402), yet they suggest using the term 'disruption' rather than 'prevention' to manage expectations of efficacy (p. 404).

2.1.2.4   Expanding the knowledge base to inform situational interventions

In addition to the criticism discussed above, I would add that situational studies of organised crimes have thus far been constrained by an incomplete knowledge base. Ekblom (2002) notes that knowledge is vital for designing crime prevention interventions and identifies five types of crime prevention knowledge (Ekblom, 2002, p. 142; see also, Ekblom, 2003, p. 243):

1. *Know-about*: Knowledge about criminal phenomena, their patterns, risk factors, theories, causes and consequences.

2. *Know-what*: Knowledge of what to do to prevent crime problems, at what cost and in which context.
3. *Know-how*: Knowledge of how to implement a crime prevention project, from analysis to evaluation.
4. *Know-who*: Knowledge of potential partners and stakeholders that can become involved in the crime prevention enterprise.
5. *Know-why*: Knowledge of the ethics and symbolic elements of crime and crime prevention.

Thus far, situational studies of organised crimes have been predominantly concerned with developing the *know-what*, identifying potential interventions (e.g. Bullock et al., 2010b), or have discussed the *know-how*, for example by proposing extensions to current analytical models (e.g. Hancock & Laycock, 2010). Given their interest in generating timely crime prevention recommendations, Bullock et al. (2010a, p. 11) suggest that situational studies of organised crime should be 'quick and dirty', using a mix of research strategies and rapid appraisal techniques (see Beebe, 1995). Such an approach, they argue, 'should be able to outline the contours of organised crimes in enough detail to guide preventive approaches and interventions' (Bullock et al., 2010a, p. 11). While there certainly is value in this approach, such studies will invariably be constrained by our incomplete knowledge about the patterns and risk factors of specific organised crime activities.

The literature on organised crime is broad (e.g. Bovenkerk & Levi, 2007; Caneppele & Calderoni, 2014; Fijnaut & Paoli, 2004; Garzón, 2008; Paoli, 2014b; Siegel & Nelen, 2008; Siegel & van de Bunt, 2012; Van Duyne, von Lampe, Jagar, & Newell, 2004; Varese, 2011b; Zaitch & Antonopoulos, 2019), and many insights derived from this corpus provide important clues regarding the *know-about*. Yet, the literature often adopts a macro perspective, rather than the micro approach required for situational analysis. Furthermore, as Kleemans (2014) notes reflecting on the applicability of research to organised crime policy:

> academic research is often too far removed from the reality of criminal investigation, as very little research effort is generally put into the most harmful criminal activities, such as organized crime, corporate crime and terrorism... As a result, academic research into organized crime is vital, but is poorly developed and barely able to answer the questions raised by policymakers and practitioners. (p. 57)

One of the main impediments to organised crime research is the lack of accessible data (Kleemans, 2014, p. 57; Bullock et al., 2010a, p. 10). Where there are good relationships between academics and practitioners, organised crime research often draws on data generated by the criminal justice system in the course of criminal investigations (e.g. Kleemans, 2007). However, as Hobbs and Antonopoulos (2014, p. 97) note, these data sources should be regarded with some scepticism, as they are filtered by the priorities of criminal justice institutions.

Possibly in response to the scarcity of data, the balance of knowledge in organised crime research reveals a disproportionate amount of qualitative studies in contrast with the amount of quantitative studies available (Sansó-Rubert Pascual, 2017, p. 29). This is problematic not because any one method should be considered superior or more valid than the other, but because the prevalence of one to the detriment of the other can hinder our understanding of organised crime phenomena. While qualitative research is better suited to unpack the complexities of the crime scripts of criminal activities, for example, it is less suited to systematically examine the patterns and risk factors associated with specific types of criminal events. Furthermore, the small and non-probabilistic samples typically used in qualitative studies present important challenges to external validity.

According to Hobbs and Antonopoulos (2014), there are four types of quantitative studies of organised crime. First, there are 'counting exercises of government departments, law enforcement agencies, NGOs, and international organizations' (p. 99-100), generally produced with the goal of estimating the scale of specific organised crime phenomena (e.g. UNODC, 2010a), though the methods used to produce them are often vague (Hobbs & Antonopoulos, 2014, p. 100).

Second, there are studies based on victimisation surveys (e.g. Mugellini, 2012; Ohlemacher, 1999; Tilley & Hopkins, 2008; van Dijk, 2007a), which have the advantage of being able to measure phenomena outside the scope criminal justice processes. However, when used to measure the extent of broadly defined organised crime phenomena—as they are commonly used (Sansó-Rubert Pascual, 2017)—the instruments tend to capture the perception of organised crime phenomena, rather than specific empirical manifestations.

Third, there are quantitative analyses of the economics of criminal markets and their consequences (e.g. Anthony et al., 2008; Killias et al., 2011; Kilmer et al., 2010). While these studies can offer interesting insights into organised crimes—though generally limited to enterprise and market-based manifestations—they are hampered by

the inherent difficulty of measuring hidden markets (Hobbs & Antonopoulos, 2014, p. 101).

Fourth, there are studies that attempt to construct indices seeking to capture the extent and power of organised crime groups in given territories (Calderoni, 2011; van Dijk, 2007b). These measures are usually constructed using a combination of official crime statistics (e.g. unsolved homicides, criminal investigations) and the perception of extra-legal governance, usually derived from surveys (Hobbs & Antonopoulos, 2014, p. 101). The limitations of such indices are that they reproduce the biases of the data used to create them (Hobbs & Antonopoulos, 2014, p. 101-102), and that it is not always clear what the measurements produced mean in practice.

As is common with the majority of the literature on organised crime, the studies presented above tend to be concerned with measuring and understanding organised crime from a macro perspective (though Tilley & Hopkins, 2008, is a notable exception). However, there is also an emerging literature of quantitative studies focused on understanding organised crime phenomena at the micro level, mainly from a situational approach. For example, Cockbain and Bowers (2019) used multinomial logistic regression to explore key differences between types of human trafficking (i.e. for sexual exploitation, forced labour or domestic servitude) using individual-level data. Additionally, studies have examined the spatiotemporal concentration patterns of specific organised crime phenomena, such as kidnapping for ransom (Pires et al., 2014; Stubbert et al., 2015), the overlaps between crime hotspots and criminal networks (Stovin & Davies, 2008), the geographic patterns of illegal drug markets (Bernasco & Jacques, 2015; Eck, 1995; Rengert, Chakravorty, Bole, & Henderson, 2000), and homicides related to organised crime (De Souza & Miller, 2012; Dugato, Calderoni, & Berlusconi, 2017).

The phenomenon of crime concentration—an almost universal finding in crime research (for a review, see Johnson, 2010)—is of central importance to the situational approach (Clarke, 2009, p. 263-264). On the one hand, by focusing on the specific places (e.g. Sherman, Gartin, & Buerger, 1989), facilities (e.g. Eck, Clarke, & Guerette, 2007), and victims (e.g. Farrell et al., 1995) that concentrate most crime incidents, crime prevention measures can have disproportionate effects on total crime counts. Additionally, studying concentration patterns can reveal the risk factors and opportunity structures driving such concentrations (i.e. the distribution of certain crime incidents may be determined by the distribution of specific opportunities).

Thus far, very few studies have analysed the concentration of crime incidents on victims—a phenomenon know as repeat victimisation—in the context of organised

crimes (for exceptions see Section 2.3). It is to this phenomenon we turn our attention next.

2.2   Repeat victimisation

One of the most consistent findings in crime research is that crime incidents are unequally distributed among potential places (Lee et al., 2017) and victims (SooHyun et al., 2017). In fact, the patterns observed have been so consistent that Weisburd (2015) has recently coined the term 'the law of crime concentration'. The concentration on specific targets is termed 'repeat victimisation' (for reviews, see Farrell & Pease, 1993; Farrell, Tseloni, & Pease, 2005; Pease, 1998; SooHyun et al., 2017; Tseloni & Pease, 2005). Repeat victimisation is observed when a person, household, business, object, or other target however defined suffers the same offence two or more times in a given time period (Grove & Farrell, 2010; Pease, 1998). In the aggregate, repeat victimisation produces highly skewed distributions of criminal incidents, with a small proportion of targets burdened with disproportionate amounts of total incidents. On a national level, it is estimated that around 40% of all crimes are repeat incidents, with variations by crime type and country (Farrell, Tseloni, & Pease, 2005, p. 7; Farrell & Pease, 2011).

2.2.1   Background on repeat victimisation research

Repeat victimisation was first identified around the 1970s, with the advent of victimisation surveys in the United States—though they are now common in many countries, conducted cross-nationally, and sometimes address specific sectors (Hough, Maxfield, Morris, & Simmons, 2007; Mugellini, 2013b; van Dijk, 2007a). Victimisation surveys were instituted around the 1960s to estimate the extent of crime in the United States, overcoming the fact that many crimes were not reported to (or recorded by) the police (Gottfredson, 1986; Sparks, 1981b; Wetzels, Ohlemacher, Pfeiffer, & Strobl, 1994). In addition to measuring the extent of victimisation, surveys capture a wealth of information regarding victim characteristics, which were used to work out why victimisation risks vary (Hindelang, Gottfredson, & Garofalo, 1978).

Most early attention focused on the prevalence of victimisation (the number of victims) (Hope & Norris, 2012, p. 546). However, a few scholars did note that incidence (the number of crime incidents) was higher than prevalence, which suggested that some victims suffered more than one crime during a given time period (Hinde-

lang et al., 1978; Sparks, Genn, & Dodd, 1977). Crucially, Hindelang et al. (1978) and Sparks et al. (1977) both found that the number of repeat victims was higher than what would be expected on the basis of chance (as estimated by a Poisson[4] process) (Hindelang et al., 1978, p. 125-149; Sparks et al., 1977, p. 88-106; see also Sparks, 1981a). This suggested that the concentration of incidents on repeat victims was not a product of 'bad luck', but that it was probably determined by an underlying process affecting crime risk (Farrell, 1992, p. 88).

Further interest in repeat victimisation was scant until Pease and colleagues (e.g. Farrell, 1992; Farrell & Pease, 1993; Forrester, Chatterton, & Pease, 1988) approached the phenomenon from a crime prevention perspective. Studying burglary in a social housing estate, Forrester et al. (1988; see also Forrester, Frenz, O'Connell, & Pease, 1990) found that past victimisations were a good predictor of future victimisation risk, and that repeat incidents against the same target tended to occur in bursts. With these insights, crime prevention resources were directed to burglary victims soon after an incident occurred, with an estimated reduction in residential burglaries of around 70% in the area where the project was implemented (Forrester et al., 1988, 1990).

Since then, repeat victimisation has become a mainstay of environmental criminology in two ways. First, the prevention of repeat victimisation provides a rational means of allocating scarce crime prevention resources on the basis of risk (Farrell, 1995; Farrell & Pease, 1993; Pease, 1998). The extent and concentration of repeat victimisation implies that focused efforts aimed at curtailing repetition can have disproportionate effects in overall crime levels (Farrell, 1995). Thus, repeat victimisation is a common focus of (often situational) crime prevention interventions, most with positive results (for a systematic review, see Grove et al., 2012). Second, the study of repeat victimisation from an analytical standpoint has proved decisive. On the one hand it has become a routine tool to understand crime patterns for practical crime analysts (Clarke & Eck, 2005; Santos, 2013), while on the other it has expanded our theoretical understanding of the dynamics of crime concentration at the micro level, with implications for spatiotemporal analysis and crime forecasting.

2.2.1.1   Causes of repeat victimisation

Non-random incidents can be thought as the result of two mechanisms. In the first instance, the likelihood of occurrence depends on exogenous factors that may not

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[4]Events generated by a Poisson process are *random* and *independent* insofar as they occur at a constant rate not affected by past events (Sparks, 1981a).

be uniformly distributed in time and space; for example, poor road conditions on certain streets that increase the likelihood of a road accident on those streets. In the second instance, the occurrence of one incident affects the likelihood of subsequent incidents at a certain time and distance from the initial event; for example, a road accident in one street may disrupt traffic and cause another accident nearby soon after the first incident. Furthermore, both mechanisms can act in concert, with the first incident being the product of an exogenous factor and a second incident being the product of the first.

In the case of repeat victimisation, the first mechanism, 'risk heterogeneity'—also referred to as 'population heterogeneity' (Lauritsen & Davis Quinet, 1995; Nelson, 1980; Osborn & Tseloni, 1998; Wittebrood & Nieuwbeerta, 2000)—considers that the baseline risk of victimisation is not equal for all potential targets because specific characteristics make one more suitable than another (Johnson, 2008; Pease, 1998). Thus, such enduring differences act as *flags* that attract different offenders. Evidence supporting the risk heterogeneity mechanism includes the fact that particular types of homes (e.g. Bowers et al., 2005; Tseloni et al., 2004), in particular types of areas (e.g. Trickett, Osborn, Seymour, & Pease, 1992) are more vulnerable than others to victimisation. Similarly, studies analysing crimes against individuals have found that individual and contextual characteristics are associated with differing risks of victimisation (Lauritsen, 2010; Lauritsen & Rezey, 2018; Miethe & McDowall, 1993; Miethe & Meier, 1990).

The second mechanism, 'event dependence'—also known as 'state dependence' (Lauritsen & Davis Quinet, 1995; Osborn & Tseloni, 1998)—alternatively suggests that the risk of victimisation is dynamic, with previous victimisations increasing—at least temporarily (Johnson et al., 1997)—the likelihood of experiencing a repeated incident (Pease, 1998; Sagovsky & Johnson, 2007). Thus, a first event acts as a *boost* for the second. A fitting explanation for event dependence draws from the fact that offenders return to victimise past targets (Bernasco, 2008), as the choice of future targets appears to be influenced by previous experience (Bernasco, 2008; Johnson, 2014; Johnson, Summers, & Pease, 2009).

Evidence supporting event dependence comes from longitudinal studies that have found that victimisations suffered in previous periods increase the risk of suffering crimes in the future, even after controlling for stable risk factors (e.g. Lauritsen & Davis Quinet, 1995; Lynch et al., 1998; Tseloni & Pease, 2003, 2004). Further evidence for event dependence is found in the temporal and spatial patterns of repeat and near-repeat victimisation (see Morgan, 2001), which show temporary increases

in risk to victimised targets and those in their vicinity shortly after an offence has taken place (Johnson & Bowers, 2004; Johnson et al., 1997; Johnson, Summers, & Pease, 2009)—a pattern usually attributed to offenders foraging the area around a victim after committing an offence (Johnson, Summers, & Pease, 2009).

Whether one of the two mechanisms is more important than the other for repeat victimisation remains a source of ongoing academic discussion (e.g. Farrell et al., 1995; Hope, 2015; Johnson, 2008; Kleemans, 2001; Tseloni & Pease, 2003)—though empirical and experimental research suggests that both have a part to play (Johnson, 2008; Pease, 1998; Pitcher & Johnson, 2011). However, it is important to note that the actual contribution from each mechanism will likely vary considerably across crime types (Johnson, 2008). Particularly relevant to extortion, Farrell et al. (1995) note that the boost effect may be more relevant when the effort and likely risk of a subsequent offence is clarified by victim response to a first offence (e.g. complying or not with an extortion demand may entice a repeated event), and when the crime implies higher degrees of co-offending, as in organised crimes.

2.2.1.2 Theoretical linkages

Both mechanisms of repeat victimisation are underpinned by environmental criminology (Bouloukos & Farrell, 1997; Farrell & Pease, 2014; Wartell & Gallagher, 2012). The rational choice perspective explains why certain target characteristics—and those of its surroundings—make some targets appear differentially attractive or vulnerable to a wide range of offenders. These characteristics are choice-structuring properties that speak to the effort, risk, rewards, excuses and provocations that offenders consider when engaging in a crime (Clarke & Cornish, 2017; Cornish & Clarke, 1987). Furthermore, rational choice can also explain event dependence. The notion that offenders learn from their past experiences is one of the cornerstones of the rational choice perspective (Cornish & Clarke, 1985). Thus, returning to victimise a target a second or more times, could be interpreted as the result of a rational calculation influenced by knowledge gleaned during the first incident.

On the other hand, while the rational choice perspective explains how different properties can influence target selection, the routine activity approach and crime pattern theory provide explanations for the heterogeneous distribution of risk (Grove & Farrell, 2010; Maxfield, 1987b). As stated earlier, routine activities and urban structure shape the convergence of offenders and targets, creating opportunities for crime. As these coalesce into somewhat stable patterns, a heterogeneous victimisation risk surface is created, with higher likelihoods where and when opportunities are con-

centrated, and lower likelihoods where and when they are scarce. Moreover, routine activities and crime pattern theory also influence boost mechanisms—particularly in the case of near-repeats—as they explain how the spatiotemporal behaviour of offenders is constrained by the socio-urban backcloth.

2.2.2   Criticisms of the repeat victimisation approach

The existence of the empirical phenomenon of repeat victimisation is undisputed. Repeat victimisation is a feature of crime distributions in all contexts where they have been studied, with variations in extent and range according to the specific crime type, location and unit of study.

However, there are some criticisms of the implications drawn from it. Regarding repeat victimisation as a focus of crime prevention, a common critique is that focusing on the characteristics of victims that apparently increase their risk of victimisation amounts to blaming the victim (Farrell & Pease, 1993, p. 24). Indeed, accusations of victim blaming are also commonly levelled against situational crime prevention, for shifting some of the responsibility for crime prevention to victims (Clarke, 2009), as well as against the routine activity approach and lifestyle/exposure theory[5] (Belknap, 1987, p. 338), for highlighting that victims' routines and lifestyle choices can be portrayed as risky. Perhaps the accusation is nowhere more problematic as when it addresses the risk of rape, though Belknap (1987) suggests that victim blaming 'has frequently occurred in rape research regardless of the theoretical approach' (p. 338).

Choosing a specific crime prevention intervention needs to balance its costs (social as well as financial) with its potential benefits (crimes and consequent harms prevented) (Clarke, 2009; Farrell & Pease, 1993). Sometimes, this calculation suggests that the 'best' intervention involves modifying target characteristics or behaviour. However, this should not be interpreted as an indication of blame. 'Fundamentally,

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[5]The lifestyle/exposure theory (Hindelang et al., 1978) suggests that the likelihood of personal victimisation is affected by daily routines which expose some individuals to offenders more often than others, thus concluding that some lifestyle choices are inherently riskier than others. As both perspectives focus on the influence of daily routines on crime risk—and hence on repeat victimisation—lifestyle theory and the routine activity approach are sometimes taken as one (e.g. Maxfield, 1987b). However, two distinctions are noteworthy. First, the routine activity approach emphasises the criminogenic effects of community structure on daily life, 'in contrast, lifestyle theory gives more attention to personal lifestyle choices in leisure life' (Allen Kringen & Felson, 2014, p. 4546). And second, while both theories were originally proposed to explain personal crimes, the routine activity approach has been extended to many other types of criminal activities (Allen Kringen & Felson, 2014). Thus, as the focus of this research is on a specific class of crimes against businesses—which by definition do not have lifestyle choices—lifestyle/exposure theory is given less attention here.

the blame for crime lies with the perpetrator, not the victim' (Farrell & Pease, 1993, p. 24). Nonetheless, this should not obscure the fact that the concentration of crime on repeat victims is an empirical, observable phenomenon, and that this concentration is sometimes the product of target characteristics and behaviours.

A second critique is that by highlighting crime risks at the micro-level, repeat victimisation diverts prevention resources away from the 'root causes' of crime. Repeat victimisation says nothing about how individuals acquire the motivation to commit crimes, nor does it address social and community factors that promote 'criminality'. More specifically, Hope (2015) notes that an explanation for repeat victimisation based on boost and flag mechanisms neglects the converse of concentration, the fact that the vast majority of targets are not victimised. The implication is that an alternative strategy would be to focus on improving the conditions that promote 'immunity' at the community level, rather than on focusing on those that reduce individual exposure to risk (Hope, 2015, p. 43; Hope, 2001), though it is not clear how such an approach would work in practice.

Practical experience provides an important counterargument. After conducting a systematic review of initiatives to prevent repeat victimisation, Grove et al. (2012) conclude that overall reductions in crime can be achieved by preventing repeats (p. 7). Furthermore, their analysis shows that, based on the evaluations they studied, appropriately tailored and properly implemented interventions based on situational crime prevention appear to be the most effective way to prevent repeat victimisation (Grove et al., 2012, p. 32-37).

This does not mean that interventions delivered at the community level, or through community support organisations are not effective means of preventing crime. Repeat victimisation analyses can identify many target characteristics that indicate higher victimisation risk. These characteristics may refer to particular properties of the targets themselves, or of their environment. Thus they can indicate whether area-level factors are associated with higher victimisation risks. If these area-level factors can be easily manipulated, there is no reason to exclude them from the pool of potential crime prevention interventions.

However, more often than not, assuming that area-level factors are evenly distributed and affect all targets within an area with the same intensity incurs in an ecological fallacy (Upton & Cook, 2014a). In addition, the spatiotemporal analysis of repeat victimisation at the micro-level of individual targets has shown that most crimes within high crime areas ('hotspots') are concentrated on specific repeatedly victimised targets ('supertargets', Farrell, Clark, et al., 2005; 'hot dots', Townsley,

Homel, & Chaseling, 2000), thus focusing on those targets can disproportionally reduce crime in the entire area and community.

Lastly, as stated earlier, the precise mechanisms that generate the highly concentrated distributions associated with repeat victimisation are still a source of discussion (e.g. Farrell et al., 1995; Hope, 2015; Johnson, 2008; Kleemans, 2001; Tseloni & Pease, 2003). Hope (2015) in particular argues that boosts and flags are mutually exclusive from a statistical standpoint (p. 34). While this point remains open for further study, the spatiotemporal signature of repeat victimisation supports the interpretation of a simultaneous effect of both mechanisms (Johnson, 2008). Furthermore, a pragmatic consideration is that they help guide crime prevention practice: flag accounts suggest where crime prevention interventions ought to focus, and boost accounts suggest when they should be deployed.

2.2.3   Current (and future) repeat victimisation research

Repeat victimisation has had a profound impact on crime and victimisation research. First, it has informed the development of victimisation surveys. Many victimisation surveys restrict the total number of incidents that respondents can report (e.g. originally, respondents of the British Crime Survey, BCS, could only report five incidents of each crime type). This practice means that estimated totals reported by capped surveys grossly undercount the true magnitude of the crime problem (Farrell & Pease, 2007). Practitioners argue that capping reduces costs, is less taxing on respondents, and 'provides more consistent comparisons and trend measures that are less impacted by relatively rare extreme outliers' (UNODC/UNECE, 2010, p. 51-52). Not capping victimisations, they argue, runs the risk of overcounting, as repeat victims may not recall the precise number of crimes they suffered (UNODC/UNECE, 2010, p. 52). While recall biases do exist, Farrell and Pease (2007) retort that

> It is truly bizarre that the victimisation survey, based as it is on the assumption that people will by and large tell the truth about what happened within the limits of their memory, suddenly withdraws its credulity when victim testimony becomes inconvenient. (p. 42)

Critiques presented by scholars concerned with repeat victimisation have contributed to 'relaxing' capping practices in some victim surveys (Farrell & Pease, 2014, p. 4377; Lauritsen, Owens, Planty, Rand, & Truman, 2012). Nonetheless, the issues surrounding the measurement of multiple and repeat victimisation, and

their impact on survey estimates, are far from settled, and have spurred a growing literature (UNODC/UNECE, 2010, p. 52).

Second, the repeat victimisation approach has also been applied to reported crime data, which overcomes the spatial limitations of crime surveys—i.e. surveys do not usually capture precise location information (e.g. geographical coordinates) about crime incidents. This has transformed our understanding of the spatiotemporal patterns of crime. For instance, Johnson et al. (1997, p. 231) noted that repeat burglary victims were more common in hotspots than in other parts of Merseyside, UK, and speculated that repeat victimisation could be one of the main drivers of hotspot formation, Furthermore, they found that repeat victimisation followed a time course, with risks of repeated incidents decaying exponentially after a first event (see also Sagovsky & Johnson, 2007). This finding, coupled with the phenomenon of near-repeat victimisation first identified by Morgan (2001), placed repeat victimisation at the centre of the spatiotemporal analysis of crime and of efforts to develop prospecting mapping techniques (Bowers, Johnson, & Pease, 2004; Johnson & Bowers, 2004; Johnson, Bowers, Birks, & Pease, 2009).

To date, repeat victimisation studies have focused on crimes such as residential burglary (e.g. Johnson et al., 1997; Kleemans, 2001; Morgan, 2001; Tseloni et al., 2004), property crimes (e.g. Osborn & Tseloni, 1998; Tseloni et al., 2002), personal crimes (e.g. Tseloni & Pease, 2003, 2004) crimes against youth (e.g. Lauritsen & Davis Quinet, 1995), intimate partner violence (e.g. Rand & Saltzman, 2003), and sexual assault (e.g. Daigle et al., 2008; Young & Furman, 2007). Moreover, most studies have been conducted using data from English-speaking and European countries (e.g. Farrell, Tseloni, & Pease, 2005; Lynch et al., 1998; Perreault et al., 2010; Sagovsky & Johnson, 2007; Townsley et al., 2000; Tseloni et al., 2004). Few have examined crimes against businesses (for exceptions, see Bowers et al., 1998; Burrows & Hopkins, 2005; Dugato, 2014; Gill, 1998; Hopkins & Tilley, 2001; Salmi et al., 2013; van Dijk & Terlouw, 1996), and only a small number of recent studies have examined patterns in radically different contexts such as Malawi (Sidebottom, 2012), Taiwan (Kuo et al., 2012) and South Korea (Park, 2015), though findings in these studies have been largely consistent with the repeat victimisation expectation. To date, there is no research that I know of that thoroughly analyses repeat victimisation in Mexico.

Similarly, studies from the repeat victimisation literature have not generally been concerned with organised crimes. This could be explained by three reasons. First, the resurgence of interest in repeat victimisation in the 1990s was driven by its impli-

cations for crime prevention, thus the crimes selected for study have mostly reflected the policy priorities of local law enforcement (Farrell et al., 2000; Laycock, 2001)—which at the time did not include organised crimes. Second, many organised crimes defy the repeat victimisation assumptions of being discrete incidents against distinct targets that can be probed using victimisation surveys (van Dijk, 2007a, 2007b). Third, even in the case of discrete organised crime incidents with distinct targets, repeat victimisation analysis is further hampered by data availability: volume crimes (those of most concern to law enforcement) are far more common (or at least more commonly reported) than organised crimes—especially in the English-speaking and European countries where repeat victimisation research has taken hold.

As the past decades have seen a substantial crime drop in 'traditional' (i.e. non-organised) crimes across many regions in the globe (e.g. Farrell, Tilley, & Tseloni, 2014; Farrell et al., 2011; Hopkins, 2016; Sidebottom, Kuo, Mori, Li, & Farrell, 2018; Tilley et al., 2015; van Dijk, Tseloni, & Farrell, 2012), crime prevention policy priorities have extended to organised crimes (e.g. Council, 2000; HM Government, 2014, 2018; UNODC, 2004). Furthermore, some predatory organised crime activities by definition do target victims—such as kidnapping, human trafficking and extortion—thus should be appropriate for victimisation research. However, incidents of this kind are often not reported to the police and are not generally captured by victimisation surveys.[6]

2.3   Repeat victimisation and organised crimes: Extortion

Only a small number of studies have examined victimisation patterns of organised crimes at the micro level. Tilley and Hopkins (2008) report the results of a pilot survey conducted to estimate the extent of business victimisation by organised crime in high crime residential neighbourhoods in English cities. The study revealed a high level of repeat victimisation among surveyed businesses, yet most incidents were judged by respondents to be unrelated to organised crime (Tilley & Hopkins, 2008, p. 449-450, p. 456). Furthermore, while the study discussed the 'crime chemistry' (Felson, 2002) of the surveyed areas to explain varying victimisation rates, the victimisation patterns were not subjected to in-depth statistical analysis.

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[6]The Mexican household victimisation survey is an exception, as it measures the extent of kidnapping (INEGI, 2014f). However, the survey reports that kidnapping incidents are relatively rare, limiting the statistical validity of analyses of its distribution and repeat victimisation patterns.

Pires et al. (2014; see also, Stubbert et al., 2015) analysed kidnapping incidents in Colombia to determine whether events were spatially and temporally concentrated. Furthermore, they also conducted a descriptive analysis to determine if victim characteristics (i.e. age, gender and profession) were associated with different victimisation risks. However, due to data limitations, they were only able to examine concentration patterns at the municipality (i.e. county) and department (i.e. state) level, thus repeat victimisation was not analysed.

There have been two studies specifically concerned with extortion victimisation. Ohlemacher (1999) surveyed German restaurants to compare the reported prevalence of extortion among the sample with the *perceived* extortion rate. However, the study did not examine repeat extortion patterns. Similarly, Chin, Fagan, and Kelly (1992) conducted a survey among Chinese-owned businesses in Chinese neighbourhoods in New York City to determine the extent of extortion victimisation by Chinese gangs. That study found that extortion victimisation was prevalent, as 69% of those surveyed had been approached by Chinese gang members (Chin et al., 1992, p. 637). Furthermore, while there were some differences in victimisation risk according to business and owner characteristics, the study did not employ robust statistical analysis techniques, possibly due to a relatively small sample size. In any case, while Chin et al. (1992) did note that businesses suffered extortion several times during the year, the study did not assess the extent of repeat victimisation in depth (see Kelly, Chin, & Fagan, 2000, for another study using the same data).

Thus, while the studies discussed above represent progress, to my knowledge no study has conducted a systematic and in-depth analysis of repeat victimisation patterns of organised crimes, examining whether the mechanisms of risk heterogeneity and event dependence contribute to such patterns. Extortion against businesses presents a good opportunity to analyse repeat victimisation patterns in the context of organised crime, as it is routinely captured by national and international commercial victimisation surveys (Mugellini, 2013c; van Dijk, 2008).

However, studying extortion from the perspective of repeat victimisation requires conceiving of the crime as a discrete incident—with a clear beginning and end—directed towards a specific target. A review of the literature suggests that extortion can refer to two criminal phenomena. On the one hand, extortion can refer to a phenomenon of extra-legal governance by organised crime groups, whereas on the other it can refer to specific victimisation incidents.

2.3.1   Extortion as extra-legal governance

The association between extortion and organised crime is so embedded that the term is often used as a defining feature of organised crime (TRANSCRIME, 2009, p. 21; Konrad & Skaperdas, 1998, p. 462; Frazzica, La Spina, & Scaglione, 2013, p. 99). However, extortion is 'an umbrella concept grouping a large array of criminal practices' (Anzola, Neumann, Möhring, & Troitzsch, 2016, p. 9).

In its extra-legal governance dimension, extortion is often used in conjunction, and interchangeably, with the concept of 'racketeering' (Frazzica et al., 2013; La Spina, Frazzica, Punzo, & Scaglione, 2014; Savona & Sarno, 2014; Savona & Zanella, 2010). The term racketeering—itself often considered to be synonymous with organised crime (Savona & Sarno, 2014, p. 4264)—was initially used to refer to the criminal influence of organised crime groups in legitimate businesses and labour unions, not necessarily through predatory relationships, but through collusion and conspiracy (von Lampe, 2016, p. 250).

In this sense, racketeering referred to two phenomena: labour racketeering and business racketeering. The first refers to 'the creation or infiltration of labor unions by criminals for criminal purposes' (von Lampe, 2016, p. 250). These purposes can vary from siphoning funds to the criminal organisation, to using the threat of strikes and industrial actions to negotiate contracts that benefit its (criminal) leaders, rather than the union's (legitimate) members. Through labour racketeering, organised criminals can exert power over industries, as well as individuals—e.g. by deciding who gets hired. Business racketeering refers to the 'creation of cartels in legal markets' (von Lampe, 2016, p. 252), i.e. the organisation of market participants in a way that stifles competition and creates de-facto monopolies for the members of the cartel. Reuter (1987) noted that business racketeering is often inherent in the structural characteristics of certain industries—e.g. a captive market with inelastic demand and little product differentiation (Varese, 2014, p. 345).

Today, however, extortion racketeering is more often understood as an institutionalised practice whereby criminal groups charge a fee in exchange for 'protection' (Elsenbroich & Badham, 2016; Volkov, 2002).

Schelling (1971) was amongst the first to suggest that the main business of organised crime groups was to establish 'rackets' to extort both illegal and legal businesses—noting that illegal businesses were more likely to be extorted due to their inability to have recourse to law enforcement protection. Gambetta (1988; see also Gambetta, 1993), on the other hand, suggested that extortion needed to be distinguished from 'protection', which is provided by organised crime groups in the

absence of state enforcement. Thus, according to Gambetta (1988), organised crime groups emerge as entrepreneurs in the market for private protection. Such protection is primarily bought by the underworld—where the state cannot by definition provide it—bringing stability to fragile markets, mechanisms for dispute resolution, and contract enforcement, through force if needed. In addition, when the state cannot or will not guarantee protection in the legitimate economy—such as in post-Soviet Russia (Varese, 2001)—the market for protection extends to the upperworld.

In contrast, Paoli's (2002) critique suggests that the distinction between protection and extortion is fallacious, with criminal groups offering 'protection' mostly from themselves. In this sense, criminal groups engaged in extortion more closely resemble 'alternative governments' (Kleemans, 2018) than firms, for their use of coercion to 'tax' businesses and extract resources (Paoli, 2002; see also Skaperdas, 2001).

Regardless of the aetiology of extortion racketeering, conceiving of the phenomenon as a form of extra-legal governance does not initially appear to lend itself to the analysis of crime concentration—and thus of repeat victimisation. As Kleemans (2018, p. 873-875) notes, the conception of extortion racketeering is distinct from that of street-level crime, as 'place' goes beyond the 'specific point in space where an offender meets a target' (p. 874). In this view, the unit of analysis of extortion racketeering is observed at the higher level of 'territory', representing regions, business sectors, villages or neighbourhoods controlled by organised crime groups (Kleemans, 2018, p. 874).

Yet, understanding extortion racketeering as 'territorial control' poses significant challenges to empirical studies, as the phenomenon cannot be directly observed. Instead, it is constructed from individual extortion victimisation incidents. As Volkov (2002) notes, the task has been 'to trace how separate episodes of extortion are transformed into a durable institutionalized, businesslike relationship' (p. 29). Such operationalisation is evident throughout the literature.

For example, Elsenbroich and Badham (2016) define extortion racketeering as the 'regular and systematic extortion of several victims by a criminal or (more usually) a criminal organisation' (par. 1.1). Similarly, Savona and Zanella (2010) note that 'when extortion is committed on a regular basis, it turns into racketeering' (p. 261; see also Savona & Sarno, 2014; TRANSCRIME, 2009), and then go on to classify distinct types of extortion racketeering ('casual' vs 'systemic') based on the frequency of extortion victimisation (Savona & Zanella, 2010). This operationalisation is consistent with the literature's concern with macro-level organised crime phenomena,

as the interest is in identifying what the individual incidents of extortion can tell us regarding the power structures of organised crime groups.

In contrast, from a situational approach, the main interest lies in the micro-level characteristics of the 'separate episodes of extortion', rather than the 'durable institutionalised, businesslike relationship'. Approaching extortion from this perspective does not deny that separate extortion incidents may reflect the existence of an institutionalised practice of extortion racketeering. However, it is argued that focusing on the overarching phenomenon neglects the fact that its constituent components—the extortion incidents themselves—may offer crucial insights that may be lost or obscured by aggregation.

2.3.2   Extortion as (repeat) victimisation

According to the *Oxford Dictionary of English*, an extortion incident involves 'obtaining something, especially money, through force or threats' (extortion, 2010). In this sense, the term can be used to refer to a wide range of situations, from the criminal (i.e. where the particular interaction is prohibited by criminal law, e.g. blackmail, hijacking, kidnapping), to the non-criminal, (i.e. when one of the parties perceives the result of an interaction as unfair, e.g. an 'extortionate' price). Often, the term is used to refer to the unlawful abuse of power by a government official for personal gain.[7]

In this research, I am concerned with criminal extortion by non-government actors and, thus will henceforth refer to extortion by government actors as 'corruption', and reserve 'extortion' for the former. As mentioned in the previous section, extortion is often equated with organised crime, though incidents of criminal extortion can be committed by individuals not necessarily associated with criminal groups.

The Mexican commercial victimisation survey, the main data source used in this research, considers an extortion victimisation to be 'any kind of threat or coercion committed against the local unit's owner or staff for the purpose of obtaining money, goods or forcing them to do or stop doing something' (Jaimes Bello & Vielma Orozco, 2013, p. 172). This definition is similar to that adopted by Chin et al. (1992) in a victimisation survey applied to businesses in New York 'Chinatowns', insofar as it treats 'demanding money or the provision of goods and services to avoid violence or harassment' as the working definition of extortion (p. 629).

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[7]Extortion is described by the *Encyclopædia Britannica* as 'the complement of bribery' (extortion, 2017).

Previous research suggests that repeated extortion attempts against the same business are common. For example, La Spina et al. (2014) comment that periodic extortion of businesses by mafia-type organisations is more common than episodic one-off victimisations in Italy. Similarly, Chin et al. (1992) and Kelly et al. (2000) note that the extortion of businesses by Chinese gangs also involves repeated incidents, with most victims suffering 3 or 4 incidents per year (Kelly et al., 2000, p. 64). Drawing from commercial victimisation survey data, Perrone (2000) finds that 45% of victims of extortion in Australia suffered repeat extortion incidents, while Mugellini (2012) find that the figure is 62% amongst extorted Italian businesses. Lastly, Broadhurst, Bouhours, Bacon-Shone, and Bouhours (2011) found that businesses that suffered extortion victimisation in China experienced an average concentration of around 2.5 incidents per business.

Nonetheless, these studies did not focus specifically on repeat victimisation. Hence, they did not analyse whether the distribution of extortion was significantly different to that expected on a chance basis, nor systematically explore factors that could explain repeat extortion at the micro-level of individual businesses.

If repeat patterns are found, research suggests that they can be produced by two mechanisms—risk heterogeneity and event dependence (see Section 2.2.1.1). It is unclear how these mechanisms contribute to repeat victimisation in the context of extortion.

Regarding risk heterogeneity, for example, Kleemans (2018, p. 874) notes that territorial control by organised crime groups is not evenly spread, thus businesses located in areas controlled by crime groups could face higher risk than businesses located in other areas. Furthermore, Savona and Sarno (2014) and La Spina et al. (2014) note that even in areas with active rackets, victim selection is not random, and instead is guided by victim vulnerability (see also Savona, 2012, p. 8), thus it is likely that business characteristics, and those of their immediate surroundings, could also be relevant predictors of extortion risk.

However, regarding event dependence, Farrell et al. (1995, p. 396) note that the risk of future events is likely to be affected by victim response to a previous event (see Section 2.2.1.1). Thus, in the case of extortion it could be possible that complying with extortion demands may increase the risk of suffering repeats. This suggests that to understand the potential role of event dependence, it may be important to understand what are the determinants of extortion compliance.

Lastly, several studies (e.g. Broadhurst et al., 2011; Chin et al., 1992; Kelly et al., 2000; Pérez Morales, Vélez Salas, Rivas Rodríguez, & Vélez Salas, 2015) suggest

that extortion incidents can take several forms. In Mexico, for example, the literature distinguishes between remote or telephone-based extortion from in-person extortion incidents. As such forms of extortion involve different modus operandi, they are likely to depend on distinct opportunity structures. Thus, they may potentially exhibit different repeat victimisation patterns.

2.4   Research questions

Based on the literature review presented above, this thesis will attempt to answer the following research questions:

1. Does extortion victimisation exhibit repeat victimisation patterns beyond what would be expected by chance?
2. What mechanisms could explain repeat extortion victimisation?
3. What are the determinants of compliance with extortion demands?
4. Do victimisation patterns and mechanisms vary according to the type of extortion suffered?

Chapter 3

Mexico: Context and organised crime violence

In the early afternoon on August 25, 2011, close to a dozen gunmen charged violently into a casino in the northern Mexican city of Monterrey, poured petrol on the floor and set the building ablaze. The attack on the *Casino Royale*—as the business was called—killed 52 people, making it one of the deadliest criminal incidents in Mexico's recent history (Corcoran, 2012). Over the next days, as the country remained in deep mourning (see Figure 3.1), it emerged that the attack had been a punishment after the casino refused to pay extortion demands made by the *Zetas* (Wilkinson, 2011), a notoriously ruthless organised crime group.

The attack on the Casino Royale was unprecedented in its level of violence. Nonetheless, extortion in Mexico has been linked to many other prominent cases of violence and national instability. For example, Guerrero-Gutiérrez (2011) reported that during the first two months of 2011 there were 119 arson attacks linked to extortion attempts in the infamous Ciudad Juárez,[1] whereas widespread extortion of farmers in the state of Michoacán in 2012 and 2013 led to exorbitant country-wide increases in the prices of avocados and limes (Selmo, 2013) and to a destabilising uprising of *autodefensas*—self-defence paramilitary groups—in many rural areas of the country (Shirk, Wood, & Olson, 2014, p. 10).

Based on such episodes, it is commonly said that extortion in Mexico is a 'booming industry' (Malkin, 2011), with gangs dominating large swathes of territory and subjecting businesses to a 'feudal regime' (Perez, 2018). Yet, the widespread preva-

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[1] A city on the Mexico-U.S. border, across from El Paso, Texas. In 2010, Ciudad Juárez was the most violent city in the world (Redacción El Universal, 2010), with a murder rate of 216 per 100,000 inhabitants (Rios, 2012).

Figure 3.1: Then-president of Mexico, Felipe Calderón, leads a national mourning ceremony in front of the remains of the Casino Royale. He is accompanied by the first lady, Margarita Zavala, state governor, Rodrigo Medina, Monterrey mayor, Fernando Larrazábal, the heads of the armed forces, and the ministers for public security and interior. Photo by Alfredo Guerrero/Gobierno Federal CC-BY-NC-SA 2.0 August 26, 2011

lence of extortion is a relatively new phenomenon. As Figure 3.2 shows, the incidence of extortion in the country has rocketed in the past two decades, increasing 10-fold since Jan-1997 (when modern record-keeping began). These figures do not account for underreporting. Thus, it is almost certain that they are gross underestimates. Nonetheless, Figure 3.2 also shows that public concern with extortion—using Google search queries as a proxy—has followed a very similar trend: several months between 2004 and mid-2005 experienced zero queries on extortion in Mexico, whereas from late 2005 onwards interest steadily climbed, closely resembling the trend in extortion incidence.

The surge in the extortion phenomenon coincides with a dramatic increase of violence related to organised crime that began around 2006. While 'organised crime' has been active in Mexico for more than a century, its main activities were in drug-trafficking and has neither traditionally been violent nor engaged in extortion (Astorga, 2005; Valdés Castellanos, 2013). Thus, in order to better understand extortion

Extortion: Incidence and search engine queries

Monthly counts and LOESS trends

Sources: SESNSP, Google trends.
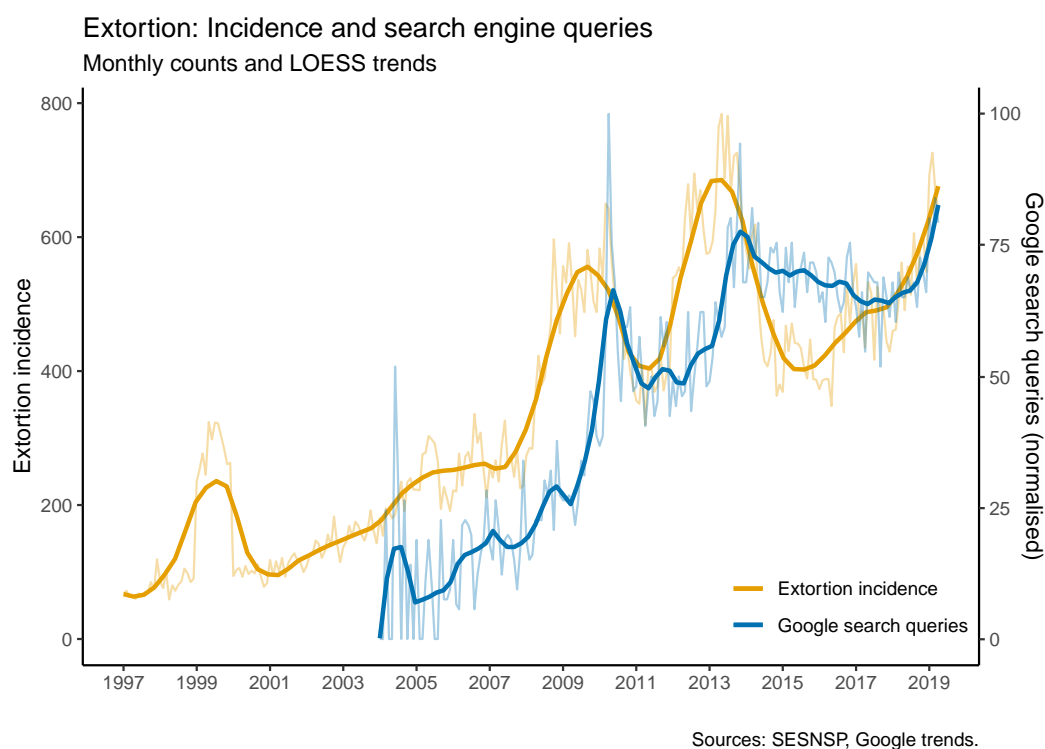
Figure 3.2: Monthly trends in extortion from Jan-1997 to Apr-2019. Extortion incidence (primary axis) refers to the absolute number of extortion incidents reported to law enforcement authorities each month, whereas Google search queries (secondary axis) represent the proportion of queries on Google using the terms 'extorsión' and 'extorsion' in Mexico for each month. Search queries are normalised with 100 representing the month with the largest proportion of queries, and 0 representing no queries using that term.

victimisation today, it is necessary to provide a historical background of organised crime violence in the country.

This chapter presents such an overview. For the benefit of readers unfamiliar with the context, the chapter begins with a description of the geography, government, criminal justice institutions, economy and society of contemporary Mexico, followed by a brief overview of the country's history. The section then focuses on the history of organised crime and violence in the country, describing the current explosion in crime, which stands in contrast with the international crime drop experienced during the twentieth century (see van Dijk et al., 2012). Then, it provides an overview of the explanations proposed to account for the increase in organised crime-related violence.
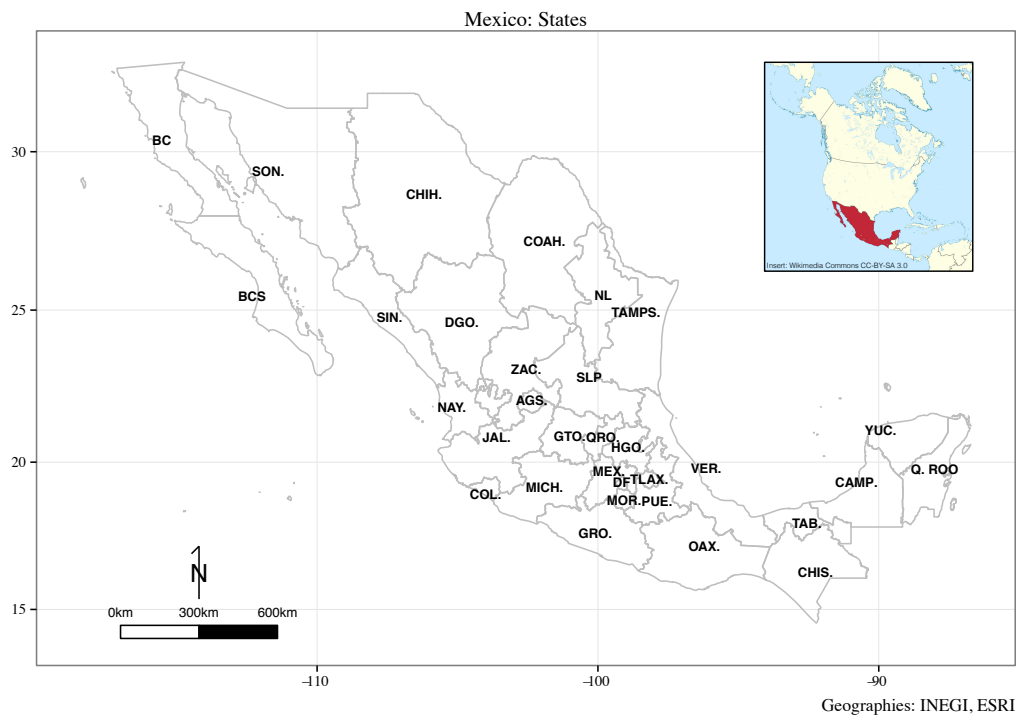
Figure 3.3: Map of Mexican states and location in North America.

3.1 Contemporary Mexico

Mexico is a sovereign country located in the North American continent (see Figure 3.3). To the north it shares a 3,000 km border with the United States—roughly the distance between Madrid and St. Petersburg. To the south it has a 1,000 km border with the Central American countries Guatemala and Belize. To the west it borders the Pacific Ocean, and to the east it borders the Gulf of Mexico and the Caribbean Sea. It's territory spans almost 2 million square kilometres—an area roughly equal to the combined surface area of Europe's four largest countries: France, Spain, Sweden and Germany. Mexico is home to a wide array of ecosystems, from tropical rainforests in the southeast to arid deserts in the north and northwest. Topographically the country is traversed by an east-west active volcanic belt in central Mexico, two north-south mountain ranges extending form the North American rockies, as well as an east-west mountain range in southern Mexico.

Politically, the country is a constitutional republic with three branches of govern-

ment (executive, legislative, and judicial), and several autonomous institutions (such as the central bank, the national statistics agency, the national electoral commission, and the human rights ombudsman).

Mexico is a federation comprised of 32 states and around 2,450 municipalities (i.e. counties). Heads of the executive branch in the three levels of government (i.e. federal, state and municipal) are elected for fixed terms (six years for federal and state posts, three years for municipal posts) using a first-past-the-post system. The federal legislature is bicameral, with a lower house of 500 deputies and an upper house with 128 senators. Legislators are chosen using a mixture of first-past-the-post and proportional representation. Deputies are elected for three year terms, while senators are elected for six year terms. State governments are similarly divided in three branches, though state legislatures are unicameral. In contrast, municipal governments are composed of an executive (i.e. a mayor) and an elected local council. Federal judges to the supreme court are appointed by the executive and approved by the senate, whereas federal circuit and district judges are selected by a judiciary council.

Public security is formally the responsibility of the three levels of government, thus there are police forces at the federal, state and municipal level—though not all municipalities have police corporations. Police institutions are generally weak and inefficient, and are (sometimes rightly) perceived as being corrupt.

There has been a somewhat inconsistent effort since the mid 2000s to strengthen and improve the police service at the three levels of government (see Sabet, 2010), though progress has been hampered by a lack of long-term commitment to reform efforts and political obstacles. A recent example is the imminent disappearance of the Federal Police, which greatly improved its capabilities after reforms passed in 2009 (see Arellano & Salgado, 2012), though it is now set to be absorbed by a new so-called 'National Guard'—a militarised force principally composed by members of the armed forces tasked with public security matters.

Judicial investigations are handled by public prosecutor's offices, of which there are institutions at the federal and state level. Seeking to overcome the arbitrary use of the criminal justice system, in 2016 Mexico implemented a wide-ranging transformation of its criminal procedure code, switching from an inquisitorial system to an adversarial system that aims to guarantee the presumption of innocence, to reduce the use of imprisonment, and to streamline the criminal justice system (see Hernández de Gante, 2017; Huebert, 2019).

State prisons remain one of the weakest links in the criminal justice system.

Overcrowding has been reduced from 130% in 2013 to 110% in 2016, though some states have overcrowding rates[2] between 130% and 230% (INEGI, 2017). In addition, some prisons are self-governed by inmates, are rife with violence and corruption, and prone to rioting. Though federal prisons are comparatively better run, they have suffered spectacular embarrassments, such as high-profile prison breaks: Joaquín Guzmán Loera (a.k.a 'El Chapo'), leader of one of the main organised crime groups in the country (the Sinaloa cartel), twice escaped from maximum security prisons, first in 2001 by smuggling himself in a laundry cart, and the second time in 2015 through a 1.5 km tunnel dug from a nearby house to his jail cell (see Harrup & Althaus, 2015).

Mexico has a complex, export-oriented economy. It has signed 12 free trade agreements with 46 countries, making it one of the most open economies in the world. However, Mexico's economic fortunes are closely tied to the health of the United States economy, its main trading partner accounting for roughly 80% of Mexican exports. The country has a diversified economy, with strengths in manufacturing (it has thriving automotive, aerospace, white goods, electronics, and textile industries), services (especially tourism), extractive industries (especially oil and gas, gold, and silver), and agriculture.

Mexican manufacturing is highly integrated into global supply chains, especially those in North America. It is estimated that around 40% of the value of Mexican exports was originally generated in the US (Koopman, Powers, Wang, & Wei, 2010). In 2017 Mexico's GDP was $1.16 trillion USD in nominal terms (OECD, 2019)—the 15th largest in the world—though per capita GDP was only $9,319 USD (IMF, 2018)—the 66th largest in the world. Macroeconomic fundamentals (e.g. inflation, public debt, interest rates, unemployment, balance of payments, exchange rate, foreign reserves) have seen unprecedented stability over the past 25 years, thanks to a strong and independent central bank and a well-run treasury.

However, due to its reliance on exports, openness to foreign capital, and the currency's exposure to foreign exchange markets (the Mexican peso is the most traded emerging market currency) Mexico's economy is particularly vulnerable to external shocks: for example, in the aftermath of the 2008 global recession, Mexico's economy was the most affected in Latin America, contracting by 6.6% in 2009 (Angeles Villarreal, 2010). Public finances are roughly in good shape, with a low debt-to-GDP ratio, though tax revenues are low and too reliant on revenue generated by the ailing

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[2]Overcrowding rates are calculated by dividing the total inmate population by the capacity installed; a figure higher than 100% represents overcrowding.

state oil company, Pemex (IMF, 2018; OECD, 2019). However, despite a relatively healthy economy, real GDP growth has been moderate-to-mediocre for an emerging country, averaging 2.5% per year in the 5 years to 2017 (OECD, 2019).

Mexico has a population of around 129 million; it is the largest Spanish-speaking country in the world. Life expectancy is estimated to be around 76 years, while median age is around 27. In 2015, 27% of the population was under 14 years or younger, while 6.5% of the population was aged 65 or more. The country is primarily urban: 79% of the population resides in cities, and 55 metropolitan areas concentrate close to 50% of the population. According to the national statistics agency[3] (INEGI), average schooling for those aged 15 or older is 9.2 years, while the literacy rate for the same group is around 95%. Health patterns resemble those in developed countries, with illnesses associated with sedentary lifestyles and obesity being a leading cause of death.

The country is ethnically diverse: the main ethnic groups are 'mestizo' (mixed European and indigenous ancestry)—though this classification can obscure wide heterogeneity in indigenous ethnic groups—white, and native indigenous (there are around 56-65 distinct ethnic groups). Linguistically, Spanish is the de facto national language, though there are more than 60 indigenous languages spoken throughout the country. Though the country prides itself on having a unique 'Mexican' mestizo cultural and ethnic identity, discrimination and inequality along ethnic and racial divides is pervasive.

Mexico is often described as a middle-class country, however, poverty and inequality remain major challenges. Unemployment is low at around 3%, though most jobs are informal and poorly paid. According to the World Bank,[4] 2.5% of the population live below the international poverty line (a measure of extreme poverty representing those earning less than \$1.90 a day), while the OECD (2019) estimates that 16.7% of the population lives in relative poverty (a measure of moderate deprivation representing those earning less than half of the country's median income). Yet, according to Mexico's more stringent measurements of multidimensional poverty (i.e. beyond income thresholds), 7.6% of the population (9.4 million) live in extreme poverty, while 43.6% (53.4 million) live in moderate poverty.[5]

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[3]Up to date indicators compiled by INEGI: `https://www.inegi.org.mx/app/areasgeograficas/?ag=00`. Accessed June 21, 2019.

[4]World Bank indicators: `http://povertydata.worldbank.org/poverty/country/MEX`. Accessed June 21, 2019.

[5]Multidimensional poverty indicators by CONEVAL: `https://www.coneval.org.mx/Medicion/Paginas/PobrezaInicio.aspx`. Accessed June 21, 2019.

3.2   History of Mexico

There is a vast literature on Mexican history. The following overview of Mexican history is based on concise works by Cosío Villegas et al. (1994), Escalante-Gonzalbo et al. (2013), Beezley and Maclachlan (2016), and Hamnett (2019).

3.2.1   Origins and colonialism

The land now known as Mexico has been continuously populated by humans at least since 12,000 years ago. Between 7,500 and 5,500 years ago, humans in what is now central Mexico developed agriculture, which allowed the development of some of the most advanced and complex civilisations in the Americas. Among these are the Olmec, Zapotec, Maya, Teotihuacan, Toltec, and Aztec civilisations. In contrast, populations in the northern half of the territory—an arid and mountainous terrain—developed comparatively less complex societies with more nomadic residency patterns, and more reliant on hunting and gathering for subsistence, though some farming was practiced.

The Spanish conquest of the Aztec empire (completed on 1521) marked the onset of three centuries of colonial rule. During this time, Mexican territory was the principal part of 'New Spain'—arguably one of the most important overseas territories of the Spanish empire, at its peak spanning from southwestern present-day British Columbia in Canada to present-day Nicaragua in Central America. The capital of New Spain was present-day Mexico City.

Colonial rule decimated the local indigenous population through disease and labour exploitation. Economically, New Spain was crucial to the Spanish empire, both as a source of silver and as a logistic hub connecting trade between Spain and its Asian colonies. Culturally, the territory inherited the language, customs, religion (Catholicism) and legal practices of Spain, though three centuries of colonial rule gave rise to new cultural identities synthesising Spanish and indigenous traditions.

3.2.2   The first century of independence

Independence from Spain was achieved in 1821. Mexico's first century as a fledgling nation was tumultuous, with conflicts arising between two groups. Liberals wanted to abolish colonial power arrangements and build a decentralised federal republic. In contrast, conservatives sought a more centralised government that preserved the privileges and power arrangements of the colonial era. The first years of independence

saw Spanish attempts at restoring colonial rule and the establishment of a homegrown Mexican empire.

The first Mexican empire was quickly overthrown and replaced by a constitutional republic. However, the country did not have the social and political conditions to enforce rule by law, leading to a series of coups and counter-coups led by military strongmen (known as *caudillos*). The first half of the century was dominated by the rule of Antonio López de Santa Anna—a general in the independence war—who ruled intermittently (switching between the liberal and conservative camps) from 1832 until 1854 as president-cum-dictator. Santa Ana's rule was disastrous. During that period Mexico lost around half of its territory—first via the independence of Texas, then in the Mexican-American war of 1846-1848.

Santa Anna's dictatorship was followed by a period of liberal rule headed by Benito Juárez, a jurist and politician. Juárez sought to bolster constitutional rule under a federal republic, abolishing corporatist interests, safeguarding individual rights, and—crucially—separating church and state. However, the new liberal constitution of 1857 provoked a conservative backlash, leading to a civil war (1857-1861) and a French military intervention (1862-1867) that, with the help of Mexican conservatives, installed Maximilian of Habsburg as head of a second Mexican empire. The second empire never came to fully control the country (though it did hold the capital), and collapsed after French forces retreated following pressure from the US government.

Back in power, liberals resumed their reform agenda, though they were overthrown by Porfirio Díaz—a liberal war hero of the French intervention. Díaz's dictatorship lasted from 1876 to 1910. During this time, violence and instability was relatively controlled—especially when compared to the first three-quarters of the nineteenth century—which allowed the modernisation the country. In particular, Díaz's rule saw an economic expansion driven by foreign investment in railroads, mining and oil. However, the benefits of such economic improvements were concentrated among foreign investors and the elite, leaving the vast majority of the population impoverished and in deplorable working conditions.

3.2.3   The making of modern Mexico: 1910-2000

Social unrest with economic and political inequality lead to the Mexican revolution, a violent civil war. While the revolution began as a successful attempt to restore democratic rule, it soon devolved into another series of coups and counter-coups fought by factions of the army, regional strongmen and popular leaders (such as

Pancho Villa, Emiliano Zapata, Venustiano Carranza, and Álvaro Obregón). In
1917, a new constitution[6] reaffirming most of the tenets set out by the 1857 charter
was promulgated.

However, military rebellions, political assassinations and a religious insurgency
ensured there would be no peace until 1929. A key issue was how to ensure a
peaceful transfer of power, as army leaders frequently rebelled when passed over for
the presidency. Pacification was finally achieved with the creation of an official state-
party in 1929, the *Partido Nacional Revolucionario* (National Revolutionary Party,
PNR) which provided a peaceful way to settle disputes for power among former
revolutionaries, and to channel social demands via corporatist organisations.

Mexico then entered a broadly peaceful period of institution-building and eco-
nomic development. The country (re)created the institutions of a modern demo-
cratic country, though power was not acquired through democratic means. Instead,
the party offered patronage and access to public office in exchange for party loyalty.
The formula worked well, with the PNR—later rebranded as the *Partido de la Rev-
olución Insitucionalizada* (Party of the Institutionalised Revolution, PRI)—ruling
practically all spheres of the country until the year 2000.

Economically, Mexico experienced an unprecedented period of economic growth
from the mid 1940s to the early 1960s—dubbed the 'Mexican miracle'—following
a policy of industrialisation through import substitution (i.e. developing an indus-
trial base by restricting imports and protecting national producers). Socially, the
country experienced a dramatic transformation, undergoing rapid urbanisation and
improvements in living standards.

However, by the mid to late 1960s, the PRI's grip on power had begun to fray.
Student movements in 1967, 1968 and 1971 were met with violent state repression,
and a clandestine military campaign—known as the 'dirty war'—was waged against
armed guerrilla groups that proliferated between 1963 and 1982. While crime and
banditry had subsided following post-revolutionary pacification, the 1960s saw a
rise in state-sponsored violence directed towards those dissatisfied with the political,
economic and social arrangements of the PRI regime. Nonetheless, Mexico's economy
kept growing thanks to a major oil boom in the 1970s, which contributed to the
permanence of the regime (oil had become a crucial component of public revenue
following the nationalisation of the oil industry in 1938).

A major economic crisis in 1982 proved to be the beginning of the end for the
economic and political model that was born out of the Mexican revolution. After

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[6]The 1917 constitution remains in force to date, though it has been amended multiple times.

more than half a century of development in an economy protected from global competition and with heavy government intervention, the PRI plunged the country in a radical transformation that embraced neoliberalism and globalisation. The country joined a precursor of the World Trade Organisation, privatised state enterprises and slimmed the public sector. Inflation was brought under control and the economy was redirected towards export markets. Politically, decades of campaigning by opposition parties and civil organisations bore fruits, as opposition parties began to win state and local elections for the first time, and came close to taking the presidency in the 1988 presidential elections, with the PRI clinging to power (probably) via electoral fraud.

In the early 1990s, the economy appeared to be recovering and the PRI seemed to be on the verge of a democratic transformation. However, 1994 was a calamitous year, marked by a guerrilla uprising protesting the North American Free Trade Agreement (enacted that year), the assassination of the PRI presidential candidate (and other high-profile politicians), and a major economic crisis. In 1997 the PRI lost control of the lower house of the legislature, to finally lose the presidency in the year 2000.

3.2.4 The new millennium

Mexico entered the new millennium on a wave of optimism and euphoria having finally ousted the PRI from the presidency: the first truly democratic transfer of power in the country's history. Yet, this 'democratic transition' (Camp, 2012) did not fully abolish the political practices acquired in more than 70 years of authoritarian rule, and it created new problems as well. The corrupt practices of the PRI continued to an extent in the local governments retained by the party, as well as being reproduced by the new ruling parties.

Furthermore, the executive was hampered by a lack of legislative majorities, leading to gridlock. Another relevant transformation (which had begun in the mid 1990s) was the decentralisation of executive power, with ever larger shares of public spending being decided by municipal and state governments. While decentralisation and divided government were important checks on what had been an almost all-powerful presidency, they also seriously impeded the federal executive's abilities to govern (Nacif, 2012).

The federal elections of 2006 proved to be the first major political crisis of the millennium. Felipe Calderón, presidential candidate of the incumbent party—the centre-right *Partido Acción Nacional* (National Action Party, PAN)—defeated chal-

lenger Andrés Manuel López Obrador—then of the centre-left *Partido de la Revolución Democrática* (Democratic Revolution Party, PRD)—by less than 1 percentage point. While the election was judged to be fair, the PRD candidate disputed the results, proclaimed himself 'legitimate president', and staged massive protests and blockades of Mexico City's main avenues.

The presidential elections of 2012 saw the return of the PRI to the presidency, under Enrique Peña Nieto. While his presidency was lauded internationally for his reformist zeal, rampant corruption and ineptitude led to the election of Andrés Manuel López Obrador in 2018—now a firebrand populist of the MORENA party.

In addition to rising crime (see Section 3.3), one of the main challenges of Mexican politics in the new millennium was widespread corruption. Through the twentieth century, corruption had been the 'mortar' that kept the country's political system together (R. E. Blum, 1997), as graft and embezzlement was widely tolerated, so long as government officials toed the party line (and lined the pockets of their political bosses). However, following the democratic transition, opportunities for graft at the municipal and state levels multiplied, while top-down arrangements that kept corrupt practices in check (or at least out of the public eye) were dissolved.

Furthermore, a nascent independent press and a growing cadre of civil society organisations became loud critics of government corruption. Lastly, organised crime became a major threat, corrupting government officials at all levels (see Section 3.3.2).

Economically, the country finally overcame the two lost decades caused by recessions in the 1980s and 1990s. It was not until 2004 that the country's per capita GDP rose to a level higher than that observed in the 1982 peak (see Figure 3.4, panel A). The two first decades of the millennium continued to see the development of export oriented industries, deeply embedded in international (chiefly North American) supply chains, though small-scale farming collapsed in the face of heavily subsidised American agriculture.

However, economic development was highly uneven, leading to 'two Mexicos': one of highly productive, globally competitive multinational corporations, and another of small unproductive traditional businesses (Remes & Rubio, 2014). Peña Nieto's presidency sought to bridge the two Mexicos with an array of structural reforms (particularly in energy, labour and education), some of which appeared to have promise. Yet, the new presidency of Andrés Manuel López Obrador mainly rolled back reform efforts.

Socially, the recessions at the turn of the millennium plunged millions into

poverty. The first two decades of the millennium saw steady (if insufficient) improvements in living standards, mainly due to very stable macroeconomic conditions and low inflation, and world-leading anti-poverty programmes. However, despite a low unemployment rate, wage growth for most Mexicans was nonexistent or negative. While those employed in the dynamic, globally competitive sectors of the economy saw improvements in living standards, those employed in the traditional sector saw their conditions worsen, leading to increases in inequality.

3.3 Violence and organised crime in Mexico

Mexico's history is a tale of progress across most indicators of human welfare. As Figure 3.4 shows, life has improved greatly for most Mexicans since the dawn of the twentieth century: Mexicans in the first two decades of the new millennium were richer, healthier and better educated than their parents and grandparents. However, the one area where this story of progress does not apply is in crime and violence.

Despite improvements seen in the twentieth century, crime and violence have seen steep increases in recent times. It is widely acknowledged that such recent increases are directly related to a radical transformation in organised crime activity. For example, Piccato (2017, p. 271) notes that the steady drop in crime suspects from 1926 until the 1980s reflects the pacification experienced after the revolution, while the increase after 1980 reflect increases in crimes related to drug trafficking, as well as increases in property crimes (see also Lajous & Piccato, 2018). Similarly, according to Knight (2013; see also Knight, 2012; Pansters, 2012) the decline in homicide rates observed between the 1950s and 2000s—though with important spikes in the 1970s—reflect declining political violence, mostly in the rural areas of the country, while the dramatic increase seen in the late 2000s is thought to be directly associated to organised crime violence (see also Osorio, 2015; Pérez Esparza, Johnson, & Gill, 2019; Rios, 2012; Shirk & Wallman, 2015).

Organised crime groups have been active in Mexico for more than a century (Astorga, 2005; Valdés Castellanos, 2013). Yet, since the 1980s, what was once a relatively tranquil and stable organised crime landscape dominated by a few drug trafficking organisations has mutated into a plethora of warring criminal groups engaged in a wide range of criminal activities—of which extortion is a quintessential example. The following sections outline the chronology of how this transformation took place, followed by a review of possible explanations.

Mexico: Key indicators, 1900–2019
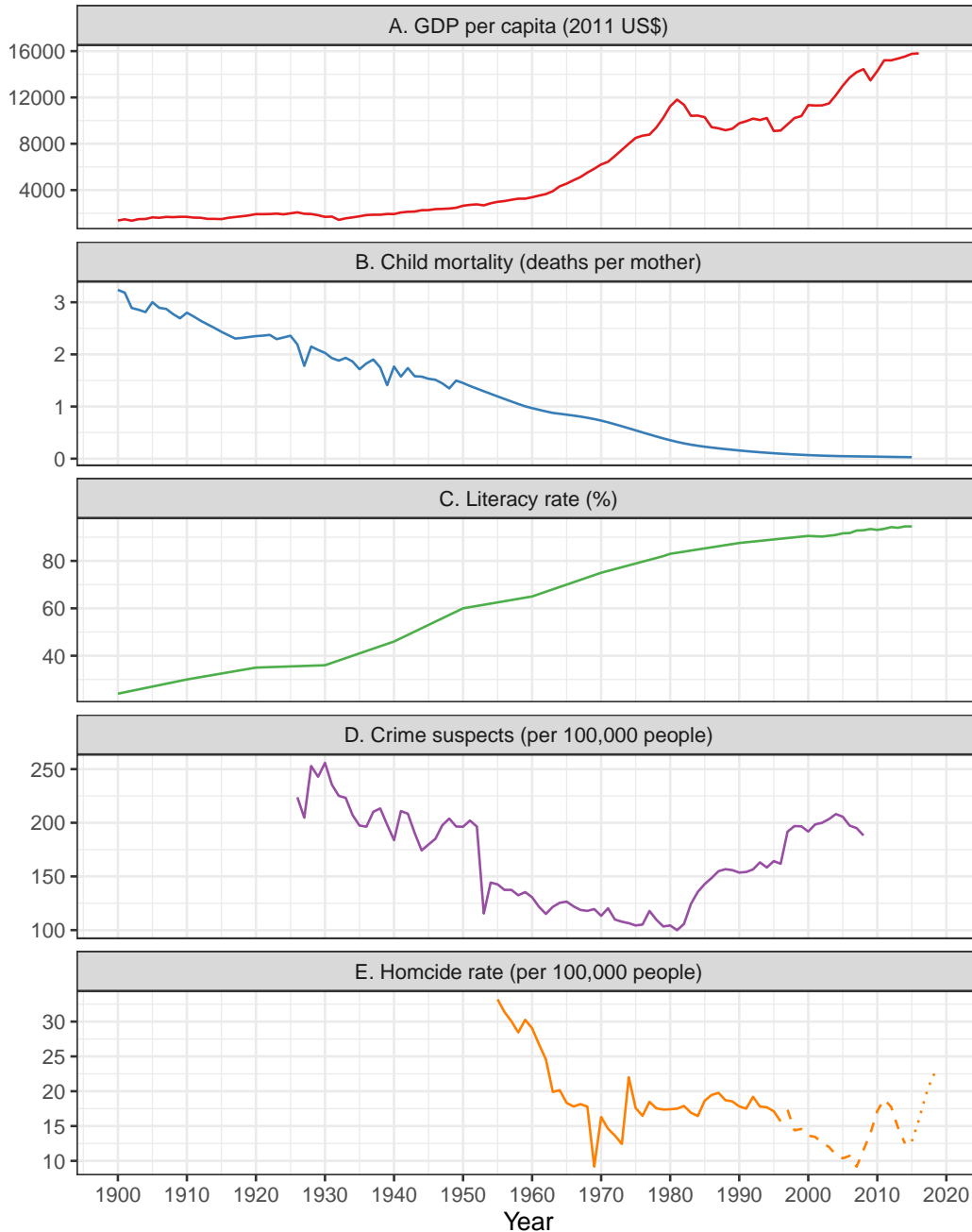
Figure 3.4: Four key indicators for Mexico, 1900-2019. Not all measures are covered for the entire duration of the period. Homicides before 1997 refer to homicide deaths from mortality statistics, while from 1997 onwards they refer to intentional homicides from criminal justice statistics. The different dash-line patterns for intentional homicides reflect a change in methodology used by the SESNSP. Homicide for 2019 forecast based on the year-on-year growth for homicides registered between January and April 2019.

3.3.1 The rise of drug-trafficking cartels: 1900-1989

Due to its proximity to one of the largest consumer markets in the world, illicit trafficking has a long history in Mexico. Knight (2012) states that 'if we expand the category to contraband in general, Mexico has over two centuries of vigorous contraband activity' (p. 119). In the early twentieth century, illicit drugs (mainly homegrown marijuana and opiates) were part of a vigorous cross-border trade in 'vice' centred around Mexico-US border towns (Beezley & Maclachlan, 2016, ch. 8; Knight, 2012; Serrano, 2012). Drugs rose in prominence during World War II, when US demand for morphine and hemp fibre stimulated the large-scale cultivation of opium poppy and marijuana plants in northwest Mexico[7] (Beezley & Maclachlan, 2016, ch. 8). Following the war, cultivation of opium poppy and marijuana, and the production of opium gum and heroin, continued apace.

Yet, the drug economy was not dominated by organised crime groups. Instead, it was comprised of a multitude of independent farmers, laboratories, and smugglers organised by market forces (Valdés Castellanos, 2013, p. 98-103). At the top of this market were state governors who took a share of the profits in exchange for turning a blind eye to the trade (Astorga, 2005; Valdés Castellanos, 2013). It was during this period that activities related to the drug economy became deeply embedded in the cultural identity of northwest Mexico.

The counterculture revolution of the 1960s and 1970s brought an unprecedented US demand for Mexican marijuana and heroin. While cultivation was still mostly conducted by independent farmers, production, packaging, transportation and smuggling into the US was beginning to become organised by larger, more professional drug trafficking organisations. In part, this 'cartelisation' was required in order to meet the gargantuan US demand. As Valdés Castellanos (2013, p. 112) notes, the three thousand tons of marijuana exported to the US per year meant that, on average, 8.2 tons of marijuana had to be smuggled through the Mexico-US border every day, requiring considerable logistical sophistication. Also, increasing seizures and eradication efforts by the Mexican government further increased the logistical pressures on Mexican drug traffickers (Beezley & Maclachlan, 2016, ch. 8; Valdés Castellanos, 2013; Serrano, 2012). Increased enforcement operations, however, should not be

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[7]Producing and exporting opium and marijuana was prohibited in Mexico and the United States, though anecdotal accounts suggest that an informal agreement between the US and Mexican governments—brokered by the US Italian Mafia—facilitated its trade (Valdés Castellanos, 2013, p. 92).

taken as growing intolerance of drug trafficking by the Mexican government, as they were mostly conducted to appease US authorities.

Indeed, another relevant transformation that occurred during this period was that the 'incestuous relationship' between drug traffickers and the state-apparatus (Knight, 2012, p. 120) shifted from one being managed by municipal and—mainly—state authorities, to one being managed by federal authorities (Valdés Castellanos, 2013, p. 148; Serrano, 2012, p. 138). The informal pact that thereafter regulated the relationship between drug traffickers and the state (with drug traffickers as the junior partner) aimed to curtail the power of drug 'cartels', to minimise violence arising from inter-cartel conflicts, and to ensure that drug production was directed towards export markets (minimising drug consumption in Mexico) (Serrano, 2012, p. 138). The arrangement distributed territories (*plazas*) among criminal groups and provided a relative freedom from government enforcement, in exchange for copious kickbacks to government officials (Serrano, 2012; Valdés Castellanos, 2013).

The 1980s brought monumental changes to the drug economy and to the nature of criminal groups. At the onset of the decade, the landscape of criminal organisations had been further concentrated to the point where essentially all drug-trafficking activity in the country was dominated by the so-called Guadalajara cartel, a federation of smaller cartels under the leadership of Miguel Ángel Félix Gallardo (Valdés Castellanos, 2013, p. 175-176).

The Guadalajara cartel elevated drug trafficking to the level of a professional multinational corporation. It invested in research and development, inventing more productive strains of marijuana, and used industrial farming techniques to boost production (Valdés Castellanos, 2013, p. 182-183). Furthermore, the collapse of Colombian cocaine-trafficking routes in the Caribbean, shifted the outstandingly lucrative business to Mexico (Astorga, 2005; Serrano, 2012; Valdés Castellanos, 2013). Their involvement with cocaine produced far-reaching changes in the cartels—in time it would become the main source of revenue (Valdés Castellanos, 2013, p. 194)—and their relationship with the state. As Serrano (2012, p. 140) notes, 'the opening of the cocaine corridor radically increased the value and thus the corrupting power of Mexico's illicit drug market'.

During this time, Mexican elites became enmeshed with the cartels, with numerous bankers and businessmen becoming involved in the drug trade, and in laundering its proceeds (Astorga, 2005). Cartel leaders bought their way into the upper class and the business establishment, became increasingly brazen in their displays of wealth, and made generous 'philanthropic' donations to city governments, churches,

and universities (Astorga, 2005; Valdés Castellanos, 2013). While in the past the government had been the more powerful partner in the relationship with the cartels, the growth of the cocaine business begun to swing the pendulum of power towards organised crime.

In 1985, however, the cocaine-fuelled ascent of the Guadalajara cartel would come to a crashing halt. Early in that year, cartel operatives assisted by the state police kidnapped, tortured and executed Enrique Camarena, a DEA agent stationed in Mexico (Astorga, 2005, p. 133-134). Camarena had been key to the discovery and subsequent destruction of a marijuana plantation and processing complex sprawling over 12 square kilometres—around 27 times the size of Vatican City—and employing around 12,000 day labourers (Astorga, 2005, p. 133). The Camarena affair prompted a swift and furious response from the US government: the border between the two countries was closed, US officials exposed the cozy relationship between the cartels and Mexican officials, and the Mexican government was pressured to punish those responsible and to dismantle the networks of corruption that had sustained them (Valdés Castellanos, 2013, p. 201-202).

Despite initial resistance, Mexican officials promptly mobilised to appease the US. By the end of the year, two of the leaders of the Guadalajara cartel were apprehended, though Miguel Ánguel Félix Gallardo eluded capture (with the aid of high-level government officials) until 1989. The Camarena affair also led to the dismantling of the *Dirección Federal de Seguridad* (Federal Directorate for Security, DFS), an intelligence and internal security agency that had been the main conduit through which the government conducted its dealings with cartels (Serrano, 2012; Valdés Castellanos, 2013). By the end of the decade, the once mighty Guadalajara Cartel had fractured into seven offshoots controlling different plazas, new cartels were emerging in northeast Mexico, and the control exerted by the government on the cartels dissolved.

3.3.2 From drug-trafficking to extortion: 1990-2006

The period that followed, roughly between 1990 and 2006, was characterised by increasingly violent confrontations between the offshoots of the Guadalajara cartel, as well as with new players: the Golfo-Zetas cartel in northeast Mexico, and *La Familia Michocana* in central Mexico. Furthermore, following the dissolution of the power arrangements between the federal government and the cartels—further aided by the weakening of the PRI's authoritarian regime—the cartels engaged in a

systematic capture of state institutions to protect their interests (and weaken their rivals) (Serrano, 2012; Valdés Castellanos, 2013).

Three main organised crime groups emerged from the remnants of the Guadalajara cartel: the Tijuana cartel based in Baja California, in the vicinity of San Diego, California; the Juárez cartel in north Chihuahua, bordering El Paso, Texas; and the Sinaloa cartel, based in the eponymous state. The Tijuana and Juárez cartels were more prominent at first, thanks in part to their easy access to the US border. While the state of Sinaloa has no US border, it was the ancestral heartland of the Guadalajara cartel, and a major drug producing region. Under to the visionary (and ruthless) command of El Chapo, the Sinaloa cartel soon overtook Tijuana and Juárez, and vied for control of their plazas (Valdés Castellanos, 2013). This initiated a violent period in border cities, as well as in cities from where the cartels managed their operations (e.g. Guadalajara, Culiacán), with assassinations, car bombs and street battles.

A notable episode in the battle between Sinaloa and Tijuana was a shootout in the Guadalajara International Airport, where the catholic archbishop of Guadalajara was murdered—presumably by accident. The high-profile killing put pressure on the Mexican government which eventually was able to capture the leaders of the Tijuana and Sinaloa cartels (Valdés Castellanos, 2013). This did not bring respite to the turf wars, however, as the Juárez cartel joined forces with Sinaloa and continued its assault on the Tijuana territory (Valdés Castellanos, 2013). This alliance would not last long, as following El Chapo's first escape from federal prison, Sinaloa and Juárez would become bitter rivals. Thus, by the beginning of the twenty-first century, the three major descendants of the Guadalajara cartel were locked in a deadly feud, and were soon to engage in a much bloodier war with a new player in northeast Mexico.

The emergence of new cartels in northeast Mexico proved to be one of the most radical transformations of the organised crime landscape. Before the 1990s, drug-trafficking to the east of the El Paso-Ciudad Juárez border crossing was marginal (see Valdés Castellanos, 2013, p. 245). This is somewhat surprising given that the eastern half of the Mexico-US border—with Texas on the US side and the states of Coahuila, Nuevo León and Tamaulipas on the Mexican side—has some of the busiest border crossings between the two countries—e.g. Tamaulipas handles 40% of the cross-border traffic between Mexico and the US (Correa-Cabrera, 2017, p. 15)—and has a long history of smuggling contraband (Flores Pérez, 2014; Valdés Castellanos, 2013).

After the Guadalajara cartel splintered and the DFS was dissolved, the region

soon became one of the major drug-trafficking regions under the control of a new organised crime group—the *Golfo* cartel (so-called for the nearby Gulf of Mexico), which began trafficking cocaine supplied by the Cali cartel[8] (Correa-Cabrera, 2017, p. 15). The Gulf cartel benefited from close links to powerful political groups (Flores Pérez, 2014). However, the key to its prominence was its alliance with the *Zetas* criminal group (Valdés Castellanos, 2013, p. 257).

Faced with rising violence due to turf-wars between criminal groups and competing claims to leadership within the Gulf organisation, the leader of the Gulf cartel created a paramilitary-like group called the *Zetas* in the late 1990s that would serve as his personal bodyguards, as well as providing an army to defend cartel territory from encroachment by the Sinaloa cartel and their allies (Correa-Cabrera, 2017, p. 21; Valdés Castellanos, 2013, p. 254). Up until that moment, cartel gunmen and foot soldiers had either been civilians with no previous military training, or (active and former) police officers on the cartel payroll. In contrast, the Zetas were deserters from elite, special forces units of the Mexican Army (Correa-Cabrera, 2017, p. 21-22; Valdés Castellanos, 2013, p. 255). They had been trained by the United States and Israeli armies in counter-insurgency, intelligence and counter-intelligence, interrogation, explosives and other forms of unconventional warfare (Correa-Cabrera, 2017, p. 22; Valdés Castellanos, 2013, p. 255).

In addition to superior combat tactics, the Zetas brought the use of heavy weaponry to the cartel wars, including military-grade assault weapons, explosives, grenade and rocket launchers, and armour-piercing ammunition (see Brophy, 2008; Kuhn & Bunker, 2011). From a small number, the Zetas grew to an impressive 3,000-strong paramilitary force (Correa-Cabrera, 2017, p. 25), thanks to an active recruitment campaign prompting soldiers and ex-soldiers to join their ranks (Valdés Castellanos, 2013, p. 255), as well as by incorporating deserters from the Guatemalan special forces, known as Kaibiles (Correa-Cabrera, 2017, p. 25). The Zetas were key to the Gulf cartel's ability to hold on to its territory, easily repelling incursions by the Sinaloa cartel using gruesome violence.

Furthermore, from the early 2000s onwards, the Gulf cartel—soon to be known as the Golfo-Zetas cartel due to the prominence of the later—embarked on a vast territorial expansion relying on the Zetas' muscle. The territory 'conquered' by the cartel ranged from the Mexico-Guatemala border to The Tamaulipas- and Coahuila-US border covering all the Mexican eastern seaboard (and its ports to move illicit

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[8]In contrast, the Guadalajara cartel (and its descendants) sourced its cocaine from the Medellín cartel, headed by Pablo Escobar and bitter rivals of Cali (Valdés Castellanos, 2013, p. 192-197).

drugs in from South America and out to Europe), as well as to the Michoacán coast southwest of Mexico City (Valdés Castellanos, 2013, p. 257). Control over Michoacán was crucial for the Gulf cartel, as it was home to vast marijuana and opium poppy plantations, and it allowed access to ports on the Pacific Ocean that offered faster transhipment of Colombian cocaine and a gateway for Asian chemical precursors for the booming trade in illicit methamphetamines (Valdés Castellanos, 2013, p. 257). While the main illicit activity of the Gulf cartel was drug-trafficking, the Zetas were given free reign to plunder their conquests.

In addition to the 'professionalization of the "killing industry" ' (Correa-Cabrera, 2014, p. 422), the other major 'innovation' that the Zetas brought to the organised crime landscape in Mexico, was the systematic exploitation of the territories under their control. Being (initially) left out of the profitable drug-trafficking business, they embraced a mafia-like business model focused on extracting tribute from 'ordinary' street criminals, monopolising local illicit markets in everything from counterfeit goods and illicit drugs, as well as international illicit markets that ranged from human trafficking and migrant smuggling to black-market oil and mineral ore (Valdés Castellanos, 2013, p, 258-260). In particular, the Zetas' reign of terror was marked by a boom in kidnapping for ransom and the systematic extortion of local businesses (Valdés Castellanos, 2013, p, 258-260; Correa-Cabrera, 2017, p 25).

Thus, the Zetas changed Mexican organised crime in two major ways that greatly contributed to the spike in violence seen from the second half of the 2000s and that persists until the present. First, their success with the use of superior armament and military techniques prompted other cartels to similarly create paramilitary wings to wage war against rivals (and the state) (Valdés Castellanos, 2013, p. 260), and stimulated an arms race to equip their foot-soldiers with military-grade weapons[9] (Kuhn & Bunker, 2011, p. 826). Second, their brutally profitable business model was soon replicated by new and existing criminal organisations. An example of this is provided by the rise of *La Familia Michoacana* in 2006, which expelled the Zetas from Michoacán claiming to be protecting the local community from Zeta extortion rackets, but ultimately proceeded to replace them as the regional mafia power (Valdés Castellanos, 2013, p. 265-268).

At the same time as these transformations were taking place, organised crime groups across the country were engaged in a systematic campaign to capture state institutions. As noted earlier, organised crime had always been in an 'incestuous

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[9]The proliferation of high-powered weapons was further facilitated by lax gun market policies in the US (Pérez Esparza et al., 2019).

relationship' with governmental authorities. However, following the dissolution of the DFS, and on the heels of a weakened PRI, the balance of power between organised crime and state officials was inverted. The cartels slowly bought entire police departments, police chiefs, prosecutors, prisons, mayors, state governors and judges (Valdés Castellanos, 2013, p. 318). The objective of such bribes was not only to ensure protection from prosecution, but also to expand the reach of organised crime into other governmental offices, such as public works and social programmes (Valdés Castellanos, 2013, p. 319).

A notorious example of state capture came in 1997, when General José Guitérrez Rebollo—then-head of the national counter-narcotics office and responsible for Mexico's counter-organised crime policy—was arrested on grounds of being on the payroll of the Juárez cartel (Valdés Castellanos, 2013, p. 241). The explosion of violence and the new business model developed by the Zetas accelerated the rate of state capture, though simple bribes were replaced by 'offers' of *plata o plomo* (silver or lead) (Rose-Ackerman & Palifka, 2016, p. 299).

3.3.3 The state responds: 2007 to the present

By December 2006, when Felipe Calderón assumed the presidency, organised crime groups controlled vast territories in the country; violence was growing due to conflicts between organised crime groups; previous presidencies had been hesitant to deal with the problem; violence on the Mexico-US border was generating conflicts with the US government; drug trafficking into the US continued unabated; and domestic drug consumption was increasing (Chabat, 2010b, p. 29). Furthermore, conflicts between organised crime groups were no longer the only source of violence, as more groups were adopting the Zetas business model centred on extracting rents from their territories (via kidnapping, extortion and the like) (Valdés Castellanos, 2013, p. 369).

Faced with few options (Chabat, 2010a), the newly sworn-in president launched a full-frontal 'war' on organised crime groups. Though it was recognised that the strategy would not be able to completely dismantle the criminal groups operating in the country, the goal was to weaken them, reducing them to a local law enforcement problem instead of the threat to national security they had become (Chabat, 2010a, p. 30). The strategy had two main components: increased counter-organised crime operations, and institution building.

First, on the operational side, the army—which had not been traditionally involved in counter-organised crime operations beyond crop eradication—would take

on the cartels with massive military operations aimed at wrestling control of territories and cities 'lost' to organised crime groups. In addition, the government implemented a 'kingpin' strategy aimed at 'decapitating' the most powerful criminal organisations by capturing (or killing) their leaders—which further added to the instability as underlings battled over control of the cartels, and competitors took advantage of weakened rivals (Calderon et al., 2015; Jones, 2013).

Most counter-organised crime operations were undertaken by the army, though naval infantry units and a revamped Federal Police would take an increasingly relevant role as well. Initially, the operations were successful in reducing violence. However, violence was soon displaced to other areas of the country and the security forces systematically committed human rights abuses against suspected criminals as well as innocent civilians caught in the cross-fire (Felbab-Brown, 2013; Flores & Villarreal, 2015; Fondevila, Massa, & Meneses-Reyes, 2019; Heinle et al., 2016; Romero Mendoza et al., 2018; Shirk & Wallman, 2015).

Second, the administration embarked on a wide-ranging transformation of the security and justice institutions, vastly expanding and improving the Federal Police (see Arellano & Salgado, 2012), as well as modernising the armed forces. The strategy also saw increased cooperation with the US (overcoming decades of mistrust), with unprecedented intelligence sharing that led to important blows against the cartels, as well as foreign aid directed at improving Mexico's security institutions (see Olson et al., 2010).

The cartels responded violently: Counter-organised crime operations led to new turf wars (as competitors seized on weakened rivals, alliances were made and unmade, and new groups replaced old groups), to more intense exploitation of their territories, and to violent clashes with authorities. As a result, homicide rates and other indicators of criminal violence grew explosively. By the end of his presidency, most Mexicans had tired of the 'war on organised crime' and blamed Calderón for intensifying the violence besieging the country (Bailey, 2014, p. 4-6).

The PRI was returned to power in 2012 with Enrique Peña Nieto at the helm. Peña Nieto's presidency mostly continued the counter-organised crime operations started by Calderón (though he greatly scaled back efforts of institutional development and US-Mexico security cooperation). While the first two years of his term saw declines in the homicide rate, this was quickly reversed as 2017 and 2018 each beat records as the most violent years since modern records began. In December 2018 president López Obrador was sworn in promising to end the war on organised crime, but has since reversed his position, ramping up the involvement of the military.

Areas of Cartel Influence in Mexico

ORGANIZED CRIME GROUPS AND THEIR SUBGROUPS

■ **Sinaloa**

Sinaloa Federation

Beltran Leyva Organization remnants

Tijuana cartel remnants

Juarez cartel remnants

■ **Tierra Caliente**

Cartel de Jalisco Nueva Generacion (CJNG)

Knights Templar remnants

La Familia Michoacana remnants

■ **Tamaulipas**

Tamaulipas

Los Zetas remnants

Gulf cartel remnants

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Figure 3.5: Areas of influence of Mexican organised crime groups, 2019. Source: Stratfor World-view (2019). *Republished with permission of Stratfor.*

More than a decade after the most recent 'war on organised crime', the organised crime landscape remained roughly similar to as it was in 2007, with some differences. Some of the organised crime groups that dominated vast tracts of the country have disappeared, but new, more violent groups have sprung up to take their place (see Figure 3.5). The risk of wholesale state capture appeared to have been fended off, while local authorities remained deeply vulnerable to organised crime intimidation (De Paz Mancera & Pérez Esparza, 2018). Yet violence remained unabated, and extortion was considered to be widespread (Malkin, 2011; Perez, 2018).

3.3.4   Why did Mexican organised crime turn violent?

Various explanations have been proposed to make sense of the spectacular rise in organised crime-related violence—and by extension in extortion—seen since the mid 2000s. These can be grouped in five categories: politics, organised-crime dynamics, consequences of law enforcement, economics, and opportunity.

First, political explanations link the decline of the PRI and the democratic transition with the rise of more powerful organised crime groups. As Knight (2013, p. 46) notes, the collapse of PRI's 'Leviathan' created a kind of 'Hobbesian' state of nature, undermining the restraints that had held organised crime groups in check. Empirical evidence supporting this view is provided by Trejo and Ley (2018), Rios (2015), Aguirre and Herrera (2013), Duran-Martinez (2015), Snyder and Durán-Martínez (2009a), and Snyder and Durán-Martínez (2009b), who found that the lack of political control over Mexican organised crime groups—operationalised using a diverse range of measurements—has led to clashes over control of illicit markets, and thus to a rise in organised crime violence.

Second, explanations based on organised-crime dynamics focus on how changes in drug markets, or in the structure and characteristics of organised crime groups led to a more violent organised crime landscape. For example, Serrano (2012) suggests that the involvement of Mexican organised crime groups in cocaine trafficking, led to vastly greater incomes, and thus more corrupting power and increased tensions between groups eyeing the lucrative cocaine market. Similarly, Correa-Cabrera, Keck, and Nava (2015) find that splits between criminal groups, and their increasing 'paramilitarisation' were two of the main factors accounting for increasing violence in the 2007-2010 period.

Third, a common explanation points towards the destabilising effect of counter-organised crime policy. Osorio (2015) and Rios (2012) find that security operations increased tensions between criminal groups triggering violent struggles between them.

This is echoed by Jones (2013), Dickenson (2014) and Calderon et al. (2015) who found that the 'kingpin' strategy aimed at removing the leaders of organised crime groups increased homicides and violence in general.

Fourth, explanations based on economics point towards 'root causes' of violence, such as income inequality and unemployment. Enamorado, López-Calva, Rodríguez-Castelán, and Winkler (2016) found that a one point increase in the Gini coefficient in Mexican municipalities—a measure of income inequality—was associated with a 36% increase in the drug-related homicide rate between 2005 and 2010 (though not before). Paradoxically, this period saw a decrease in income inequality, while drug-related homicides saw notable increases. Dell, Feigenberg, and Teshima (2019), on the other hand, found that job losses due to increased competition with China saw increases in drug-relate homicides during 2007-2010, presumably due to lower labour opportunity costs of joining criminal groups.

And fifth, recent explanations have focused on the role of opportunity factors to explain the rise organised crime-related violence. In particular, Pérez Esparza et al. (2019) found that changes in US gun laws that facilitated access to high-powered weapons—which in turn increased the availability of such weaponry in Mexico—were associated temporally and spatially with higher homicides (see also, Dube, Dube, & García-Ponce, 2013).

3.4   Chapter conclusion

This chapter has provided an introduction to Mexico for the benefit of readers unfamiliar with the country. It began by describing contemporary Mexico, geographically, politically, economically and socially. Then it presented an overview of Mexican history, before moving on to a history of Mexican organised crime.

The goal of the chapter was to provide sufficient background to understand the context in which this study of extortion victimisation patterns is situated. As noted in the introduction, extortion is widely acknowledged to be a prevalent phenomenon closely linked to the transformation of organised crime groups, which shifted from being primarily concerned with drug-trafficking to being involved in extortion and other predatory activities.

The chapter also presented a brief review of the explanations suggested by academic research to account for this transformation of Mexican organised crime. While these explanations are not specifically concerned with extortion and focus on organ-

ised crime violence broadly defined, they suggest two narratives to understand the shift towards extortion.

In the first narrative, extortion can be understood as a natural consequence of the rise in extra-legal governance exerted by organised crime groups—which developed in the wake of the power vacuums created by the democratic transition. In contrast, the second narrative views the shift towards extortion as a 'business strategy' followed by organised crime groups seeking to diversify their incomes. In this narrative, as incomes from drug-trafficking decreased (due to lower demand and/or increased enforcement) and costs increased (due to violent competition with other cartels and the state), groups expanded their business models into extortion, kidnapping and other predatory criminal activities.

These narratives—rooted in distinct approaches to organised crimes, such as the illicit-enterprise approach and the extra-legal governance approach discussed in Section 2.1.1—may help understand why extortion became more prevalent at the national, sub-national, or even city level. However, considering the situational approach employed in this thesis, they are insufficient to systematically understand the micro-level risk factors that may explain why some businesses within the same context would suffer more extortion incidents than others (the focus of this thesis).

Chapter 4

Measuring and analysing extortion

This chapter presents the data sources and research settings used in this thesis. It begins with a discussion of the methodological difficulties associated with measuring extortion, and introduces crime surveys as a suitable option for doing so. Then it provides a brief overview of the sources of Mexican crime statistics, followed by a more detailed discussion on the national commercial victimisation survey, the main data source for extortion measurements used in this research. It concludes with a description of the research settings and workflow used to generate the analyses and results reported in the following chapters.

4.1   Measuring extortion

As noted in Section 2.3, analysing the (repeat) victimisation patterns of extortion against businesses requires micro-level measurements of the phenomenon. There are two main sources of measurements of extortion. On the one hand there are official crime statistics (e.g. the counts of crimes reported to and recorded by the police, also known as administrative crime statistics, see Mosher, Miethe, & Phillips, 2002), while on the other there are measurements obtained using commercial victimisation surveys.

As crimes against businesses tend to be poorly measured by official crime statistics, and as businesses may be particularly hesitant to report extortion incidents due to fear of retaliation by extortionists, victimisation surveys are considered to offer more reliable measurements of extortion than official crime statistics (Mugellini, 2013c).

4.1.1   Official crime statistics

Though businesses may report crimes to the police or similar authorities, official crime statistics are often inappropriate to gauge the level of victimisation experienced by businesses (Mugellini, 2013a, 2013c). This is because the crime classifications used to record and report administrative crime statistics do not usually consider crimes against businesses to be a different type of crime as those suffered by households.

For example, as Burrows and Hopkins (2005) note, in Britain, a burglary against a business would be recorded as 'burglary other than a dwelling', which includes 'from schools to garden sheds', impeding detailed analysis of the extent of burglary against businesses. Furthermore, even if crime categories were refined to include crimes against businesses as additional categories, administrative statistics are unlikely to capture many details regarding the characteristics of the business (such as business type, size, and so on) that are crucial to properly understand business victimisation patterns.

Nonetheless, in the case of extortion, such potential improvements in administrative statistics would not address the second issue, the reluctance to report extortion incidents due to fear of reprisals. Extortion—like domestic violence (e.g. McLean, 2016, p. 53) and sexual assault (e.g. National Research Council, 2014, p. 1)—is a crime thought to be greatly affected by underreporting (e.g. Chin et al., 1992, p. 628; Alvazzi Del Frate, 2004, p. 151-152). Asmundo and Lisciandra (2008) note that the amount of extortion incidents (in Italy) that are reported to the police is essentially nil, thus the 'dark figure' (i.e. the percentage of crimes not reported to the police) for extortion coincides with the actual extent of the phenomenon (p. 227).

4.1.2   Victimisation surveys

Victimisation surveys offer a suitable alternative to administrative statistics for the measurement and study of extortion against businesses, as they largely overcome the issues outlined above. On the one hand, surveys specifically designed to estimate the prevalence and incidence of crimes against businesses are now routinely conducted across several countries, regions and internationally (for a review, see Mugellini, 2013b).

By directly interviewing businesses about their past victimisation experiences (usually within a 12 month period), commercial victimisation surveys are able to measure the extent of 'conventional' (e.g. burglary, robbery, assault, among others) and 'non-conventional' (e.g. cybercrime, counterfeiting, corruption, extortion, among

others) crimes against businesses, overcoming the classification limitations imposed by administrative statistics systems (Mugellini, 2013c). Furthermore, as commercial victimisation surveys capture a wealth of information regarding the characteristics of respondents and their surroundings (such as business type, size, location type, etc.), they are particularly suited to analyse how micro-level crime patterns vary according to such characteristics (Mosher et al., 2002, p. 137).

Victimisation surveys were specifically instituted to overcome the underreporting (and underrecording) that affects administrative crime statistics. As Wetzels et al. (1994, p. 14) note, 'victimization surveys were seen as a means for overcoming the bias of police crime statistics and promising a solution to the problem of hidden crimes (dark figure) caused by unreported and/or unrecorded criminal incidents'. Thus, commercial victimisation surveys ought to be well-suited to measure crimes affected by underreporting, such as extortion.

4.1.2.1 Validity of victimisation surveys

Some scholars are sceptical of the validity of using victimisation data to measure extortion. Di Gennaro and La Spina (2016; see also La Spina, 2008a; La Spina et al., 2014) suggest that victimisation surveys are not reliable instruments to measure extortion (p. 4)—though it is worth noting that their criticism is based on Italian victimisation surveys, particularly one by Confcommercio-GFK Eurisko (2007), and another by TRANSCRIME (Mugellini, 2012). Their main contention is that the surveys' low response rates (6.3% and 14%, respectively) lead to self-selected samples unlikely to produce reliable outcomes (Di Gennaro & La Spina, 2016, p. 4).

Additionally, Asmundo and Lisciandra (2008) note that 'victims of extortion are unlikely to come forward as such' in victimisation surveys (p. 227). They ascribe this reticence to the fact that for many Italian—and especially Sicilian—businesses, 'extortion is considered as "normal" and made endogenous by the economic and social system, as an (ordinary) component of production costs,' and as such it loses its 'criminal profile' (Asmundo & Lisciandra, 2008, p. 227)—i.e. they do not consider themselves victimised.

However, while such objections may be relevant in the Italian context, I do not find them to be applicable to *all* commercial victimisation surveys, and certainly not to the survey used in this thesis. First, the inclusion of extortion in commercial victimisation surveys is standard practice. In a review of commercial victimisation surveys, Mugellini (2013c) identified 14 large-scale international, European and national commercial victimisation surveys, of which 10 (71%) included questions

regarding the prevalence and incidence of extortion. If survey estimates of extortion were indeed regarded as invalid or unreliable, it is unlikely that national and international statistics agencies would continue to include extortion in commercial victimisation surveys.

Second, while low response rates can be a serious threat to the validity of survey measures—by systematically biasing the population estimates obtained (Bethlehem, 2009, p. 209)—not all commercial victimisation surveys have response rates as low as those cited by Di Gennaro and La Spina (2016). In the review by Mugellini (2013c), most commercial victimisation surveys have response rates higher than 30%, with those relying on face-to-face interviews seeing response rates higher than 59%. The commercial victimisation survey used in this thesis has a response rate of around 85% (see Section 4.2.2)—probably the highest figure among commercial victimisation surveys—which should assuage most concerns of self-selection and non-response bias.

Third, it is not clear if the process of extortion 'endogenisation' described by Asmundo and Lisciandra (2008) applies to contexts other than Italy. In the case of Mexico, for example, the opposite appears to be true. Extortion is a relatively new phenomenon (see Chapter 3). Faced with increases in extortion and other organised crime related violence, the response from the business community in Mexico has ranged from vociferous protest, to proactive involvement in the improvement of public security institutions (Shirk et al., 2014).

For example, in Ciudad Juárez and Monterrey—two northern industrial powerhouses ravaged by extortion and organised crime violence—the business community was at the forefront of a series of protests and initiatives aimed at restoring security and the rebuilding of the police, in association with civil society organisations (Conger, 2014). Thus, I find little reason to believe that businesses in Mexico would consider that extortion has lost its 'criminal profile', to the extent that they do not consider themselves to be victimised when confronted with extortion demands.

4.1.2.2 Limitations of victim surveys

Measurements of crime derived from victimisation surveys present important limitations (see Lynch, 2006; Mosher et al., 2002; Mugellini, 2013c; Skogan, 1986a; UN-ODC/UNECE, 2010). Mosher et al. (2002, p. 168) identify four main ones: First, the scope of criminal activity that is measured depends on the type of survey (i.e. household, commercial, etc.) and the crime categories used. If a type of crime is not covered in the survey, it cannot be measured. Second, victimisation surveys suffer from methodological limitations inherent in survey research, such as sampling error,

sampling bias, nonresponse bias, and the constraints imposed by the availability of suitable sampling frames.

Third, survey measurements are subject to the perceptions and biases of respondents. This means, for example, that 'trivial' events that would not necessarily qualify as a crime from a legal perspective could be reported if respondents deemed them to be so. Furthermore, survey measurements are also affected by recall errors—such as forward-telescoping (reporting events that occurred before the reference period) and backward-telescoping (not reporting events that occurred during the reference period because they are misremembered to have occurred before)—and to potential respondent unwillingness to provide truthful answers.

Fourth, and related to the previous point, survey measurements are highly sensitive to design and implementation choices, such as the type of data collection method used (e.g. face-to-face interviews, computer-assisted telephone interviews, mail surveys, web-based surveys, etc.), the order in which questions are presented, and the specific wording of the questions.

Such limitations, however, are not fatal. Mosher et al. (2002, p. 168) note that the limitations of victimisation surveys 'are neither more nor less serious than the problems with official data and self-report measures of crime', and also note that 'problems of definitional ambiguity, limited coverage, reporting biases, and various sources of measurement error plague each method of counting crime' (p. 168).

Furthermore, many limitations of victimisation surveys can be addressed by sensible design choices and rigorous training for those tasked with carrying them out. Scope and coverage issues can be addressed by implementing a variety of surveys each focusing on a particular population (e.g. households, businesses, university students, youth, etc.) and a set of crime types (e.g. property crime, violent crime, cybercrime, corruption, sexual abuse, intimate partner violence, etc.). Complex sampling designs that account for nonresponse bias, and poststratification adjustments can help mitigate systematic sampling errors. Definitional ambiguity and subjective interpretation of crime types can be addressed using plain-language non legal definitions of crime (Mugellini, 2013c; UNODC/UNECE, 2010), with the challenge of being broad enough to accommodate the perspectives of different respondents, and narrow enough to avoid misinterpretations (Alvazzi Del Frate, 2008; Mugellini, 2013c).

Telescoping errors can be addressed by the use of bounding (i.e. anchoring the reference period to a specific date, such as New Year's Day, a birthday, etc.), and by specific bounding questions that can capture the events prior to the reference period (i.e. asking 'in the past 3 years, have you suffered any of the crimes listed in the card?',

before asking about specific victimisations during the reference period) (Mugellini, 2013c, p. 36; Lynch, 2006, p. 254). Mis-recall can also be addressed by sophisticated screening procedures, where the identification and classification of criminal incidents is performed two-steps, and by the use of cues that vary the wording of questions to help prompt respondents' memories (Lynch & Addington, 2010, p. 255-257).

Lastly, to minimise biases due to design and implementation choices, the development of victimisation surveys goes through lengthy quality assurance processes that include consultations with experts, cognitive testing of questionnaires, preparation of field materials, staff training, pre-tests and pilot surveys (UNODC/UNECE, 2010). Once implemented, the results must be analysed to ensure data quality (UNODC/UNECE, 2010), and the design and implementation of the survey must be as consistent as possible in subsequent sweeps so that measurements are comparable from year-to-year (Mosher et al., 2002, p. 168).

Though victimisation surveys exhibit important limitations that can be somewhat mitigated, it is important to note that all estimates are approximations of the 'true' extent of the crime phenomenon. Furthermore, as Mugellini (2013c, p. 16) notes, the limitations of victim surveys 'tend more to underestimate rather than over-estimate the number of victims of crime'.

4.2 Mexican crime statistics

Mexican crime statistics have undergone a profound transformation over the past two decades. On the one hand, the increase of crime and violence seen since the 1980s onwards (see Section 3.3) revealed Mexico's dearth of quality data to analyse and understand the problem, which prompted policies that sought to address the information gap. On the other, the development of the national statistics agency (*Instituto Nacional de Estadística y Geografía*, INEGI) has further greatly improved the data available.

Since the eruption of violence and crime at the turn of the new millennium, the Mexican government has sought to overhaul the fragmented landscape of municipal, state and federal public security institutions—which include police agencies and prosecutor's offices—into a more or less coordinated system, dubbed the National System for Public Security (*Sistema Nacional de Seguridad Pública*, SNSP). A by-product of enhanced cooperation was the regular publication of statistics of all crime incidents

reported to federal and state prosecutor's offices.[1] These statistics are overseen by the National Centre for Information (*Centro Nacional de Información*, CNI) of the Executive Secretariat of the SNSP (*Secretariado Ejecutivo del Sistema Nacional de Seguridad Pública*, SESNSP, 2015). They are the closest Mexican equivalent to the United States' Uniform Crime Reports (UCR).

Besides the figures published by the SESNSP (2015), the national statistics agency also publishes a set of additional administrative statistics from the judicial sector (e.g. criminal sentences), as well as more detailed statistics from the prosecutor's offices.

Nonetheless, administrative statistics are usually not available at the incident-level, but instead are aggregated at the municipal or state level. Furthermore, they tend to be aggregated by month. Lastly, they suffer from widespread quality issues as well as underreporting (see Echarri Cánovas, 2012, for a discussion).

To overcome the limitations of administrative statistics, INEGI has conducted large-scale victimisation surveys of households and businesses since 2011. This push into victimisation surveys happened in the context of a radical transformation of the national statistics agency. As chronicled by Palma (2012), in 2008 INEGI gained constitutional autonomy, the highest level of technical and legal independence a public institution can have.[2] Following constitutional autonomy, INEGI created the National Subsystem for Government, Public Security, and Justice Information, which allowed it to overhaul administrative statistics and to create new victimisation surveys.

The new surveys conducted by INEGI replaced previous attempts by civil society and private groups to conduct victimisation surveys in Mexico (some conducted in cooperation with INEGI). While the early attempts were important to draw attention to the technique, they were of limited scope and coverage, and were plagued by inconsistencies and reliability issues (partly stemming from the constraints faced by independent NGOs in terms of funding and capacity). From the lessons learned in these previous exercises, INEGI launched the national household victimisation survey (*Encuesta Nacional de Victimización y Percepción de la Seguridad*, ENVIPE) in 2011—with yearly sweeps conducted to date—and the national commercial victim-

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[1] In Mexico, incidents reported to the police are not classified as crimes until they are reported to a public prosecutor.

[2] Other institutions with constitutional autonomy in Mexico include the central bank, the national electoral commission, the national human rights ombudsman, and the information commissioner.

isation survey (*Encuesta Nacional de Victimización a Empresas*, ENVE) in 2012—
conducted every two years since then.

The development of INEGI's surveys was modelled on international experience
and followed the recommendations of the United Nations Office on Drugs and Crime
(UNODC) (Jaimes Bello & Vielma Orozco, 2013; Palma, 2012). As a token of
INEGI's commitment to quality statistics in the criminal justice sector, the agency
co-established a Centre of Excellence Statistical Information on Government, Crime,
Victimisation and Justice with the UNODC, which 'aims to support research on these
matters as well as the exchange of information through seminars, courses, workshops,
and an annual international conference' (Palma, 2012, p. 152) both in Mexico and
at the regional and international levels.[3]

4.2.1   Extortion in Mexican administrative statistics

The main administrative statistics covering extortion in Mexico are the counts of
incidents reported to prosecutor's offices published by SESNSP (2015). A plot of the
reported extortion incidents between January 1997 and April 2019 can be found in
Figure 3.2 in Chapter 3.

The estimates of extortion published by SESNSP (2015) have some advantages.
As they are not drawn from sample estimates, they represent the population level es-
timates of reported extortions. Thus, they are available at a lower spatial resolution,
providing aggregate counts at the municipal and state level. Furthermore, they are
not constrained to cross-sectional measurements, as they are reported aggregated by
month.

On the other hand, they present important limitations that make them unsuit-
able for the purposes of this study. Chief amongst them is that they are affected by
underreporting. According to Jaimes Bello and Vielma Orozco (2013, p. 185), only
38.7% of commercial victimisations were reported to a competent authority in 2012,
based on estimates from Mexico's commercial victimisation survey. Furthermore,
there was a wide variation in reporting rates between crime types. For example,

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[3]In the spirit of full disclosure, it should be noted that my MRes dissertation on repeat extortion
victimisation (Estévez-Soto, 2015b)—and a precursor to this thesis—was awarded the prize for 'Best
Master's level dissertation' at an international dissertation competition organised by the Centre
of Excellence. The results of the dissertation were presented at the award ceremony at the 3rd
International Conference of Statistics on Government, Public Security, Victimisation and Justice
organised by the centre in June, 2016.

88.4% of all motor vehicle thefts[4] experienced by businesses were reported. In contrast, only 7.9% of all extortion incidents were reported to a competent authority. Therefore, it is quite likely that the estimates of extortion based on administrative statistics will be severely biased.

Another important disadvantage is that administrative statistics provided by SESNSP (2015) are not available in a disaggregated form (i.e. at the victim and incident level). Thus, it is not possible to analyse the patterns of repeat victimisation using such data. Lastly, and related to the previous point, the aggregated SESNSP (2015) data do not allow extortions committed against businesses to be distinguished from those experienced by households and individuals, nor do they allow 'remote extortion' incidents to be distinguished from the more serious 'in-person extortion' incidents (see Chapters 6 and 7).

Recent developments have seen the publication of disaggregated crime reports, including extortion, by an open data initiative of Mexico City's government.[5] These data have the advantage of being disaggregated at the incident level, which allows carrying out sophisticated spatiotemporal analyses. However, they have the same disadvantages of SESNSP (2015) administrative statistics regarding the extent of underreporting, and the inability to distinguish between extortions against businesses from those against households and individuals, and between remote and in-person extortions. Thus, they are unsuitable for the purposes of this study.

4.2.2 Mexico's Commercial Victimisation Survey – ENVE

Arguably, the most accurate and reliable measurements of extortion against businesses in Mexico are those provided by Mexico's National Commercial Victimisation Survey (*Encuesta Nacional de Victimización de Empresas*, ENVE) (see Jaimes Bello & Vielma Orozco, 2013, for a review).

The ENVE is, to my knowledge, the largest sample survey of business crime victimisation that is regularly conducted and provides a rare opportunity to subject extortion patterns to systematic quantitative analysis. The main objectives of the ENVE are (Jaimes Bello & Vielma Orozco, 2013, p. 166-167):

- To estimate the prevalence and incidence of crimes against business.

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[4]Motor vehicle thefts is the crime type with one of the highest reporting rates (Mosher et al., 2002). This is usually because insurance claims require victims to report the theft to a competent authority.

[5]Available at `https://datos.cdmx.gob.mx/pages/home/`. The open data initiative began on January 2019.

- To estimate the 'dark figure' of crimes against business and the reasons for not reporting crimes to the police.
- To collect information on the characteristics of crimes against businesses.
- To measure businesses' perception of safety in the areas they operate.
- To measure businesses' confidence in public security authorities.
- To measure fear of crime among businesses.
- And to estimate the cost of crimes against businesses.

The survey is designed to be representative at the national and subnational (state) level, and covers all economic sectors, with the exception of agriculture and the public sector. Regarding crime types, the survey covers 'the majority of common and complex crimes which could affect them' (Jaimes Bello & Vielma Orozco, 2013, p. 166), including:

- Theft of motor vehicles
- Theft of motor vehicle parts
- Robbery of merchandise in transport
- Shoplifting
- Robbery and burglary
- Other types of thefts and burglary
- Fraud
- Cybercrime
- Extortion
- Kidnapping (of owners and/or staff)
- Damages to premises
- Corruption or bribery
- Other types of crimes

The design and scope of the survey was developed by INEGI in close consultation with the business community and the Centre of Excellence in statistics established by INEGI and UNODC.

The ENVE is a premises-based survey, as opposed to a head offices-based survey (Burrows & Hopkins, 2005, p. 489), meaning that measurements are taken at the level of individual local units. Thus, in the case of a business with several premises (i.e. retail outlets, storage units, hubs, corporate offices), each location is considered as a different statistical unit subjected to sampling, and the crime experiences of each unit is counted independently. The only exception to this is in the case of

businesses in mining, transportation and construction, for which the sampling unit is the business (rather than specific premises) (INEGI, 2014c). The sampling frame is obtained from Mexico's national statistical directory of economic units, which is constructed from economic censuses conducted every 5 years.

The sampling approach is random with stratification according to business size.[6] Businesses are deliberatively over-sampled to account for non-response rates observed in the previous victimisation surveys (Jaimes Bello & Vielma Orozco, 2013, p. 173). ENVE sweeps have a response rate of around 85%, though this is mostly due to errors in the sampling frame (e.g. businesses that moved or closed and could not be found), as only around 1% of sampled businesses usually refuse to be interviewed (Jaimes Bello & Vielma Orozco, 2013, p. 173; INEGI, 2014b, p. 6-7).

Interviews are conducted face-to-face with a 'suitable informant', which corresponds to the highest-ranking person in micro and small businesses, and with security or finance managers in medium and large businesses. Computer assisted telephone interviewing (CATI) is used to follow up incomplete questionnaires (Jaimes Bello & Vielma Orozco, 2013, p. 167). Data collection occurs between May and July of a given year, and the reference period is the previous calendar year (e.g. if the survey was conducted between May and July of 2014, the measurements collected refer to crimes that occurred between January 1 and December 31, 2013). Interviewers undergo a specific training programme to ensure the data are reliably collected (Jaimes Bello & Vielma Orozco, 2013, p. 169).

As in other victimisation surveys, the ENVE interview consists of two parts. First, a main questionnaire is answered by all respondents. The main questionnaire collects the characteristics of businesses and respondents; measures the perception of security and fear of crime; gauges trust in the police and other security authorities; measures the prevalence and incidence of victimisation using the screening section; collects information on the effect of crime on business decisions; and estimates the prevalence and incidence of corruption victimisation (Jaimes Bello & Vielma Orozco, 2013, p. 170).

If a business reports a victimisation incident in the screening section, a second questionnaire—known as the victimisation form—is used to gather information about the context in which the crime took place, the level of violence involved, whether the crime was subsequently reported to an authority, and the costs that the business

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[6]Micro businesses have 10 employees or fewer; small businesses employ between 11 to 50 people (11 to 30 in commerce); medium businesses employ between 51 to 250 in industry, 31 to 100 in commerce, and 51 to 100 in services; large businesses are those with 101 or more employees (251 or more in industry).

incurred as a results of the victimisation experience (Jaimes Bello & Vielma Orozco, 2013, p. 170-171). The incidence figures captured in the screening section are un-capped, though the ENVE implements a cap of 7 incidents per crime type, and a total cap of 15 incidents per business in the victimisation forms.

According to Jaimes Bello and Vielma Orozco (2013, p. 173), interviews with non-victims took 25 minutes in average, whereas interviews with businesses that suffered at least one victimisation incident took 36 minutes in average. Minimising the time required for interviews was considered an important objective, as long interview times can lead to respondent fatigue and compromise the quality of the data collected (Jaimes Bello & Vielma Orozco, 2013, p. 173).

The ENVE has been conducted biennially since 2012. The studies presented in this thesis analysed the ENVE 2014 sweep (measuring crimes that took place in 2013), as this was the most recent dataset available when the current research project began. In the 2014 sweep, the sample size selected for the survey consisted of 33,479 business. After non-located businesses and non-response, the effective sample size was 28,179 businesses (INEGI, 2014b).

4.2.3   Limitations of the ENVE

Among the limitations of the ENVE are that measurements at the unit-level are cross-sectional, meaning that it is not possible to assess how victimisation risks change across time. Furthermore, while the measurements allow estimation of victimisation risks at the micro and the state-level, the data do not allow exploration of how risks vary at the spatial levels in between, such as cities and municipalities.

Another limitation is that the sampling frame only contains businesses with a fixed address in a permanent structure, thus the victimisation experiences of itinerant businesses in non-permanent structures (e.g. street vendors, pop-up shops, farmers' market stalls) are not captured by the survey.

The ENVE estimates of extortion are also affected by the limitations that all victimisation surveys suffer (detailed earlier in this chapter). Nonetheless, the ENVE attempts to mitigate them as best as possible. Nonresponse bias is not considered to be a cause for concern, as the sampling strategy tries to overcome this by oversampling, and the response rate is possibly the highest of any commercial victimisation survey.

Ambiguity in the understanding of crime types is addressed by the use of cards with the non-legal definitions of crime, while telescoping is addressed by the use of specific bounding references and bounding questions (Jaimes Bello & Vielma Orozco,

2013, p. 169). Further limitations of the ENVE are addressed in the analyses presented in the thesis.

While it is recognised that the extortion estimates captured by the ENVE are imperfect, they represent the best possible data source available to analyse the micro-level victimisation patterns of extortion against businesses.

4.3   Research settings

Though the data captured by the ENVE are part of the public domain, they are not publicly accessible, as access to the micro-level datasets is restricted by INEGI. This is because the combined characteristics of each respondent could potentially be used to infer the identity of individual respondents, even if responses to the survey are anonymised.

INEGI offers two options for researchers who need to use the ENVE data for analyses. They can access the data set in a secure data lab in INEGI's facilities in Mexico City, or they can remotely submit programming scripts for STATA or R, which are then run by INEGI staff in Mexico City. The analyses presented in this thesis were all conducted using the second option, with programming scripts for R (R Core Development Team, 2015).

The remote processing approach represented important challenges to the research project. First, it was not possible to work with the data interactively. This severely increased the time required to perform even the simplest analysis, as the programming scripts had to be developed, tested locally, sent to INEGI, run by INEGI staff, undergo revision to ensure the analyses did not compromise confidentiality, before results could be returned to the author. Initially, as I was not yet proficient in the development of programming scripts in the R language, the entire cycle from development to results could easily take up to two months. By the end of the research project, as my programming skills improved and the analyses became more refined, the development-to-results cycle was reduced to about two weeks.

Despite this improved turnaround time, analyses advanced slowly, as data analysis is an iterative cycle where later analyses normally build upon findings of previous ones. To minimise the frequency of remote processing requests (and thus minimise the amount of time waiting for results), programming scripts were developed with the goal of including all the exploratory analyses, statistical models, post-hoc checks and robustness tests required, anticipating potential errors and different scenarios if the data did not support a particular test (e.g. implementing a different type of

test if the assumptions were not met in an earlier test). However, this made the development of the programming scripts a more complicated and time-consuming process than it would otherwise have been.

A second challenge was the fact that the programming scripts had to be developed 'blind', without actual access to the data set, and thus it was not always guaranteed that the programmed routines would execute correctly. Though INEGI provides a detailed data dictionary, a synthetic data set mimicking the structure provided by the INEGI dictionary had to be constructed locally. This was required to test the programming scripts to ensure that any unforeseen errors could be addressed before they were sent for remote processing. Local tests were conducted exhaustively on Windows, Linux and macOS machines to ensure compatibility and reliability across platforms.

Despite this, unforeseen errors would occasionally occur. This required using a different programming paradigm instead of the sequential approach used in standard R scripts—which stops processing at the first error encountered. Thus, programming scripts were developed using Rmarkdown documents, which combine text with executable code 'chunks' and provide excellent error handling.

A third challenge was the lack of control over the settings in which the programming scripts were executed. This affected everything from the hardware capabilities and operative system of the computed used to run the analysis, to the software available to run the analysis. Programming scripts could be sent to be run in STATA or R. However, as STATA is proprietary software, there was less control over the particular version of STATA available (and the associated commands required for the analysis). The models used in the thesis—specifically multilevel negative binomial-logit hurdle models—are only available on the newest versions of STATA, which were not available in the research settings.

In contrast, as R is open-source software and is available in a free, non-commercial license, R offered much more flexibility to expand the resources available in the research settings. This allowed me to use bleeding-edge statistical packages as they became available throughout the research project. A downside of this flexibility is that R software is provided without warranty and some packages are still experimental, a situation I encountered when a particular analysis produced nonsensical results due to a bug. Lastly, as there was no control over the research settings, the code could not be optimised for speed using parallel processing and other techniques, which meant the analyses took longer, further increasing the turnaround time required in the development-to-results cycle.

Nonetheless, the entire process was made as painless as possible by the excellent standard of service offered by INEGI staff who were always ready to assist.

The remote processing workflow also offered important advantages. Not being able to work interactively also forced the analysis to be more strategic and carefully considered. It minimised the opportunities for embarking on 'fishing expeditions', and forced me to think carefully about the research design choices made before the analysis was actually conducted.

The approach also ensured that the results presented herein are reproducible, as all analyses had to be written in a reproducible format. The programming scripts used to generate the analyses presented in this thesis were subsequently published in online repositories (Estévez-Soto, 2015a, 2016, 2018, 2019a, 2019b).

Chapter 5

A hurdle model of repeat extortion victimisation

This chapter offers preliminary answers to the first two research questions presented in Chapter 2: Does extortion victimisation exhibit repeat victimisation patterns beyond what would be expected by chance? And, what mechanisms could explain repeat extortion victimisation? Repeat victimisation is one of the most consistent findings in crime research, yet it is not known if the same patterns of victim concentration apply to extortion against businesses. This study has two aims. First it aims to identify whether repeat extortion victimisation occurs at a rate that exceeds chance. If this is the case, the study then aims to identify the mechanisms driving extortion concentration using a multilevel negative binomial-logit hurdle model.

5.1   Background

Decades of research suggest that crime is concentrated on a small proportion of places (Lee et al., 2017) and victims (SooHyun et al., 2017). However, it is unclear how universal this empirical pattern might be across countries, as well as crime and target types, as most research has focused on the US and Canada, a handful of European cities, and Australia[1] (e.g. Andresen et al., 2016, 2017; Curman et al., 2015; Farrell, Tseloni, & Pease, 2005; Johnson & Bowers, 2010; Lynch et al., 1998; Perreault et al., 2010; Sagovsky & Johnson, 2007; Tseloni et al., 2004), and on 'traditional' crimes

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[1]Only a small number of recent studies have examined patterns in radically different contexts such as Brazil (Melo et al., 2015), Malawi (Sidebottom, 2012), Taiwan (Kuo et al., 2012) and South Korea (Park, 2015).

against individuals and households[2] (e.g. Daigle et al., 2008; Johnson et al., 1997; Kleemans, 2001; Osborn & Tseloni, 1998; Tseloni et al., 2002; Tseloni & Pease, 2003, 2004; Tseloni et al., 2004; Young & Furman, 2007).

In particular, there is a notable scarcity of research that has systematically studied the concentration of organised crimes, an area of study that could benefit considerably from more rigorous quantitative assessments (Sansó-Rubert Pascual, 2017, p. 29-30). Thus, this study is concerned with understanding the concentration patterns of extortion—an archetypal organised crime (Tilley & Hopkins, 2008, p. 449). Specifically, it examines patterns of extortion among Mexican businesses to determine if concentration occurs, and if it does, to determine the factors that may explain it.

As discussed in Chapter 2, current research suggests that repeat victimisation is driven by two mechanisms: *Risk heterogeneity* (Johnson, 2008; Pease, 1998) proposes that enduring differences in target characteristics make some targets more attractive than others; while *event dependence* (Johnson, 2008; Pease, 1998) suggests that the risk of victimisation is dynamic, with the risk to victimised targets increasing—at least temporarily—following an initial offence.

Though studies have found that both mechanisms have a part to play (e.g. Johnson, 2008; Lauritsen & Davis Quinet, 1995; Lynch et al., 1998; Pitcher & Johnson, 2011; Tseloni & Pease, 2003, 2004), it is generally assumed that the risk factors associated with victimisation *prevalence*—the likelihood of becoming a victim—also explain its *concentration*—the number of incidents per victimised target (Pease & Tseloni, 2014, p. 31). Thus, analytic studies generally focus on explaining *incidence*—the number of incidents per potential target—using a single set of predictors to examine the entire distribution of crime, rather than examining whether the predictors that differentiate victims from non-victims do explain the amount of crime suffered by victimised targets (Pease & Tseloni, 2014, p. 31).

However, this assumption is largely based on previous findings concerning household property crimes (Osborn, Ellingworth, Hope, & Trickett, 1996), and it is unlikely to apply in the case of extortion. To explain, extortion requires the victim's cooperation for the offender to succeed (Best, 1982, p. 109), thus repetition may be influenced by a victim's level of cooperation (which can only be observed through interaction), rather than by a stable set of characteristics. Furthermore, extortion is

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[2]For exceptions see Andresen et al. (2017), Bowers et al. (1998), van Dijk and Terlouw (1996), Salmi et al. (2013), Burrows and Hopkins (2005), Gill (1998), Hopkins and Tilley (2001), Matthews et al. (2001), and Yu and Maxfield (2014).

often characterised as a long-term relationship between victims and offenders (Elsenbroich & Badham, 2016; Kelly et al., 2000, p. 64); thus, repetition may be unaffected by stable risk factors once an extortive relationship has been established.

To examine this, this study uses data from Mexico's national commercial victimisation survey to trial a novel modelling strategy—the multilevel negative binomial-logit hurdle model—to compare whether the predictors associated with the likelihood of extortion victimisation are also associated with the number of repeat extortions suffered by businesses. If predictors are inconsistent across the two measures, this would suggest that extortion concentration is fuelled by a process distinct from that which might explain extortion prevalence.

Thus, this study contributes towards expanding our understanding of micro-level patterns of crime concentration in two ways. First, to my knowledge, this study represents the first application of a multilevel negative binomial-logit hurdle model to study crime concentration,[3] highlighting its potential usefulness to study other crime types where repetitions are thought to be driven by distinct processes—such as domestic violence[4] (Biderman, 1980; Rand & Saltzman, 2003). Second, the study contributes to the literature on crime concentration by examining whether or not the patterns consistently observed elsewhere also apply to: a) a crime type that has received little research attention, and b) a country that has so far been neglected in the literature.

The chapter proceeds as follows. In the next section I review the literature on modelling repeat victimisation, and on the predictors of extortion victimisation. The next section covers the data and analytical strategy employed, followed by the research findings and a discussion of their implications and limitations.

5.2 Modelling repeat victimisation

Most early approaches to modelling victimisation focused on the prevalence of victimisation. These studies applied logistic regression to identify the factors associated with the risk of being victimised (e.g. Maxfield, 1987a; Miethe, Stafford, & Long,

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[3]However, the approach has been used in crime research to study sentencing (Hester & Hartman, 2017; Rydberg, Cassidy, & Socia, 2017), intimate partner violence (Hellemans, Loeys, Dewitte, De Smet, & Buysse, 2015), specific types of homicides (Baller, Zevenbergen, & Messner, 2009; Guerrero-Gutiérrez, 2011), and the influence of incarceration on health care availability (Wallace, Eason, & Lindsey, 2015).

[4]Though Hellemans et al. (2015) used hurdle models in a study of intimate partner violence (IPV), their study is focused on the relationship between lifetime experience with IPV and victims' relational and sexual well-being, and does not address the factors associated with IPV repeat victimisation.

1987). Such approaches, however, disregard the differential risks associated with repeat victimisation (Pease & Tseloni, 2014, p. 35). Pease and Tseloni (2014, p. 35) ascribe this to the fact that the significance of repeat victimisation had been somewhat neglected, and to a lack of accessible statistical tools and techniques suitable for the analysis of count data.

Crime incidents are recorded as discrete counts with a lower bound of zero, requiring special modelling frameworks such as the Poisson (e.g. Berk & MacDonald, 2008; MacDonald & Lattimore, 2010). Furthermore, incidence data tend to be heavily right-skewed, with many observations for zero incidents and a long tail with few observations for targets that suffered many incidents. This leads to overdispersion, which occurs when the variance of a distribution exceeds its mean (Cameron & Trivedi, 2013, p. 4; Hope & Norris, 2012, p. 544). The implication of this for modelling is that the standard Poisson model (which assumes that the mean of a distribution equals its variance) can generate erroneous standard errors (Rydberg & Carkin, 2016, p. 63).

Thus, the preferred distribution to model crime incidence is the negative binomial (see Pease & Tseloni, 2014; Tseloni, 1995). This allows overdispersion to be incorporated via a dispersion parameter (see Section 5.6), which captures unexplained differences in crime incidence between two targets that are otherwise identical in terms of the covariates included in the model (hereafter 'unexplained heterogeneity', Osborn & Tseloni, 1998). This modelling approach has been further strengthened by the use of multilevel[5] models (e.g. Goldstein, 2011) which can incorporate hierarchically structured and repeated measures data and can help (in the context of crime and place) distinguish how much unexplained heterogeneity can be attributed to area and individual-level sources.

With this modelling framework, studies test the risk heterogeneity hypothesis by incorporating covariates thought to affect a target's expected victimisation incidence. For example, in a study on burglary victimisation across Europe, Tseloni and Farrell (2002) used a multilevel negative binomial model to investigate the effects of household and country-level characteristics on burglary incidence in eight European countries. Controlling for the effect of previous victimisations, the study found significant sources of risk heterogeneity consistent with the routine activities theory: absence of guardianship (e.g. being single or divorced), being close to likely offenders (as measured by household poverty), and increases in target attractiveness

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[5]Terminology varies according to specific disciplines, but multilevel models are also known as mixed effects models and hierarchical linear models (Bell, Ferron, & Kromrey, 2008, p. 1112).

(e.g. car ownership as a sign of household affluence) were associated with increases in burglary incidence, to cite a few examples (Tseloni & Farrell, 2002, p. 156-157). Furthermore, the study also found there was essentially no unexplained heterogeneity due to between-country differences, meaning that unexplained differences in burglary risk were likely due to target and subnational (e.g. city or region) level differences (Tseloni & Farrell, 2002, p. 155-156).

Event dependence, on the other hand, can be tested by incorporating the temporal dimension using longitudinal data (Lynch et al., 1998, p. 15). While Tseloni and Farrell (2002) included measures of previous victimisation experiences, the cross-sectional nature of the data they used (the International Crime Victims Survey, see Mayhew & van Dijk, 2014) impeded their ability to explicitly model the effects of event dependence on crime incidence (see Lynch et al., 1998). Studies that have employed longitudinal victimisation data (i.e. repeated interviews with the same target), have found that prior victimisation is a significant predictor of future victimisation, even after controlling for risk heterogeneity (e.g. Lauritsen & Davis Quinet, 1995; Lynch et al., 1998; Tseloni & Pease, 2003, 2004).

However, most victimisation surveys employ cross-sectional designs (Lynch, 2006, p. 249; Mayhew & van Dijk, 2014, p. 2604). In practice, this means that models based on cross-sectional data—the type of data used in this study—cannot conclusively distinguish between event dependence and risk heterogeneity, lumping the effects of the former with those of unexplained heterogeneity (Heckman, 1981; Osborn et al., 1996; Osborn & Tseloni, 1998; Pease & Tseloni, 2014).

A potential workaround initially considered to explore the effect of event dependence in the absence of longitudinal data was to assess whether the factors that explain one-time victimisations differ from those that explain repeated incidents. In a seminal paper, Osborn et al. (1996) employed a 'double hurdle' bivariate probit model to compare the transition probabilities from non-victim to victim and from one-time victim to repeat victim for household property crimes, but found that the predictors of first and repeated victimisations were generally the same (Osborn et al., 1996, p. 243). This finding has been influential in subsequent studies and is widely cited as a justification to use a single set of predictors to explain the entire distribution of crime incidents (e.g. Tseloni et al., 2002, p. 113; Pease & Tseloni, 2014, p. 31; Tseloni & Pease, 2014, p. 5).

However, this consensus fails to consider that the effect and relative contributions of risk heterogeneity and event dependence to repeat victimisation may vary considerably across different crime types (Johnson, 2008, p. 236). One of the most

parsimonious explanations for event dependence draws from the fact that offenders often return to victimise past targets (Bernasco, 2008; Everson & Pease, 2001), suggesting that the choice of future targets is influenced by previous experience (Bernasco, 2008; Johnson, 2014; Johnson, Summers, & Pease, 2009).

It follows that the contribution of event dependence will likely be higher for crimes where 'the effort and/or risk of a second offence is clarified by victim response to a first offence' (Farrell et al., 1995, p. 396). For example, in a study of bank robbery, Matthews et al. (2001) found that success in past robberies was positively associated with future incidents—the amount stolen in past incidents adequately predicting future risk. Thus, as extortion is a crime where success depends on a victim's (reluctant) willingness to cooperate (Best, 1982, p. 109), the manner in which the victim responds may have a strong bearing on an offender's decision to repeat the offence against the same target. For example, compliance in one incident could beget further victimisations as the victim is known to be lucrative and responsive.

Furthermore, the importance of event dependence is likely to be decisive in crimes where repeated victimisations are the product of an ongoing relationship between victims and offenders, such as recurrent violent episodes framed within an abusive relationship (Biderman, 1980, p. 29; Rand & Saltzman, 2003). It is likely that extortion falls within this category of offences, as repeated extortions are often characterised as an ongoing condition (Biderman, 1980, p. 29; Elsenbroich & Badham, 2016; Kelly et al., 2000, p. 64). Thus, concentration on repeatedly extorted targets may be unaffected by risk heterogeneity and instead indicate that such an enduring relationship exists. Therefore, it is conceivable that the risk factors for extortion prevalence may be distinct from those that affect extortion concentration, which warrants a modelling strategy that is able to differentiate such mechanisms.

5.3   A hurdle model of extortion victimisation

The hurdle model (Cameron & Trivedi, 2013; Mullahy, 1986) is a suitable alternative for distinguishing the factors that influence prevalence from those that influence concentration. These models (unrelated to the 'double hurdle' bivariate probit used by Osborn et al., 1996) combine two processes: one that generates positive counts (≥ 1) versus zero counts ($= 0$); and another that generates only positive counts (≥ 1) (Hilbe, 2011, p. 355). The first process corresponds to the prevalence risk and is usually modelled using logistic regression, whereas the second estimates concentration

using a truncated count model—usually the truncated-at-zero negative binomial, as the distribution remains overdispersed (Cameron & Trivedi, 2013).

An alternative is the zero-inflated model (Lambert, 1992). Zero-inflated models are similar to the hurdle framework insofar as they consider that counts are produced by a mixture of two distinct mechanisms. However, these types of model were developed to handle a specific problem encountered with some data—excess zeroes (e.g. Hilbe, 2011, p. 355; Park & Fisher, 2015, p. 1138; Tseloni & Pease, 2014, p. 22). Rather than explicitly distinguishing between the processes that lead to prevalence and concentration, zero-inflated models consider that there is one process granting 'immunity' to some targets, and a second that determines the incidence of victimisations that non-immune targets experience (e.g. Park, 2015; Park & Fisher, 2015). Crucially, the process generating counts does not only estimates positive counts, but zero counts as well. The latter correspond to targets that, although not deemed to be statistically immune to victimisation, did not experience any incidents during the period sampled.

Thus, given that zero-inflated models do not explicitly distinguish prevalence from concentration, they cannot determine whether predictors are constant across both measures, and as such are unsuitable for the purposes of this study. Furthermore, the data used in the current study showed no signs of zero-inflation when compared to a negative binomial expectation (see Section 5.7), and hence would also be unsuitable for this reason.

In contrast, hurdle models first estimate the risk of victimisation prevalence across all targets, and then estimate the concentration of incidents experienced by victimised targets. If victimisation patterns are taken as an indirect measurement of offender-decision making (Hough, 1987), then the hurdle model allows indirectly testing of whether the factors that influence victim-selection decisions are distinct from those that affect the decision to target past victims.[6] Such an interpretation would be consistent with the effect of event dependence discussed above, where the decision to commit a repeat extortion is associated with the outcome of the first extortion attempt. Similarly, the hurdle model can also be seen as a more appropriate model of an extortive relationship, with predictors for prevalence explaining the risk of being initially targeted for an extortive relationship, and the predictors for concentration explaining how much exploitation businesses can expect once the relationship has been established.

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[6]Assuming that repeats are the product of the same offenders, a somewhat reasonable assumption (Bernasco, 2008).

In any case, to empirically assess if extortion exhibits a pattern of repeat victimisation consistent with the hurdle framework, the observed distribution of extortion must first be shown to exceed chance expectation, as some level of repeat victimisation is to be expected by chance. Thus, the first hypothesis is:

- **H1:** There are significantly more repeat extortion incidents than would be expected on the basis of random victimisation.

If repeat extortion is found to be non-random—and given that the role of event dependence is expected to be more prominent in the case of extortion, and that extortion often leads to enduring victim-offender relationships—I expect that once a business is victimised, extortion concentration will not be consistently associated with the predictors of extortion prevalence.

- **H2:** Once a business is extorted, the predictors that explain extortion prevalence are different from those that explain extortion concentration.

5.4 Predictors of extortion victimisation

Analyses of repeat victimisation (e.g. Tseloni & Farrell, 2002) have found that victim-level characteristics tend to be more important predictors of victimisation risk than area-level characteristics. However, as discussed in Chapter 2, most of the research on extortion from the organised crime literature approaches the phenomenon as a form of extra-legal governance exerted by criminal groups, whereby businesses operating in territories controlled by criminal groups are subjected to an illicit 'tax' in exchange for 'protection' (Frazzica et al., 2013; Kleemans, 2018; Savona & Sarno, 2014).

Kleemans (2018, p. 874), for example, notes that the concentration of extortion racketeering occurs at the level of territory, rather than the 'specific point in space where an offender meets a target'. Thus, it would appear that a sensible starting point to model extortion concentration would be at the macro-level. It is important to note that this review does not aim to list all possible sources extortion risk, but to identify variables that may be used to test H2.

5.4.1 Macro-level influences

If extortion is a form of 'alternative governance' exerted by organised crime groups in the absence of legitimate governance structures (Gambetta, 1993; Kleemans, 2013;

Paoli, 2002; Varese, 2014), then a potential predictor of extortion risk at the macro-level is the 'strength' of legitimate governance structures across Mexican states (Skaperdas, 2001; Sung, 2004).

Furthermore, researchers have noted that beyond the presence of the state, the quality of legitimate governance matters, with widespread predatory government corruption linked to increased extortion risks (e.g. Díaz-Cayeros, Magaloni, & Romero, 2015; Frye & Zhuravskaya, 2000; Morris, 2013; Tulyakov, 2001).

In addition, as detailed in Chapter 3, Mexican organised crime groups tend to specialise into two broad types: those that remain mostly focused on drug trafficking, and those that are more reliant on Mafia-style 'protection' and extortion (Corcoran, 2013; Guerrero-Gutiérrez, 2011; Jones, 2016). Thus, an increased prevalence of drug trafficking may be negatively associated with extortion risks. On the other hand, given the reliance of criminal groups on a violent reputation to induce extortion payments (Guerrero-Gutiérrez, 2011, 2012; Jones, 2016), extortion risks may be higher where organised crime groups have a greater capacity to inflict violence.

While such macro-level variables may explain why businesses in different areas of the country may face different levels of extortion risk, they cannot explain why businesses *within* the same area might face systematically different extortion victimisation risks. Thus, it is also important to examine how micro-level variables could be associated to differential extortion risks.

5.4.2 Micro-level influences

Though the literature on extortion is not primarily focused on patterns at the micro-level, it is recognised that victim selection is not random, and is instead guided by victim vulnerability (La Spina et al., 2014; Savona, 2012; Savona & Sarno, 2014). While no research exists that has systematically analysed business-level explanations for extortion risk in the Mexican context, findings from other contexts suggest predictors for this study:

- *Corruption victimisation:* While corruption at the macro-level suggests an indirect relationship between the quality of governance and extortion risk, the often close relationship between organised criminals and government officials in Mexico (Díaz-Cayeros et al., 2015, p. 255-256; Morris, 2013) suggests that a direct relationship between extortion and corruption victimisation at the micro-level is also plausible. Alternatively, a relationship at the micro-level could be due to the presence of a variable independently affecting extortion and corrup-

tion risk—e.g. a vulnerability that separately attracts both extortionists and corrupt officials. This would be consistent with findings on multiple victimisation that suggest not only that a) specific types of crime are concentrated on a small subset of targets, but also that b) those who repeatedly suffer one type of crime are more likely to suffer other types (Tseloni et al., 2002).

- *Business age:* The literature suggests that older businesses may be somewhat protected from extortion due to long-standing ties developed in their communities (and hence with organised criminals that operate there) (Varese, 2011a, 2014), and that new businesses may inadvertently attract organised criminals by drawing attention to themselves through opening ceremonies or advertising (Chin, 2000; Chin et al., 1992).

- *Business type:* Research on extortion by the Italian Mafia (e.g. Di Gennaro & La Spina, 2016; Frazzica et al., 2013; La Spina et al., 2014) and Chinese gangs (e.g. Chin, 2000; Chin et al., 1992; Kelly et al., 2000) suggests that some business types—particularly restaurants, hotels and bars—are at especially high risk of extortion. It is assumed that these business types are particularly at risk due to being inherently vulnerable to intimidation (Schelling, 1971, p. 648–649).

- *Business size:* Several studies have found business size to influence crime risk in general and extortion in particular, however the precise mechanism behind this relationship is unclear. Gill (1998) notes that small businesses in the UK suffer disproportionally more crime, which may suggest that risk is related to victim vulnerability. Yet, there is also evidence pointing to elevated extortion risks for larger businesses (Broadhurst et al., 2011; Kelly et al., 2000), which suggests that extortionists might select victims on the basis of potential rewards. I speculate that there is a trade-off between vulnerability and profitability: while smaller business may be more vulnerable, they offer fewer potential rewards making them less attractive to extortionists.

In the next sections, I discuss the data analysed and the analytical strategy adopted.

5.5   Data and measures

The primary data analysed are from the 2014 sweep of Mexico's nationally representative commercial victimisation survey, the *Encuesta Nacional de Victimización*

de Empresas (see Section 4.2.2 for more detail). The survey is conducted biennially, sampling all business sectors except agriculture and the public sector. The first part of the survey, the main questionnaire, records the prevalence and incidence of crimes suffered by respondents during the previous calendar year (in this case, 2013). The victim form focuses on information concerning each incident of victimisation (though the survey is capped at 7 victim forms per crime type per victim, Jaimes Bello & Vielma Orozco, 2013). The study analysed responses captured in the main questionnaire, as these offer a readily available uncapped summary of victimisation experiences[7] (Farrell & Pease, 1993; Trickett et al., 1992).

Access to the anonymised individual responses collected by the ENVE is restricted by INEGI, as the combined characteristics of each respondent could potentially be used to infer their identity. To ensure reproducibility, all of our analyses were conducted using automated R scripts and remotely processed by INEGI staff in Mexico City on a Windows (64 bit) platform and R version 3.1.1 (R Core Development Team, 2015).

5.5.1 Dependent variable

The dependent variable is the number of incidents of extortion suffered by surveyed businesses. The ENVE defines extortion as 'any kind of threat or coercion committed against the local unit's owner or staff for the purpose of obtaining money, goods or forcing them to do or stop doing something' (Jaimes Bello & Vielma Orozco, 2013, p. 172). This definition is similar to that adopted by Chin et al. (1992, p. 629) in a victimisation survey of businesses in New York 'Chinatowns,' insofar as it treats 'demanding money or the provision of goods and services to avoid violence or harassment' as the working definition of extortion. Given that only licit businesses were sampled, this study does not consider extortions committed against other criminal actors or enterprises.

The prevalence rate was 80.46 victims per 1,000 businesses, whereas the incidence rate was 132.77 incidents per 1,000 businesses. The concentration rate was thus 1.65 extortions per victim. However, the distribution of extortion, shown in Table 5.1, reveals that extortion victimisation is far more concentrated than such summary statistics would suggest. Repeat victims—i.e., businesses that suffered two or more extortion incidents in 2013—constituted 2% of all respondents (27% of victims) but accounted for 56% of all extortion incidents. Businesses that experienced three or

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[7]To prevent the risk of misclassification, interviewers provide respondents with an index card detailing the different crime types and their non-legal definitions (INEGI, 2014c).

Table 5.1:   The distribution of extortion victimisation, and the percentage of potential targets affected.

Events	Prevalence	Incidence	Target %	Victim %	Incident %
0	25895	–	91.953	–	–
1	1654	1654	5.873	72.992	44.236
2	338	676	1.200	14.916	18.080
3	139	417	0.494	6.134	11.153
4	55	220	0.195	2.427	5.884
5	22	110	0.078	0.971	2.942
6	12	72	0.043	0.530	1.926
7	3	21	0.011	0.132	0.562
8	8	64	0.028	0.353	1.712
10	20	200	0.071	0.883	5.349
12	3	36	0.011	0.132	0.963
15	4	60	0.014	0.177	1.605
20	3	60	0.011	0.132	1.605
24	1	24	0.004	0.044	0.642
25	1	25	0.004	0.044	0.669
30	2	60	0.007	0.088	1.605
40	1	40	0.004	0.044	1.070
Totals	28161	3739	100%	100%	100%

more incidents amounted to less than 1% of the sample (12% of victims), yet suffered 38% of all incidents of extortion. Moreover, the distribution clearly exhibits overdispersion (Cameron & Trivedi, 2013, p. 4), with its variance (0.547) being more than four times larger than its mean (0.133).

5.5.2   Independent variables

Given the potential predictors identified in an earlier section, four macro-level variables measured at the state level (*rule of law*, *corruption prevalence*, *federal weapon crimes*, and *federal drug crimes*), and four micro-level variables measured at the level of individual business units (*corruption victimisations*, *years in business*, *business type*, and *business size*) were operationalised as independent variables. I included three additional macro-level variables (*number of surveyed businesses*, *population* and *competitiveness*[8]) as controls. Table 5.2 presents descriptive statistics for the independent variables, while Figure 5.1 presents a series of thematic maps summarising how these variables, as well as key indicators of extortion, vary across Mexico.

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[8]I used a modified version of IMCO's competitiveness index (IMCO, 2016) that assesses states on a 100 point scale (higher is better) according to their 2013 performance in nine subindices measuring business friendliness. The version I used excluded the rule of law component as this is used as a dependent variable.

Table 5.2: Descriptive statistics of independent variables.

Variable	Obs.	%	Mean	S.D.	Min.	Max.
Business-level variables						
Corruption victimizations	28161		0.1	1.3	0	98
Years in business						
0 to 5 (*base*)	6772	24.0%				
6 to 9	5921	21.0%				
10 to 14	4984	17.7%				
15 to 23	5500	19.5%				
24 to 212	4984	17.7%				
Business type						
Retail (*base*)	10088	35.8%				
Mining	89	0.3%				
Construction	820	2.9%				
Manufacturing	3707	13.2%				
Wholesale	1952	6.9%				
Transport	720	2.6%				
Media	259	0.9%				
Finance	318	1.1%				
Real estate	417	1.5%				
Prof. services	753	2.7%				
Maintenance	908	3.2%				
Education	955	3.4%				
Health	1157	4.1%				
Leisure	316	1.1%				
Hotels, Rest. & Bars	2787	9.9%				
Other	2915	10.3%				
Size						
Large (*base*)	3052	10.8%				
Medium	3640	12.9%				
Small	5840	20.7%				
Micro	15629	55.5%				
State-level variables						
Corruption prevalence	32		40.1	18.4	14	101
Federal weapon crimes	32		559.6	451.6	31	1632
Federal drug crimes	32		526.9	871.7	37	3738
Rule of law index	32		54.4	13.3	21.4	78.4
Competitiveness index	32		47.7	8.5	25.3	67.8
Population (in millions)	32		3.7	3.15	0.7	16.4
N sampled businesses	32		880.6	236.4	534	1657
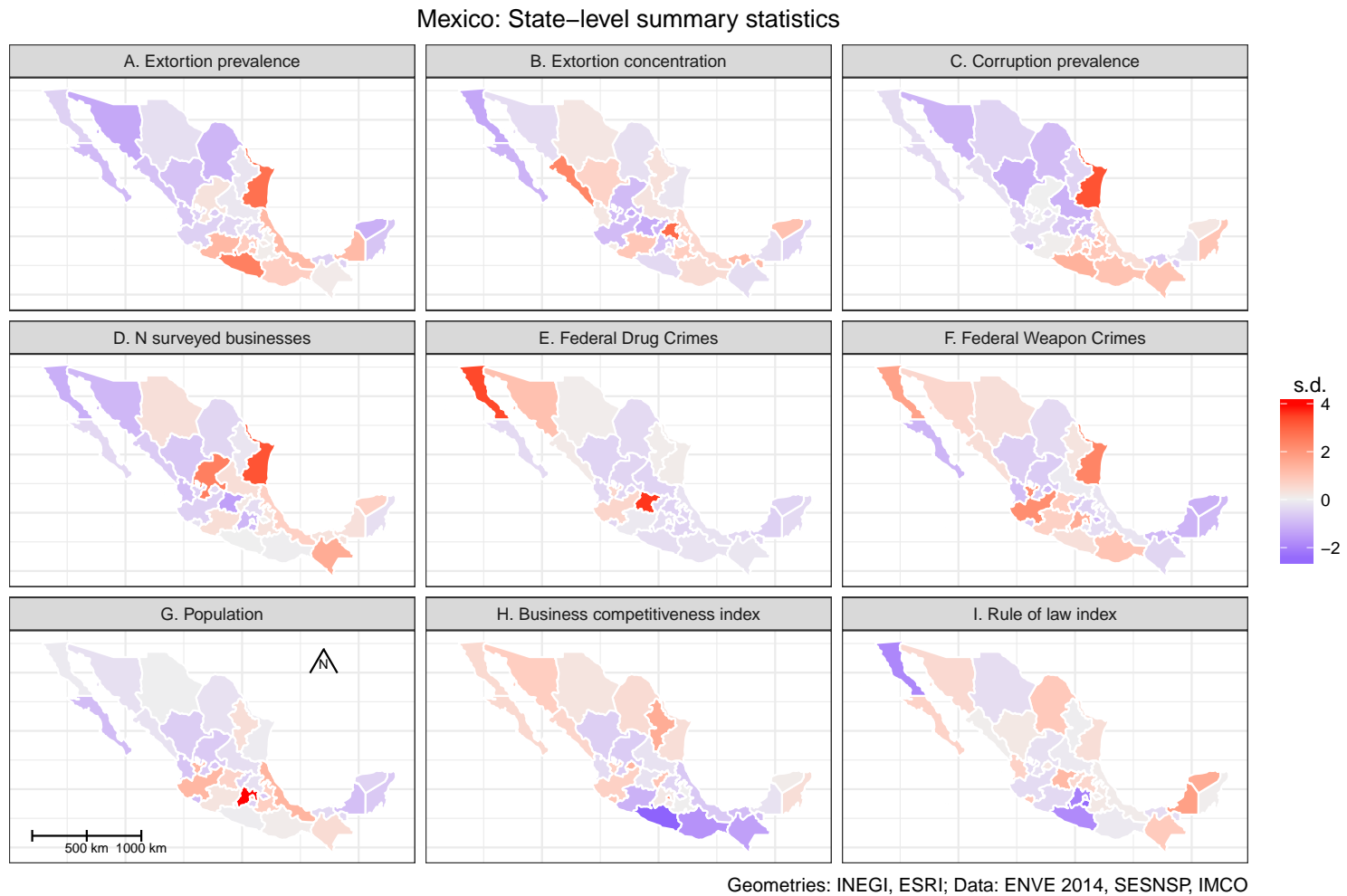
Figure 5.1: Thematic maps showing variations in state-level variables, and state-level measures of extortion.

5.5.2.1 Macro-level variables

- *Rule of law*: To measure the strength of the legitimate governance structure, I used a rule of law index obtained from the Mexican Institute for Competitiveness (*Instituto Mexicano para la Competitividad*, IMCO, 2016), a think tank.[9]
- *Corruption prevalence*: Measures the number of businesses in a state that reported being the victim of corruption in the ENVE.
- *Federal drug crimes*: To estimate the amount of drug trafficking activities in each state, I used the number of crimes per state related to the General Health Law (used to regulate prohibited substances) as reported in 2013 by the Attorney General's Office (*Procuraduría General de la República*, PGR) to the Executive Secretariat of the National System for Public Security (*Secretariado Ejecutivo del Sistema Nacional de Seguridad Pública*, SESNSP, 2015).
- *Federal weapon crimes*: The number of crimes relating to the Federal Law on Firearms and Explosives as reported for 2013 by the PGR to the SESNSP (2015). This variable serves as a proxy measurement of organised crime groups' capacity to inflict violence, as such crimes refer to those involving automatic weapons—as well as seizures of such weapons and ammunition—traditionally associated with organised crime groups.

The state-level variables weapon crimes, drug crimes, corruption prevalence, population, and the number of surveyed businesses were log-transformed to reduce overdispersion. All state-level variables were centred around the national mean[10] to facilitate interpretation.

5.5.2.2 Micro-level variables

- *Corruption victimisations:* Captured as counts in the ENVE by the question: 'In total, how many separate acts of corruption did you suffer during 2013?' (INEGI, 2014e). An act of corruption refers to a situation where a public servant—or a third party acting on their behalf—directly asked for, suggested,

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[9]I used a revised version of the index grading states on a 100 point scale (higher is better) based on 2013 measures of kidnapping incidence, vehicle theft, costs of crime, total personal and household crime incidence, the dark figure, fear of crime, availability of notaries, and contract enforcement. I excluded homicide rates in the revised index, as these were collinear with our other independent variables.

[10]Log transformed variables were centred around the log of the national mean ($log(x) - log(\bar{x})$).

or set the conditions for the payment of a bribe by the business (INEGI, 2014e; Jaimes Bello & Vielma Orozco, 2013).

- *Years in business:* Calculated by subtracting the year respondents reported that their business started operations from the survey reference year (i.e. 2013). As our interest is modelling the effect of being a new business in comparison to older businesses, rather than the effect of an additional year in business, nominal categories were considered more appropriate. Thus, businesses were binned into quintiles from the 20% youngest to the 20% oldest.
- *Business type:* Captured according to the North American Industrial Classification System's second level[11] (*Sistema de Clasificación Industrial de Norte América*, SCIAN, INEGI, 2007).
- *Business size:* Categories (micro, small, medium and large) were provided by INEGI (2014b) and are based on the number of employees reported by each business.[12]

5.6 Analytical strategy

The analysis was conducted in two parts. First, using an implementation of the Kolmogorov-Smirnov test (KS test, Upton & Cook, 2014b) for discrete distributions proposed by Arnold and Emerson (2011), I assessed H1 by comparing the observed distribution of extortion to that expected under the null hypothesis of random victimisation—the latter estimated by a Monte Carlo simulation of a Poisson process with 500 replicates. Additionally, to assess if the observed distribution presented more zeroes than expected, I compared the observed prevalence to that expected under simulated Poisson and negative binomial distributions using contingency tables.

Next, I used statistical modelling to assess H2. The standard model used to

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[11]The categories are, in industry: mining, construction, and manufacturing; in commerce: retail and wholesale; in services: transport, media, finance and insurance, real estate, professional scientific and technical services, maintenance providers, education, health, leisure, restaurants, hotels and bars, and other services. Observations corresponding to 18 businesses classified as utilities and corporate offices were excluded as there were problems of complete and quasi-complete separation, which occur when a categorical variable perfectly (or almost perfectly) predicts the value of the dependent variable.

[12]Micro businesses have 10 employees or fewer; small businesses employ between 11 to 50 people (11 to 30 in commerce); medium businesses employ between 51 to 250 in industry, 31 to 100 in commerce, and 51 to 100 in services; large businesses are those with 101 or more employees (251 or more in industry).

estimate victimisation counts is the multilevel negative binomial[13] model (MNB)
(Tseloni & Farrell, 2002). Considering y_{ij} is the count of extortion victimisations
suffered by the ith business, in the jth state, and that x'_{ij} is a vector of covariates
thought to determine y_{ij}, the MNB model for the mean of event counts, $\mathrm{E}[y_{ij}|x'_{ij}] = \mu_{ij}$, can be represented by:

$$ln(\mu_{ij}) = \beta_0 + \beta_1 x'_{ij} + u_{0j} + \varepsilon_{ij}$$

$$u_{0j} \sim N(0, \sigma^2_{u_0})$$
$$exp(\varepsilon_{ij}) \sim \Gamma(1, \alpha)$$

(5.1)

where β_0 is the intercept, and β_1 is a vector of fixed regression coefficients that
quantify the relationship between x'_{ij} and $ln(\mu_{ij})$. u_{0j} is the random variation in
β_0 associated with each state j, and ε_{ij} is a gamma distributed error term that
incorporates overdispersion via the α parameter (see Cameron & Trivedi, 2013; Hilbe,
2011; Tseloni & Farrell, 2002). The probability function of the MNB model (see
Cameron & Trivedi, 2013; Hilbe, 2011) is given by:

$$\Pr[y_{ij}|x'_{ij}] = \frac{\Gamma(y_{ij} + \alpha^{-1})}{\Gamma(y_{ij} + 1)\Gamma(\alpha^{-1})} \left(\frac{1}{1 + \alpha\mu_{ij}}\right)^{\alpha^{-1}} \left(1 - \frac{1}{1 + \alpha\mu_{ij}}\right)^{y_{ij}}$$

(5.2)

When $\alpha \to 0$, the probability function collapses to the Poisson (Cameron &
Trivedi, 2013, p. 85), meaning that there is no business-level unexplained hetero-
geneity. Conversely as α becomes larger, unexplained heterogeneity between busi-
nesses increases. Heterogeneity at the state level is captured by $\sigma^2_{u_0}$, and the formula
$\rho = \sigma^2_{u_0}/(\sigma^2_{u_0} + \alpha)$, allows the calculation of the intra-class correlation (ICC), which
represents the correlation of the mean of extortion incidents between two identical
businesses in the same state (see Goldstein, 2011; Tseloni & Farrell, 2002). Con-
versely, the inverse of the ICC, $1 - \rho$, represents the probability of two identical
businesses anywhere in the country experiencing the same number of extortion vic-
timisations, after controlling for between-state differences.

I hypothesised (H2) that extortion concentration is produced by a process differ-
ent from that which generates extortion prevalence, thus the MNB model is unsuit-
able for the purposes of the study—as it uses the same probability function (eq. (5.2))
for all values of y. The multilevel negative binomial-logit hurdle model (MNB-LH),
in contrast, is a suitable alternative. The fundamental logic underpinning hurdle

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[13]The standard NB2 formulation of the negative binomial variance function was used: $\sigma^2_{ij} = \mu_{ij} + \alpha\mu^2_{ij}$ (Cameron & Trivedi, 2013).

models (Mullahy, 1986) is that they allow the specification of distinct probability functions for observations where $y = 0$, and $y > 0$ (Cameron & Trivedi, 2013):

$$\Pr[y] = \begin{cases} f_1(0) & \text{if } y = 0 \\ (1 - f_1(0))\frac{f_2(y)}{1-f_2(0)} & \text{if } y > 0 \end{cases} \tag{5.3}$$

where $f_1(0)$ is the probability of observing a zero count. If the hurdle is crossed (if $y > 0$), the truncated count density is given by $f_2(y)/(1 - f_2(0))$, which needs to be multiplied by $1 - f_1(0)$ to ensure that probabilities sum to one (Cameron & Trivedi, 2013). In practice, $f_1(\cdot)$ can be estimated using the logit model, specified in its multilevel form (Goldstein, 2011) as such:

$$ln(\pi_{ij}) = \gamma_0 + \gamma_1 x'_{ij} + v_{0j}$$

$$ \tag{5.4}$$

$$v_{0j} \sim N(0, \sigma^2_{v0})$$

where γ_0 is the intercept for the binary model, γ_1 is a vector of fixed coefficients that quantify the relationship between x'_{ij} and the odds, π_{ij}, and v_{0j} represents the random variation in γ_0 associated with each state j. The probability of observing zero ($f_1(0)$) is given by (Hilbe, 2011):

$$\Pr[y_{ij} = 0|x'_{ij}] = \frac{1}{1 + \pi_{ij}} \tag{5.5}$$

and the probability of crossing the hurdle $(1 - f_1(0))$ is thus (Hilbe, 2011):

$$\frac{\pi_{ij}}{1 + \pi_{ij}} \tag{5.6}$$

Taking the standard negative binomial density in eq. (5.2) as $f_2(\cdot)$, the truncated density needs to be rescaled as shown in eq. (5.3). The $f_2(0)$ density is $(1-\alpha\mu_{ij})^{-1/\alpha}$ (Hilbe, 2011), and $1 - f_1(0)$ is shown in eq. (5.6). Thus, the multilevel truncated negative binomial density for $y_{ij} > 0$ is:

$$\Pr[y_{ij}|x'_{ij}] = \left(\frac{\pi_{ij}}{1 + \pi_{ij}}\right)\left(\frac{\frac{\Gamma(y_{ij}+\alpha^{-1})}{\Gamma(y_{ij}+1)\Gamma(\alpha^{-1})}\left(\frac{1}{1+\alpha\mu_{ij}}\right)^{\alpha^{-1}}\left(1 - \frac{1}{1+\alpha\mu_{ij}}\right)^{y_{ij}}}{1 - (1 - \alpha\mu_{ij})^{-1/\alpha}}\right) \tag{5.7}$$

where μ_{ij} is estimated using eq. (5.1) and restricting $y_{ij} > 0$. The complete multilevel negative binomial-logit hurdle model is therefore:

$$\Pr[y_{ij}|x'_{ij}] \begin{cases} \frac{1}{1+\pi_{ij}} & \text{if } y_{ij} = 0 \\ \left(\frac{\pi_{ij}}{1+\pi_{ij}}\right)\left(\frac{\frac{\Gamma(y_{ij}+\alpha^{-1})}{\Gamma(y_{ij}+1)\Gamma(\alpha^{-1})}\left(\frac{1}{1+\alpha\mu_{ij}}\right)^{\alpha^{-1}}\left(1-\frac{1}{1+\alpha\mu_{ij}}\right)^{y_{ij}}}{1-(1-\alpha\mu_{ij})^{-1/\alpha}}\right) & \text{if } y_{ij} > 0 \end{cases} \tag{5.8}$$

All models were estimated using the 'glmmADMB' package (Bolker, Skaug, Magnusson, & Nielsen, 2012; Fournier et al., 2012). I estimated the standard MNB model as a baseline to compare the estimates of the MNB-LH model. The MNB-LH model was estimated separately, with a multilevel logit (ML) estimating the likelihood of observing a victimisation incident, and a multilevel truncated negative binomial (MTNB) estimating the expected concentration among victimised targets. Model significance of each individual model (MNB, ML and MTNB) was assessed using likelihood ratio tests (Cameron & Trivedi, 2013, p. 49; Hilbe, 2011, p. 177). Given that MNB and MNB-LH models are not nested—and hence not suitable for comparison using likelihood ratio tests—they were compared using the Akaike (AIC) and Bayesian (BIC) information criteria (Cameron & Trivedi, 2013, p. 197), with lower values indicating a better model. AIC and BIC estimates for the hurdle model were calculated by adding the AIC and BIC estimates of the constituent models (e.g. $AIC_{MNB\text{-}LH} = AIC_{ML} + AIC_{MTNB}$; see Hilbe, 2014, p. 188).

5.7 Univariate analysis results

Table 5.1 shows the distribution of crimes across targets. This can also be displayed using Lorenz curves (Upton & Cook, 2014c), which show the cumulative share of crime experienced by the cumulative share of the population that experiences them (Tseloni & Pease, 2005). If crime is evenly distributed, the Lorenz curve will approximate the line of equality shown in the figure. Deviation from this indicates that crime is unequally distributed (Tseloni & Pease, 2005, p. 77).

Figure 5.2 shows Lorenz curves for the observed and expected distributions, the latter being the distribution of the simulated replicates. The panel on the left shows that both observed and expected frequencies are highly concentrated among all businesses, which is to be expected given that the vast majority of businesses were not extorted. The right-hand panel, however, shows the distribution for victimised businesses—thus representing repeat victimisation. The curve of the expected distribution is very close to the line of equality, while the curve of the observed distribution exhibits far more concentration. Crucially, a KS test (D = 0.044, $p < 0.001$) confirmed that the differences between the distributions were statistically significant—there was more repeat victimisation than that expected under random victimisation.

Lastly, considering the shape of the statistical distribution, Table 5.3 and Figure 5.3 show that there were more zeros than would be expected assuming a Poisson distribution ($\chi^2 = 293.2$, df = 1, $p < 0.001$). However, after taking account of
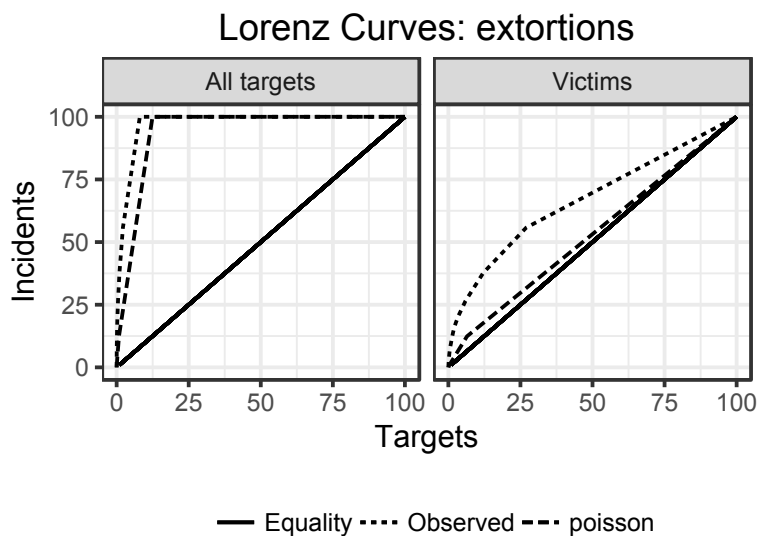
Figure 5.2: Lorenz curves with the observed and expected distributions of extortion victimisation.

Table 5.3: Observed and expected prevalence calculated using a Monte Carlo simulation with 2000 replicates.

	Observed	Poisson	Negative Binomial
0	25912	24680	25930
≥ 1	2267	3499	2249

overdispersion by modelling a negative binomial distribution, there were no significant differences between the number of observed and expected zeroes ($\chi^2 = 0.56$, df $= 1$, $p = 0.45$), hence the modelling strategy does not need to account for zero-inflation.

5.8 Statistical modelling results

Table 5.4 presents model statistics for null and fully specified versions of estimated models. Goodness of fit was assessed using likelihood ratio tests. Fully specified models were found to be significantly different than null models. Multilevel specifications significantly improved fit when compared to single-level models. Similarly, the MNB and MTNB models proved a significant improvement over Poisson and truncated Poisson models. AIC and BIC values for the hurdle model were smaller than for the MNB model ($AIC_{MNB-LH} - AIC_{MNB} = -219$, and $BIC_{MNB-LH} - BIC_{MNB} = -38$), which suggests that the hurdle model of extortion
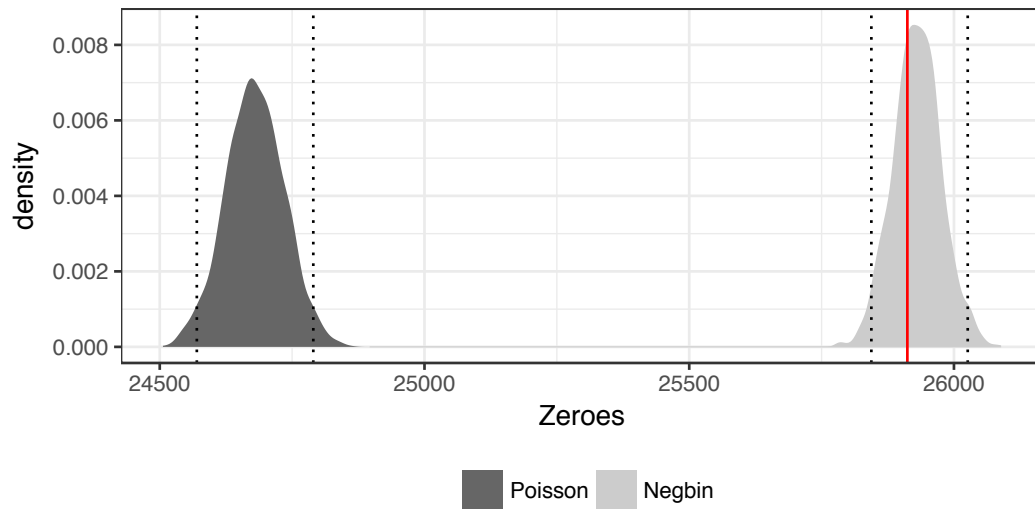
Figure 5.3: Amount of zeroes predicted by 2000 Monte Carlo replicates of a Poisson and a Negative Binomial distribution based on the observed distribution of extortion. The observed prevalence of zeroes is within the 95% CI of the negative binomial distribution but outside the Poisson expectation.

victimisation is more appropriate. The table also presents estimates for state-level variance, the α parameter, and the intra-class correlation (ICC), which are discussed in detail in a later section.

Lastly, multi-collinearity was not deemed to be significant, as variance inflation factors (VIF, Wooldridge, 2009) were quite small, with the largest being 3.7—lower than the threshold of 10 regarded by many practitioners as a sign of severe multi-collinearity (O'Brien, 2007).

Table 5.5 presents the model estimates in the raw scale (log and log-odds). To facilitate interpretation, Figure 5.4 shows exponentiated model coefficients (e^{β} and e^{γ}). For count MNB and MTNB models, the exponentiated estimates represent incidence rate ratios (IRR, Hilbe, 2014, p. 60), whereas for the binary ML model they represent odds ratios (OR, Weisburd & Britt, 2014, p. 568). Subtracting 1 from the IRR ($IRR - 1$) gives the percentage change on the concentration of extortion victimisation for a one unit increase in the independent variable, while $OR - 1$ gives the percentage change in the prevalence risk. For categorical independent variables, the percentage change is relative to the reference category. IRRs and ORs for log transformed independent variables represent change for a 10% increase in the independent variable (given by 1.10^{β} and 1.10^{γ}).

Table 5.4: Model statistics for null and fully specified multilevel negative binomial (MNB), multilevel negative binomial-logit hurdle (MNB-LH), multilevel logit (ML) and multilevel truncated negative binomial (MTNB) models.

	MNB		MNB-LH		ML		MTNB	
	Null	*Full*	*Null*	*Full*	*Null*	*Full*	*Null*	*Full*
Log-lik.	-10111	-9841	-9992	-9700	-7679	-7455	-2313	-2244
AIC	20228	19748	19995	19529	15363	14975	4632	4555
BIC	20253	20020	20029	19982	15379	15239	4649	4744
σ^2	0.23	0.08	–	–	0.25	0.09	0.31	0.21
α	9.12	7.48	–	–	–	–	148.41	148.41
ICC	0.02	0.01	–	–	–	–	0.00	0.00
LRT		540.3***		–		447.9***		137.7***
n	28161	28161	–	–	28161	28161	2266	2266
Groups	32	32	–	–	32	32	32	32

Degrees of freedom for likelihood ratio tests (LRT), 30. ***$p < 0.001$

Table 5.5: Model estimates (log scale) for multilevel negative binomial (MNB), multilevel logit (ML) and multilevel truncated negative binomial (MTNB) models.

		Hurdle	
	MNB (SE)	ML (SE)	MTNB (SE)
Intercept	–2.28*** (0.12)	–2.84*** (0.12)	–4.37*** (0.22)
Business-level variables			
Corruption victimizations	0.28*** (0.04)	0.11*** (0.02)	0.14*** (0.04)
Business age (base: 0 to 5)			
6 to 9	0.29*** (0.08)	0.33*** (0.07)	0.09 (0.16)
10 to 14	0.40*** (0.08)	0.36*** (0.08)	0.14 (0.17)
15 to 23	0.43*** (0.08)	0.45*** (0.07)	0.18 (0.16)
24 to 212	0.44*** (0.08)	0.35*** (0.08)	0.31 (0.16)
Business type (base: Retail)			
Mining	–0.33 (0.44)	–0.14 (0.40)	–0.29 (0.85)
Construction	–0.02 (0.14)	0.08 (0.12)	–0.41 (0.26)
Manufacturing	–0.21* (0.08)	–0.17* (0.08)	–0.14 (0.16)
Wholesale	0.06 (0.10)	0.07 (0.09)	0.05 (0.18)
Transport	–0.03 (0.15)	0.23 (0.12)	–0.71** (0.27)
Media	–1.54*** (0.37)	–1.19** (0.36)	–1.41 (0.85)
Finance	0.20 (0.24)	0.15 (0.21)	–0.25 (0.47)
Real estate	0.18 (0.21)	0.26 (0.18)	–0.03 (0.39)
Prof. services	0.23 (0.15)	0.18 (0.13)	–0.14 (0.29)
Maintenance	–0.32* (0.15)	–0.04 (0.14)	–0.93** (0.31)
Education	–0.15 (0.14)	–0.14 (0.12)	–0.24 (0.26)
Health	0.14 (0.13)	0.11 (0.11)	0.05 (0.24)
Leisure	–0.20 (0.25)	–0.11 (0.23)	–0.04 (0.51)
Hotels Rest Bar	0.39*** (0.08)	0.36*** (0.07)	0.30 (0.16)
Other	–0.15 (0.10)	–0.15 (0.09)	0.08 (0.20)
Business size (base: Large)			
Medium	0.11 (0.09)	0.21* (0.09)	–0.25 (0.18)
Small	0.02 (0.09)	0.35*** (0.08)	–0.72*** (0.16)
Micro	–0.69*** (0.08)	–0.35*** (0.08)	–1.08*** (0.16)
State-level variables			
Corruption prevalence (log)	0.36* (0.17)	0.48** (0.18)	–0.27 (0.29)
Weapon crimes (log)	0.45*** (0.11)	0.44*** (0.12)	0.14 (0.19)
Drug crimes (log)	–0.31*** (0.08)	–0.26** (0.09)	–0.28 (0.15)
N businesses (log)	–0.45 (0.29)	–0.53 (0.31)	0.31 (0.51)
Population (log)	–0.10 (0.11)	–0.15 (0.12)	0.15 (0.20)
Competitiveness index	–0.02** (0.01)	–0.02* (0.01)	–0.02 (0.01)
'Rule of law' index	0.00 (0.01)	0.00 (0.01)	0.01 (0.01)
n	28161	28161	2266
Groups	32	32	32

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$
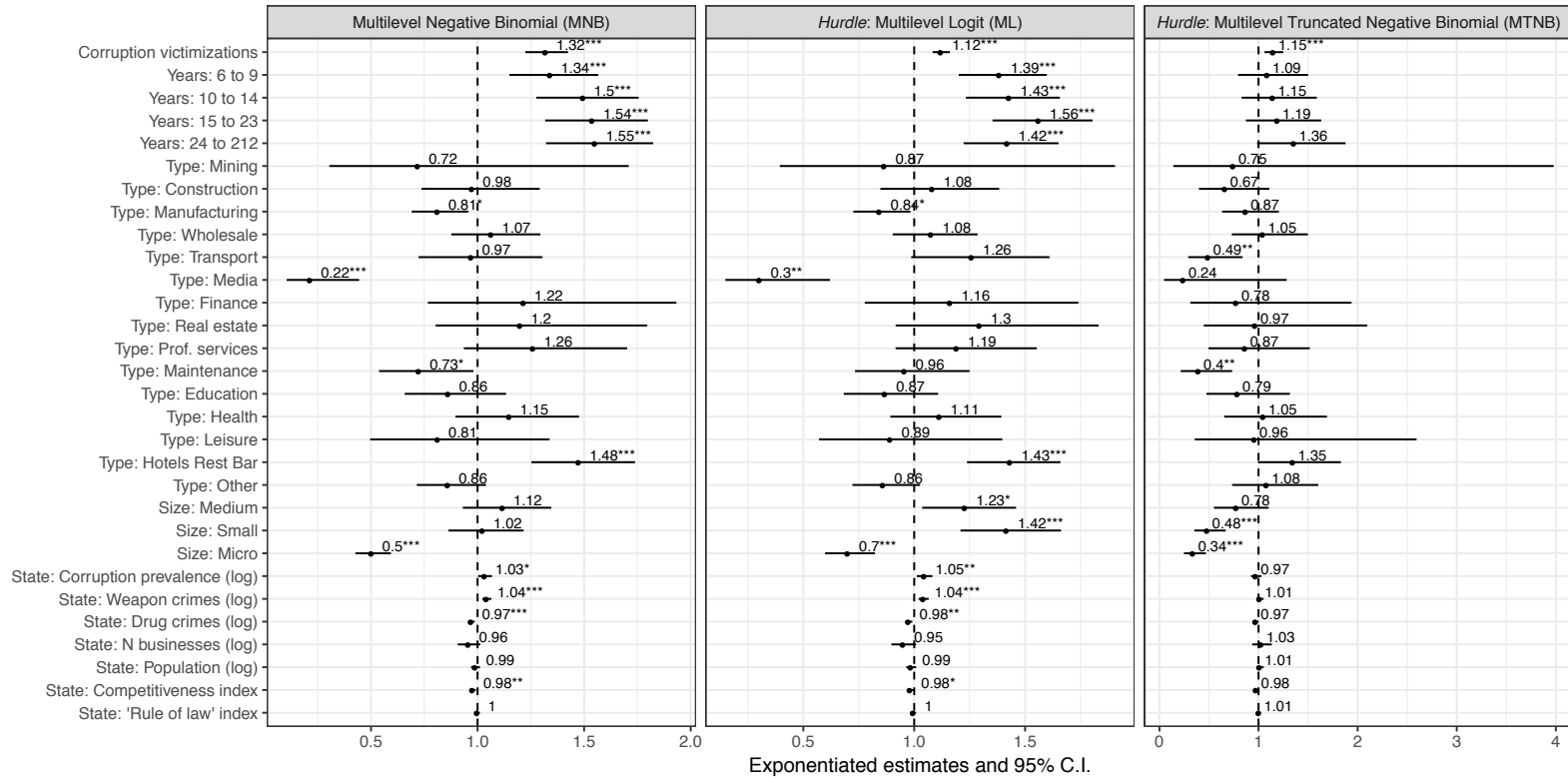
Figure 5.4: Forest plot with exponentiated model coefficients. Significance: ${}^{***}p < 0.001$, ${}^{**}p < 0.01$, ${}^{*}p < 0.05$.

5.8.1 Macro-level effects

Overall, the associations between extortion and state-level variables were quite weak. Moreover, the associations were inconsistent for the prevalence and concentration components, as no state-level variable was significant in the count part (MTNB) of the hurdle model. Thus, the associations in the MNB model appear to reflect differences in prevalence risk captured by the ML model, rather than a state-level effect on repeat extortion victimisation.

All else being equal, the ML model found that a 10% increase in the number of corruption victims in a state was associated with a 5% increase in the likelihood of a business becoming a victim of extortion. Similarly, a 10% increase in the number of federal weapon crimes in a state, was associated with a 4% increase in extortion prevalence risks. In contrast, a 10% increase in the number of federal drug crimes in a state was associated with a 2% reduction in the likelihood of a business becoming a victim of extortion. Differences in the rule of law index between states showed no association with extortion risks, while a one unit increase in a state's attractiveness to entrepreneurs (as measured by the competitiveness index), was associated with a 2% reduction in extortion risks.

5.8.2 Micro-level effects

Business-level effects were also inconsistently associated across the components of the hurdle model, with the exception of corruption victimisations and being a micro-sized business.

The MNB model indicated that a one unit increase in the number of corruption victimisations experienced by a business was associated with a 32% increase in the number of extortion victimisations a business can expect. Estimates from the hurdle model suggest that the effect of corruption victimisations was consistent for both the prevalence and concentration of extortion. The ML model suggests that a one unit increase in the number of corruption victimisations was associated with a 12% increase in the likelihood of becoming a victim of extortion, whereas the MTNB model suggests that victims of extortion saw a 15% increase in the amount of extortion concentration, for a one unit increase in the amount of corruption incidence experienced.

Business size categories had contrasting effects for the prevalence and concentration components. Results from the MNB model suggest that micro-sized businesses suffered an average of 50% fewer extortion incidents than large businesses (the refer-

ence category). The insignificant coefficients for small and medium-sized businesses in the MNB model suggest that they suffered extortion victimisation at the same rate as large businesses. However, the results of the hurdle model paint a more nuanced picture. The effect of being a micro-sized business was consistent across the hurdle: they were 30% less likely to become victims of extortion, and experienced 66% fewer extortion repeats if victimised. On the other hand, small businesses faced a 42% higher risk of becoming a victim of extortion, yet they experienced 52% fewer extortion repeats once extorted. Medium businesses also saw higher risks of extortion prevalence (23%), yet they experienced repeat extortion at the same rate as large businesses, as the MTNB coefficient was not significant.

With few exceptions, most business types faced no difference in extortion risks relative to retailers (the reference category), though some categories presented contrasting effects across the hurdle components. Hotels, restaurant and bars suffered 48% more extortion incidents than retailers (MNB), though the hurdle model suggests that this was mainly due to differences in the prevalence risk, rather than due to repeat victimisation. The category faced a 43% higher risk of becoming a victim of extortion (ML), though it showed no significant effect in the concentration of repeat victimisation (MTNB). Manufacturers, maintenance service providers, and media businesses experienced fewer extortion incidents overall (from MNB: -19%, -27%, and -78%, respectively), though for manufacturers and media businesses, such differences were apparently due to a lower risk of becoming victims (from ML: -16% and -70% respectively), as they did not suffer differential rates of repeat extortion according to MTNB estimates. On the other hand, the opposite appears to be true for maintenance service providers, whose odd ratios were not significantly different from 1, though they experienced 60% less repeat extortion than retailers. Lastly, while overall MNB and ML estimates did not reveal significant differences between retailers and transport providers, MTNB estimates suggest that once victimised, transport providers experienced 51% fewer repeats.

Business age also showed a contrasting effect across the components of the hurdle model. Though the MNB model showed a positive and significant effect for all age categories, the hurdle model suggests that this was due to changes in prevalence risk. According to estimates from the ML model, businesses aged 6-9, 10-14, 15-23, and 24 years or more were 39%, 43%, 56%, and 42% respectively more likely to become victims of extortion, when compared with businesses that had been in operation for 5 years or fewer (the reference category). However, once victimised, business age

categories had no effect on the expected concentration of repeat extortion, as the coefficients in MTNB were not significant.

5.8.3 Unexplained heterogeneity

Unobserved heterogeneity refers to differences in extortion victimisation that remain unexplained by the independent variables in the study. Between-business unobserved heterogeneity (α in Table 5.4) arises when two identical businesses—in terms of those characteristics included in the model—suffer unexplained differences in extortion incidence. The independent variables selected reduced individual unobserved heterogeneity by 18%, from $\alpha_{null} = 9.12$ in MNB, to $\alpha = 7.48$ in the fully specified MNB model. The relatively high value of unexplained heterogeneity that remains suggests that there are factors not included in the model that clearly influence extortion concentration. Such variables could relate to risk heterogeneity or event dependence, though it is not possible to tell with this model. On the other hand, the very substantive amount of unobserved heterogeneity in the count part of the hurdle model ($\alpha = 148.41$ in MTNB), which was essentially unaffected by the inclusion of explanatory variables associated with risk heterogeneity, suggests that an alternative process, such as event dependence, may be responsible.

In contrast, unobserved heterogeneity between states (level 2 variance in Table 5.4) refers to differences in extortion risk faced by businesses in different states, after controlling for the variables specified in the model. In the MNB model, level 2 variance was reduced significantly by the inclusion of independent variables (-65%, from $\sigma^2_{u_0 null} = 0.23$ to $\sigma^2_{u_0} = 0.08$). The hurdle model, suggests that much of this reduction is due to differences in the risk of extortion prevalence, rather than in repeat victimisation, as the ML models saw reductions of 64% (from $\sigma^2_{u_0 null} = 0.25$ to $\sigma^2_{u_0} = 0.09$) and the MTNB models reduced between-states unobserved heterogeneity by 32% ($\sigma^2_{u_0 null} = 0.31$ to $\sigma^2_{u_0} = 0.21$).

Both the MNB and the MTNB models suggest that the intra-state correlations (ICC in table 5.4) are very small, and that between-businesses variations are more relevant to explain micro-level extortion risks. When comparing all businesses, the ICC for MNB suggests that the probability of two identical businesses—in terms of the variables included in the model—experiencing the same extortion incidence due to being in the same state was only 1%. Conversely, the probability of two identical businesses experiencing the same number of extortion victimisations, after controlling for between-state differences, was 99% ($1 - ICC$). For repeat victimisation, the MTNB model suggests that this probability was 99.9%.

5.9   Discussion

This chapter set out to systematically examine victimisation patterns of extortion against businesses in Mexico to determine if incidents concentrate on repeat victims, and to explore if the factors that explain the risk of becoming a victim of extortion also explain the concentration of repeat extortion victimisation.

Using data from Mexico's commercial victimisation survey, extortion incidents were found to concentrate above what would be expected by chance (H1), with repeat extortion victims suffering a disproportionate amount of total crime incidents—patterns consistent with findings on repeat victimisation for most crime types in many countries (e.g. Farrell & Pease, 2011; Farrell, Tseloni, & Pease, 2005). In all, there were more repeat extortion victims than one-time victims, and close to 40% of all incidents were repeats.

The literature on repeat victimisation has traditionally considered that the factors that explain the prevalence of victimisation also account for its concentration (e.g. Pease & Tseloni, 2014, p. 31). However, given that the role of event dependence may be more prominent in determining the risk of repeat victimisation in the case of extortion, and that extortion often leads to enduring victim-offender relationships, I hypothesised that the factors that explain extortion concentration would be distinct from those that explain extortion prevalence (H2).

Using a multilevel negative binomial-logit hurdle model, the study found support for H2. Overall, only two independent variables (corruption victimisation and being a micro-sized business) showed a consistent effect for both prevalence and concentration. Most variables showed inconsistent effects (e.g. a positive effect for prevalence but a not significant effect for concentration), though some presented contradictory ones (i.e. a positive effect for prevalence and a negative effect for concentration).

The literature on protection theory has tended to prioritise area-level explanations of extortion patterns over micro-level explanations focused on specific factors associated with individual businesses. However, the findings presented in this study suggest that state-level variables were only marginally relevant for predicting extortion prevalence. Nonetheless, the direction of the effects of the significant state-level variables did fit with theoretical expectations: Businesses in states with more corruption (and hence with poorer governance), and with more weapon-related crimes (and hence with more violence-prone organised crime groups) experienced a higher risk of becoming victims of extortion, while businesses in states with more drug trafficking activity experienced lower risks of becoming victims of extortion. Unobserved

state-level heterogeneity for extortion prevalence was comparatively smaller than for extortion concentration, though the latter was dwarfed by the residual between-business unexplained heterogeneity. This suggests that any area-level explanations for repeat extortion are unlikely to be found at the state level, and instead may be explained by variables measured at sub-state level (e.g. municipality, city, neighbourhood).

Business-level effects appeared to be far more important in explaining extortion risks, though they mostly affected extortion prevalence rather than concentration. I hypothesised that an association at the micro-level between corruption and extortion could be explained by direct relationships between extortionists and corrupt officials in Mexico—a link documented in the literature (Díaz-Cayeros et al., 2015; Morris, 2013). While our analysis cannot refute the possibility of a spurious relationship (e.g. that extortionists and corrupt officials are attracted to the same kind of businesses), the fact that corruption victimisation increased the likelihood of becoming a victim of extortion and the amount of repeat extortion incidents that businesses suffer once they have been extorted suggests that the relationship is substantive and robust. Nonetheless, having established that an association exists, exploring this issue further would seem to be important for future work.

Business size categories showed inconsistent relationships for prevalence and concentration components—with the exception of micro sized businesses which were consistently less likely to be extorted, and suffered fewer repeats once victimised. Small businesses were more likely to be extorted than large businesses (possibly due to their relative vulnerability), though they suffered significantly fewer repeat victimisations thereafter (as potential rewards were possibly clarified following the first offence). Similarly, the higher prevalence risk for medium businesses suggests more inherent vulnerability, though the similar rates of repeat extortion suggest less variability regarding potential rewards.

As expected, hotels, restaurants and bars experienced higher risks of extortion, though they did not experience more repeat incidents. The lower prevalence risks amongst manufacturers may point to accessibility as an additional factor influencing vulnerability to extortion: manufacturers tend to interact mostly with other businesses, while hotels, restaurants and bars are generally open to the public, and thus are naturally easier to access for extortionists. In contrast, the lower prevalence risk for media businesses may be related to risks perceived by extortionists, as extorting a news outlet such as a newspaper or a television station could lead to exposure. Results also showed that after being victimised, most business types experienced similar

rates of repeat extortion, apart from maintenance and transport service providers, which experienced less repeat extortion. I believe that such negative relationship may be related to factors affecting event dependence, such as victim response to the first offence (Farrell et al., 1995, p. 396). For example, transport providers may decide to avoid certain routes on which they have been previously victimised.

Contrary to expectations, new businesses (those with 5 or fewer years in operation) experienced substantially lower risks of becoming victims of extortion, though years in operation categories were not associated with extortion concentration. I speculate that the association may be explained by target visibility, rather than by an inherent attractiveness or vulnerability linked to businesses' age. All else being equal, new businesses may face lower risks because they are less likely to be known by offenders—i.e. they are less likely to feature in an offender's awareness space (Brantingham & Brantingham, 2011)—and 'offenders can only commit crimes against targets of which they are aware' (Hepenstal & Johnson, 2010, p. 266). However, once a business is victimised (and thus known to offenders), businesses appear to be equally vulnerable and attractive to extortionists regardless of how long they have been in business.

An important advantage of the hurdle model is that it allows clarifying the role of between-business unobserved heterogeneity for overall extortion risks (captured by the MNB model) and for the specific risks of extortion concentration (captured by the MTNB model). Many significant business-level predictors in the MNB model were in fact capturing differences in the prevalence risk, rather than in the risks of repeat extortion. Similarly, the between-business unobserved heterogeneity in MNB captured unexplained differences in both prevalence and concentration risks. By restricting observations to extortion victims, the between-business unobserved heterogeneity reported in the MTNB model refers only to unexplained differences in (repeat) extortion concentration. The high value of between-business unobserved heterogeneity, and the fact that it was unaffected by the inclusion of predictors, strongly support the hypothesis that (repeat) extortion concentration is fuelled by a process distinct from that which explains extortion prevalence. I ascribe such differences to the effects of factors affecting event dependence—such as victim response to a first offence, or the institutionalisation of extortive relationships. However, it was not possible to directly test this conjecture, given the cross-sectional design of the study. Thus, future research that incorporates a longitudinal dimension to the study of extortion victimisation is needed.

There are, of course, other limitations to the present study. Chief amongst them

is that the extortion incidents captured in the screening section of the ENVE do not take into account the type of extortion suffered. Research on extortion in Mexico (see Locks, 2015; Mugellini, 2013a; ONC, 2014; Pérez Morales et al., 2015) notes that extortion incidents can be broadly classified intro three distinct types: 'remote' extortion, in which threats are made by telephone or other media; 'in-person' extortion, in which threats are made face-to-face; and *cobro de piso*, which also take place in person but are believed to involve regular payments. Given that these different types of extortion are likely to be associated with different opportunity structures, future research should analyse their patterns of (repeat) victimisation separately, rather than in aggregate form (see Chapter 7). Nonetheless, the findings presented here are important to test the feasibility of the modelling approach using the uncapped data provided by the screening section.

Other important limitations refer to the temporal horizon imposed by the cross-sectional design based on a one year period. First, by collapsing the temporal scale to one year, the study cannot capture the time-course of repeat victimisation (Johnson et al., 1997)—i.e. it cannot measure how extortion risks change after a victimisation incident. Second, the reference period artificially imposes a time-window on repeat victimisation—i.e. some extortions early in the period may be repeats of extortions that took place before the period began and some extortions at the end of the period may have repeats after it ends—which would lead to an undercounting of repeat victimisation (Farrell & Pease, 1993, p. 19). Such limitations are difficult to overcome with the current data, though perhaps future iterations of the ENVE could incorporate an 'embedded panel' (Hopkins & Tilley, 2001) to address some temporal variation.

5.10 Chapter conclusion

In conclusion, this study applied a novel modelling strategy—the multilevel negative binomial-logit hurdle model—to identify whether the processes that lead to extortion prevalence are the same as those that lead to extortion concentration, as tends to be considered in the repeat victimisation literature. The findings support the use of the hurdle model over the canonical negative binomial model. Thus, studies on crimes where repeats are thought to be strongly influenced by event dependence mechanisms (such as domestic violence), would do well to test whether the hurdle model is a better fit. Furthermore, the study expands the crime concentration literature by focusing on a non-traditional crime type (extortion) in a new context (Mexico).

The chapter should not be taken as a definitive analysis of (repeat) extortion victimisation, but as a first step towards a systematic quantitative analysis of the extortion phenomenon. Thus, the findings highlight areas that need to be researched further—such as the differences in victimisation risks according to extortion type, or the specific contribution of event dependence to future extortion risk. The next chapters in the thesis will attempt to explore these issues further, using the methodological approach presented in this chapter as a useful starting point to build upon and develop finer insights.

Chapter 6

Determinants of extortion compliance

This chapter aims to identify the determinants of extortion compliance in Mexico. In the context of a study of repeat extortion victimisation patterns, the main motivation for the study—as outlined in Chapter 2—is the recognition that the manner in which a victim responds to an extortion attempt may be an important contributor to event dependence.

6.1   Background

After petty theft and robbery, extortion—understood here as the use of intimidation to demand money and other goods from business-owners (Elsenbroich & Badham, 2016; Savona & Sarno, 2014)—is the third most common crime against businesses in Mexico, with a prevalence rate of around 802 victims per 10,000 businesses (INEGI, 2014a). Alongside homicide and kidnapping, extortion is considered one of the most harmful crimes besieging the Mexican population, though extortion is far more common. In the context of a seemingly unassailable crime wave that has rocked the country since 2005 (see Aburto & Beltrán-Sánchez, 2019; Aburto, Riffe, & Canudas-Romo, 2018; Heinle et al., 2016), extortion is routinely described as a pervasive, 'booming industry' (Malkin, 2011) fuelled by the 'war on drugs' (Locks, 2015).

However, despite its high prevalence rate, statistics suggest that compliance with extortion demands is relatively rare. According to Mexico's 2014 commercial victimisation survey (the *Encuesta Nacional de Victimización de Empresas*, INEGI, 2014c), victims complied with extortion demands in only about 13% of incidents.

The relatively low compliance rate contrasts with the public perception of extortion in the country as a 'feudal regime' (Perez, 2018) with gangs dominating large swathes of territory and extorting all businesses within them. Evidence from Italy (Frazzica et al., 2013; Savona & Sarno, 2014) suggests that compliance with extortion demands is common where organised crime groups exert a strong territorial control, which would give grounds to assume that extortion compliance is widespread in Mexico. Similarly, given anecdotal evidence of the dramatic consequences faced by those who refuse to comply with extortion demands, such as the episode described in the opening of Chapter 3, and the cases described by Guerrero-Gutiérrez (2011) and Hale (2016), one would expect refusals to comply to be the exception, rather than the norm.

Nonetheless, the relative rarity of extortion compliance does not diminish the gravity of the extortion phenomenon—using data from a different survey, Locks (2015) estimated that illicit revenues from extortion in Mexico ranged between \$2.2 and \$7.4 billion USD in 2012. However, it does raise a relevant question of academic and practical importance: Why are most extortion incidents in Mexico not complied with?

The literature on organised crime—particularly on Italian mafias—suggests that, in addition to avoiding fear of reprisals, compliance with extortion can be attributed to social and cultural factors related to the vulnerability of particular regions to mafia control (e.g. La Spina et al., 2014; La Spina, Militello, Frazzica, Punzo, & Scaglione, 2016). Some communities see paying protection money as 'normal' or 'natural' due to long-standing organised crime governance arrangements (La Spina et al., 2016). However, such research is mostly focused on sustained compliance in the context of systematic extortion rackets,[1] and does not explore the *situational* characteristics that explain why some incidents in the same context lead to compliance while others do not.

In contrast, research on coercion and decision theory (e.g. Gambetta, 1994; Luckenbill, 1982; Nacci & Tedeschi, 1973; A. Smith & Varese, 2001; Tedeschi & Felson, 1994) provides a suitable framework to understand the situational determinants of extortion compliance. From this perspective target compliance is the result of a rational choice: victims choose to comply when the costs of doing so are lower than

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[1]Elsenbroich and Badham (2016) defines extortion rackets as 'the continuous, regular and systematic extortion of several victims.' Researchers use various terms to refer to similar phenomena: racketeering (McIntosh, 1973), extortion racketeering (Savona & Sarno, 2014; Savona & Zanella, 2010), extortion racket systems (Frazzica et al., 2013; La Spina et al., 2014), private protection (Gambetta, 1993; Varese, 2001), and violent entrepreneurship (Volkov, 2002), among others.

of not complying. Thus, this literature points towards the situational characteristics that help participants in the extortion interaction weigh the costs and benefits of compliance. However, as most research concerning extortive interactions from this perspective has been theoretical or based on experimental data (e.g. Elsenbroich & Badham, 2016; Konrad & Skaperdas, 1997; A. Smith & Varese, 2001), there is a need for studies that assess extortion compliance empirically using real-world interactions.

From a practical perspective, identifying the situational determinants of extortion compliance can provide more nuanced characterisations of extortion incidents—a crucial step to design more effective crime prevention interventions (Clarke, 2009). Furthermore, being more crime specific not only helps improve the targeting of such interventions, but it can also reveal 'pinch-points' (Bullock et al., 2010a; Read & Tilley, 2000) in the sequence of events involved in extortions—i.e. the crime script (Cornish, 1994)—which can point to the mechanisms that could underpin successful interventions.

Thus, using novel incident-level data from Mexico's 2014 commercial victimisation survey—one of the largest victimisation surveys of its kind—this study aims to identify the situational determinants of victim compliance in extortion incidents. The chapter proceeds as follows: In the next section I review the literature to inform the hypotheses to be tested in the study. Then I describe the data and analytical approach used. This is followed by the results and discussion.

6.2 Factors affecting extortion compliance

As noted above, it is generally assumed that victims choose to comply with an extortion demand when doing so is less costly than not complying. However, as the true costs of noncompliance are uncertain—threats may not materialise—game theoretical models of extortion note that the main determinant of compliance is the victim's estimation of the likelihood of punishment for noncompliance (e.g. Gambetta, 1994; Konrad & Skaperdas, 1997, 1998; A. Smith & Varese, 2001). Given that this likelihood is unknown, Konrad and Skaperdas (1997) argue that victims consider threat credibility (the rate at which the extortionists punished noncompliant victims in the past) (see also Konrad & Skaperdas, 1998). On the other hand, Gambetta (1994), and A. Smith and Varese (2001) broaden this to include more subjective perceptions, and consider that it is the reputation groups have for their willingness to use violence, rather than actual retaliations for noncompliance, which matters most in influencing the likelihood of compliance. However, this allows 'pi-

rates' (Gambetta, 1994) and 'fakers' (A. Smith & Varese, 2001) to exploit someone else's reputation spuriously, e.g. by pretending to be a member of an organised crime group (an example of Felson's 'mimicry' principle, 2006a).

One of the central issues determining the victim's perception of the likelihood of punishment for noncompliance—and hence of their decision to comply—is the offender's ability to convince the victim of the authenticity of the threat. Gambetta (1994) argues that extortionists establish their 'authenticity' using symbols and signals that communicate their belonging to a particular organised crime group. However, as actors in an extortive strategic interaction (Best, 1982; Goffman, 1970) have implicit incentives to deceive their opponents, explicit signals and symbols can still be mimicked. Therefore, victims may be forced to rely on additional cues gleaned from the interaction to determine whether the threats should be believed (Luckenbill, 1982).

In a communicative interaction, the medium used is itself a source of information that can deeply influence how the message being exchanged is interpreted (McLuhan, 1964). Thus, in the context of extortion, the communication medium or channel used by the threat's sender (the extorter) to convey the message (the actual avowed threat) to the receiver (the extorted) can have a strong bearing in believability. As O'Hair, Bernard, and Roper (2011) note, 'those who threaten others have a number of communication channels available to them... Channel selection is sometimes a spontaneous and convenient choice, whereas in cases of predation the choice of channel can be quite strategic' (p. 57).

According to media richness theory (Daft & Lengel, 1986; Lengel & Daft, 1989), communication channels can be classified based on the amount of information (verbal, non-verbal, visual, etc.) they can convey. Lengel and Daft (1989) classify face-to-face interactions as the richest form of media, while other interactive media, such as telephone and other technology-mediated channels, are considered relatively leaner, as they 'lack the element of "being there"' (p. 226). Senders strategically select rich media when they aim to reduce uncertainty and equivocality (the possibility of deriving several meanings) (Daft & Lengel, 1986, p. 555).

6.2.1   Types of extortion and communication channels

According to the media richness of the channels used to convey threats, extortion incidents in Mexico can be classified into 'remote' (lean media) and 'in-person' (rich media) extortion. Remote extortion relies on the use of technology mediated channels to convey the threat. In the most common type of remote extortion, threats

are communicated over the telephone. According to ONC (2014), there are several variations of how telephone extortion is carried out. Incidents generally begin by offenders cold-calling victims and attempting to convince them to pay an amount into a financial account or mobile phone number. To achieve this, offenders use advanced-fee scams,[2] 'virtual kidnappings',[3] or claim to be a member of an organised crime group[4] and threaten to carry out severe punishments if victims do not comply with the demands (ONC, 2014, p. 30). Particularly for the last two types, offenders use personal details obtained on social media, through data breaches or in previous calls, to convince victims of the authenticity of the threats (ONC, 2014).

The internet is another common channel used in remote extortion. Internet extortion incidents rely on the same tactics as telephone extortion, the difference being that offenders contact victims via email, social media, or electronic means other than a telephone (ONC, 2014, p. 32). An exception is 'ransomware' extortion, which relies on malware—a computer virus—that encrypts the victim's computer or infrastructure until a ransom is paid, usually using a cryptocurrency such as bitcoin (Darrel, 2013, 'ransomware'). Whereas in ransomware incidents the threats are levelled against digital assets (the data or applications under ransom), the threats in internet extortion incidents are usually aimed at the victims' personal safety.

On the other hand, in-person extortion incidents rely on face-to-face communication to convey threats. In-person incidents are also known as *cobro de piso*,[5] and are thought to be carried out by 'authentic' members of an organised crime group. In these incidents, offenders threaten victims with damage, assault, death, or other harms if they refuse to pay a fee (or provide some requested service) (Mugellini, 2013a; ONC, 2014). Mugellini (2013a) notes that offenders can also offer 'protection' from other criminal groups in these types of incident (p. 34). Furthermore,

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[2]An advanced-fee scam is 'a form of fraud . . . in which the victim is invited to pay financial fees in the hope of sharing in a much greater reward' (Daintith & Wright, 2008). For example, the extortionist claims the victim has won a prize from a contest or raffle, but requires the victim to pay a sum before receiving the reward. Sometimes, the scams are used to obtain personal details that will be used in subsequent calls for virtual kidnappings or threatening calls (ONC, 2014, p. 30).

[3]In a virtual kidnapping, offenders pretend to have kidnapped a family member and request a ransom payment. Offenders sometimes use stand-ins for kidnapping 'victims' pleading for help and mount audible abuse situations while the extortion victim is on the phone, hoping to convince them that a real kidnaping has taken place (Moor & Remijnse, 2008, p. 8).

[4]A variation of this scheme is for offenders to pretend they are government officials and 'blackmail' victims by threatening to arrest an acquaintance or family member who has been supposedly detained at an airport, customs office or similar facilities (ONC, 2014, p. 30).

[5]A literal translation for *cobro de piso* is a 'fee for the floor', and refers to a form of illicit tax that organised crime groups levy on businesses operating in their territories (Díaz-Cayeros et al., 2015).

ONC (2014) considers that *cobro de piso* extortions involve periodic payments at a regular frequency—e.g. monthly, weekly. However, in-person extortion incidents can also be committed by non-organised criminals who demand one-off payments.

Thus, given that use of leaner media has been associated with a higher likelihood of engaging in deceptive behaviour, and that receivers are less likely to trust messages sent using leaner media (Rockmann & Northcraft, 2008), it is reasonable to expect that victims would be more likely to believe in-person extortion threats are authentic, when compared to remote extortion threats, and would therefore be more likely to comply with the former than the latter. The first hypothesis in this study is:

- **H1**: The likelihood of compliance with an extortion threat is higher in cases of in-person extortion incidents, when compared to remote extortion incidents.

6.2.2   Other factors affecting extortion compliance

In addition to threat believability, Luckenbill (1982) suggests that compliance under threat of severe punishment is also affected by the severity of the potential punishment, the offender's capacity to inflict such punishment, and the victim's capacity to oppose or resist the threat (p. 811-812).

Anecdotal accounts of punishments inflicted on noncompliant victims—which include homicide, assault, arson and other extensive criminal damage (e.g. Guerrero-Gutiérrez, 2011; Hale, 2016; Wilkinson, 2011)—suggest that the punishments threatened for noncompliance in an extortion interaction are probably quite severe. However, as the incident-level dataset used in this study does not contain precise information on the severity of punishment for noncompliance, it is not possible to ascertain its effect on compliance patterns.

The effect of the offender's capacity to inflict punishment on the likelihood of compliance cannot be understood in isolation, but must also be considered with respect to the victim's capacity to resist such potential punishments. As compliance is assumed to be the result of a rational calculus, victims are more likely to comply if they perceive that the offender's capacity to punish is greater than their own capacity to resist, i.e. when there is a perceived power asymmetry in favour of the offender (Bacharach & Lawler, 1976; Luckenbill, 1982; Michener, Lawler, & Bacharach, 1973).

However, as Bacharach and Lawler (1976) note, 'power capabilities are typically ambiguous; hence conflicting parties must use situational cues to form subjective power estimates' (p. 3). Common situational factors that clearly signal power asymmetry in favour of the offender are the presence of lethal resources (i.e. weapons,

Luckenbill, 1982, p. 814) or of multiple offenders. Thus, the second set of hypotheses is:

- **H2.a**: The likelihood of compliance with an extortion demand is higher when offenders use weapons.
- **H2.b**: The likelihood of compliance with an extortion demand is higher when there is more than one offender involved.

Furthermore, research on organised crime suggests that contextual factors can also have an effect in determining the likelihood of extortion compliance (Gambetta, 1994; La Spina et al., 2014, 2016; A. Smith & Varese, 2001). Such contextual factors are not unique to each incident and instead represent area-level characteristics related to the perceived costs of using violence and the reputation of organised crime groups in a victim's area. The perceived costs of violence can be captured using a general measure, such as the strength of the rule of law. On the other hand, the reputation of organised crime groups can be captured by their readiness to use violence (e.g. the amount of crimes involving weapons), and by the type of illicit markets they are involved in (e.g. groups involved in drug-trafficking are usually less likely to be involved in extortion) (Corcoran, 2013; Guerrero-Gutiérrez, 2011; Jones, 2016). Thus, the third set of hypotheses is:

- **H3.a**: The likelihood of compliance with an extortion demand is higher in areas where the rule of law is weaker.
- **H3.b**: The likelihood of compliance with an extortion demand is higher in areas with more weapon-related crimes.
- **H3.c**: The likelihood of compliance with an extortion demand is higher in areas with fewer drug crimes.

Victim vulnerability can similarly be classified into situational and contextual measures. At the situational level, victim characteristics may have a part to play. For example, findings from Chapter 5 and previous research suggest that some business types are inherently more susceptible to intimidation (e.g. restaurants, Schelling, 1971, p. 646), and empirical studies confirm that some business types are more likely to comply with extortion demands (Chin et al., 1992, p. 641). Business size could also be indicative, as smaller businesses are inherently more vulnerable than larger businesses (see Chapter 5). Lastly, the number of years that a business has been in operation could be negatively associated with compliance, as older businesses can be

expected to have more social capital—a source of power to resist extortion demands (Anzola, 2016).

- **H4.a**: The likelihood of compliance with an extortion demand is associated with business type.
- **H4.b**: Small businesses are more likely to comply with extortion demand, when compared to larger businesses.
- **H4.c**: Newer businesses are more likely to comply with an extortion demand, when compared to older businesses.

The literature on repeat victimisation suggests that, in some crimes, the probability of suffering a repeat is associated with how the victim responds to a previous offence (Farrell et al., 1995, p. 396). For example, in the case of extortion, compliance in an initial event could entice further attempts, as the victim is known to be acquiescent. Thus, in the case of extortion, it is reasonable to expect an association between the likelihood of compliance and the amount of extortion incidents suffered by a business.

Similarly, previous research on extortion has found strong associations between corruption victimisation and extortion (see Chapter 5). While it is not yet clear why this association exists, it is possible that businesses that suffer more corruption victimisation are inherently more vulnerable to extortion. Thus, it is reasonable to expect an association between business-level experiences of corruption and the likelihood of compliance with extortion.

- **H5.a**: The likelihood of compliance with an extortion demand is positively associated with the amount of extortion demands a victim receives.
- **H5.b**: The likelihood of compliance with an extortion demand is positively associated with the amount of bribes victims are asked to pay.

6.3   Data and measures

The study uses the 2014 sweep of Mexico's nationally representative commercial victimisation survey, ENVE (see Section 4.2.2 for more detail). The survey is conducted biennially, sampling all business sectors—except those in agriculture and the public sector. As is common in other victimisation surveys (e.g. UNODC/UNECE, 2010), the instrument is divided in two parts. First, a screening questionnaire records prevalence (whether a respondent was victimised) and incidence (how many crimes

victims experienced) measures for crimes that took place during the previous calendar year (in this case 2013), as well as gathering business characteristics. The second section—the victim form—is used for victimised businesses only, capturing details on each crime incident reported in the screening questionnaire—however, there is a cap of 7 incidents per crime type per business (INEGI, 2014c). As compliance with extortion demands is captured at the incident level, the study uses information primarily from the victim forms, with business-level data coming from the screening questionnaire (for a detailed review of the ENVE, see Jaimes Bello & Vielma Orozco, 2013), and area-level data from other sources (detailed in the following sections).

The survey has nationwide coverage and is representative at the national and subnational scale (state level). In 2014, a stratified sample of 33,479 premises[6] was drawn from a sampling frame comprising 3.8 million units (INEGI, 2014a, 2014b). Interviews were conducted through face-to-face interviews, with computer-assisted telephone interviews to follow up (Jaimes Bello & Vielma Orozco, 2013). The response rate was around 85% (INEGI, 2014b).

To protect anonymity, access to the disaggregated incident-level responses is restricted by the data provider. Thus, analyses were carried out using custom-written R scripts (R Core Development Team, 2015) processed by INEGI staff in Mexico City.

6.3.1 Dependent variable

The dependent variable, compliance with extortion, is captured in the victim forms after businesses have indicated that they suffered at least one extortion incident in 2013.[7] For each incident, compliance was coded as '1' when respondents responded 'yes' to the question 'did you comply with the extortionist's demands?' ('*¿Entregó lo que le exigió el extortsionador?*', INEGI, 2014c), and '0' if otherwise. The survey captured 3,369 extortion incidents (among 2,259 victimised businesses). Compliance was observed in only 425 incidents (12.6%), whereas compliance was not observed in the remaining 2,944 incidents (87.4%).

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[6]The sampling unit for all business types except mining, transport and construction was premises; in the exceptions, the unit was the business (INEGI, 2014b).

[7]The specific question in the screening questionnaire is did the business suffer in 2013 'any kind of threat or coercion committed against the local unit's owner or staff for the purpose of obtaining money, goods or forcing them to do or stop doing something'? (Jaimes Bello & Vielma Orozco, 2013, p. 172).

6.3.2   Independent variables

This section describes the independent variables selected to test hypotheses. Incident-level variables are presented first, followed by victim- and area-level measures respectively. Table 6.1 presents descriptive statistics of all incident- and business-level variables used in the study.[8]

Categories with very small number of observations were recategorised to avoid complete and quasi complete separation, which occur when a categorical variable perfectly (or almost perfectly) predicts the value of the dependent variable (i.e. when all or nearly all observations of a particular category have the same value in the dependent variable). The presence of complete and quasi complete separation means that estimations using maximum-likelihood estimation will be unreliable (see Zeng & Zeng, 2019).

Extortion type (H1) was recorded as 'telephone extortion', 'by internet/email', 'on the street', 'on the premises', '*cobro de piso*', and 'other'. Incidents categorised as 'telephone' and 'internet' extortion were recategorised as 'remote' extortion, while incidents classified as 'other' were dropped from the analysis.[9] According to INEGI (2014a), 'on the street', 'on the premises', and '*cobro de piso*' incidents are considered to be 'in-person' extortion incidents, though there is no precise distinction provided for *cobro de piso* and other in-person extortions. Nonetheless, the distinct categories were retained to explore if they are associated to different patterns of compliance.

Weapon use (H2.a) was determined based on responses to the question 'Did offenders have weapons?', with possible 'no', 'yes', and 'dk/da' options.[10] The *number of offenders* involved in an incident (H2.b) was recorded using the following categories: '1', '2', '3', '4', '5', '6 or more', and a dk/da option. However, as '5' and '6 or more' exhibited complete and quasi complete separation, these categories were combined with '4' into a '4 or more' category.

Regarding victim-level variables, *business type* (H4.a) was captured by the survey according to the North American Industrial Classification System (SCIAN, INEGI, 2007). However, using this classification system, there were some categories with few or no observations. Thus only the following[11] categories were kept in a compromise

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[8]Descriptive statistics of state-level variables can be found in Chapter 5.

[9]There were only 8 (0.2%) incidents of internet extortion and 9 (0.3%) incidents categorised as 'other'.

[10]Unless otherwise noted, missing values for independent variables were classified as 'dk/da'.

[11]Categories with few observations were aggregated into the higher-order classification offered by the SCIAN. For example, 'Mining', 'Construction', and 'Manufacturing' belong in 'Industry'. As 'Mining' and 'Construction' exhibited quasi complete separation, but 'Manufacturing' did not, the former were aggregated in an 'Other industry' category, while 'Manufacturing' was kept.

Table 6.1: Descriptive statistics of incident- and business-level variables, per extortion compliance categories.

Extortion compliance:	No (N=2944)	Yes (N=425)	Total (N=3369)
Extortion type†***			
Remote	2700 (91.7%)	153 (36.0%)	2853 (84.7%)
Street	27 (0.9%)	27 (6.4%)	54 (1.6%)
Premises	186 (6.3%)	183 (43.1%)	369 (11.0%)
Cobro de piso	31 (1.1%)	62 (14.6%)	93 (2.8%)
Num. offenders†***			
1	918 (31.2%)	104 (24.5%)	1022 (30.3%)
2	157 (5.3%)	99 (23.3%)	256 (7.6%)
3	54 (1.8%)	43 (10.1%)	97 (2.9%)
4+	37 (1.3%)	52 (12.2%)	89 (2.6%)
DK/DA	1778 (60.4%)	127 (29.9%)	1905 (56.5%)
Had weapon†***			
No	817 (27.8%)	128 (30.1%)	945 (28.0%)
Yes	73 (2.5%)	127 (29.9%)	200 (5.9%)
DK/DA	2054 (69.8%)	170 (40.0%)	2224 (66.0%)
Extortion concentration‡***			
Mean (SD)	2.965 (4.05)	1.951 (2.35)	2.837 (3.90)
Range	1 - 40	1 - 24	1 - 40
Corruption incidence‡***			
Mean (SD)	0.452 (3.18)	0.482 (1.05)	0.456 (2.99)
Range	0 - 98	0 - 6	0 - 98
Business type†***			
Retail	863 (29.3%)	164 (38.6%)	1027 (30.5%)
HotelsRestBar	464 (15.8%)	49 (11.5%)	513 (15.2%)
Manufacturing	367 (12.5%)	43 (10.1%)	410 (12.2%)
Other industry	133 (4.5%)	13 (3.1%)	146 (4.3%)
Other serv.	779 (26.5%)	78 (18.4%)	857 (25.4%)
Transport	90 (3.1%)	37 (8.7%)	127 (3.8%)
Wholesale	248 (8.4%)	41 (9.6%)	289 (8.6%)
Business size †**			
Large	374 (12.7%)	54 (12.7%)	428 (12.7%)
Medium	565 (19.2%)	59 (13.9%)	624 (18.5%)
Small	911 (30.9%)	118 (27.8%)	1029 (30.5%)
Micro	1094 (37.2%)	194 (45.6%)	1288 (38.2%)
Years in business†**			
0 to 5	439 (14.9%)	78 (18.4%)	517 (15.3%)
6 to 9	594 (20.2%)	100 (23.5%)	694 (20.6%)
10 to 14	555 (18.9%)	88 (20.7%)	643 (19.1%)
15 to 23	711 (24.2%)	66 (15.5%)	777 (23.1%)
24 to 212	645 (21.9%)	93 (21.9%)	738 (21.9%)

†Chi-squared test, ‡Kruskal-Wallis rank sum test, $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

between avoiding separation and theoretical relevance: 'Retail', 'Wholesale', 'Hotels, restaurants and bars', 'Transport', 'Other services', 'Manufacturing', and 'Other industry'. The same *Business size* (H4.b) and *business age* (H4.c) categories used in Chapter 5 were used. The former were defined by the survey and are determined by the number of employees,[12] whereas the latter was calculated by subtracting the year respondents reported that their business started operations from the survey reference year (2013). Then, businesses were binned into quintiles from the 20% youngest to the 20% oldest.

The number of extortion incidents (H5.a) suffered by businesses—henceforth *extortion concentration*—was taken from the uncapped extortion victimisation experiences reported in the screening questionnaire. Similarly, the amount of bribes (H5.b) demanded from businesses—henceforth *corruption incidence*—was taken from the uncapped figure captured in the screening questionnaire in response to the question:[13] 'In total, how many separate acts of corruption did you suffer during 2013?' (INEGI, 2014e). As the estimates for these variables were overdispersed, a log transformation was used.[14]

Area-level variables measure variation at the state-level. The strength of the *rule-of-law* (H3.a) was measured using a revised index calculated by IMCO (2016); a composite 100 point score composed of kidnapping incidence, vehicle theft, costs of crime, total personal and household crime incidence, the crime underreporting rate, fear of crime, availability of notaries, and contract enforcement (higher scores represent a stronger rule of law). For this study, homicide rates were excluded from the index, as these were collinear with other crime covariates used. Measures for *weapon-related crimes* and *drug-related crimes* (H3.b and H3.c) were taken from the Executive Secretariat of the National System for Public Security (*Secretariado Ejecutivo del Sistema Nacional de Seguridad Pública*, SESNSP, 2015) as reported in 2013 by the Attorney General's Office (*Procuraduría General de la República*, PGR).

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[12]There are four categories: Micro businesses have 10 employees or fewer; small businesses have between 11 to 50 employees (11 to 30 in the commerce sector); medium businesses in industry employ between 51 to 250 people, 31 to 100 in commerce, and 51 to 100 in services; large businesses are those with 101 or more employees (251 or more in industry).

[13]An act of corruption refers to a situation where a public servant—or a third party acting on their behalf—directly asked for, suggested, or set the conditions for the payment of a bribe by the business. (INEGI, 2014e; Jaimes Bello & Vielma Orozco, 2013)

[14]As corruption incidence includes 0, the function $log(x+1)$ was used for this variable.

Lastly, the area-level *corruption prevalence*, an *economic competitiveness* index,[15] the *population*, and the *number of businesses* surveyed in each state were used as controls.

The state-level variables weapon crimes, drug crimes, corruption prevalence, population, and the number of surveyed businesses were log-transformed to reduce overdispersion. All state-level variables were centred around the national mean[16] to facilitate interpretation.

6.4 Analytical approach

The cross-tabulations shown in Table 6.1 indicate that there are statistically significant associations between compliance and incident- and business-level measurements. For example, regarding extortion type, row percentages indicate that victims complied with remote extortion incidents in only 5.4% of the cases, whereas in-person extortion incidents lead to compliance in 49.6% and 66.7% of the cases, respectively. Similarly, the use of a weapon in an extortion incident lead to compliance in 63.5% of the cases, whereas victims complied in only 13.5% of the incidents with no weapons. Lastly, extortion incidents with 2 or more offenders had compliance rates between 38.7% and 58.4%, while incidents with 1 offender had a compliance rate of 10.2%. Nonetheless, a bivariate analysis of compliance patterns could lead to spurious inferences, as it does not control for confounding.

In order to mitigate confounding and to estimate the partial effect of each variable, the relationship between compliance and the selected independent variables must be evaluated using a multiple regression method. As the study is concerned with testing the effects of several independent variables on the likelihood of compliance—a dichotomous dependent variable with responses taking either 0 or 1 values—a multiple logistic regression is considered an appropriate approach. However, an additional complication is that the data have a hierarchical structure, as some businesses suffered more than one incident and businesses are grouped within states (see Table 6.2 and Figure 6.1). This is a violation of the assumption of independence for logistic regressions. One option considered was the use of the multilevel modelling framework used in Chapter 5. However, this was judged to be unsuitable due to the unbalanced

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[15]The index used was a slight revision of IMCO's competitiveness index (2016), based on 9 subindices measuring sustainable development, social development and health, political stability, government effectiveness, labour productivity, economic stability, infrastructure, and international connections.

[16]Log transformed variables were centred around the log of the national mean ($log(x) - log(\bar{x})$).

Table 6.2: Descriptive statistics illustrating the nesting in the data.

	Incidents	Businesses	States
Incidents	$n = 3369$		
Businesses	1.49 [1–7]	$n = 2259$	
States	105 [27–257]	70.6 [19–179]	$n = 32$
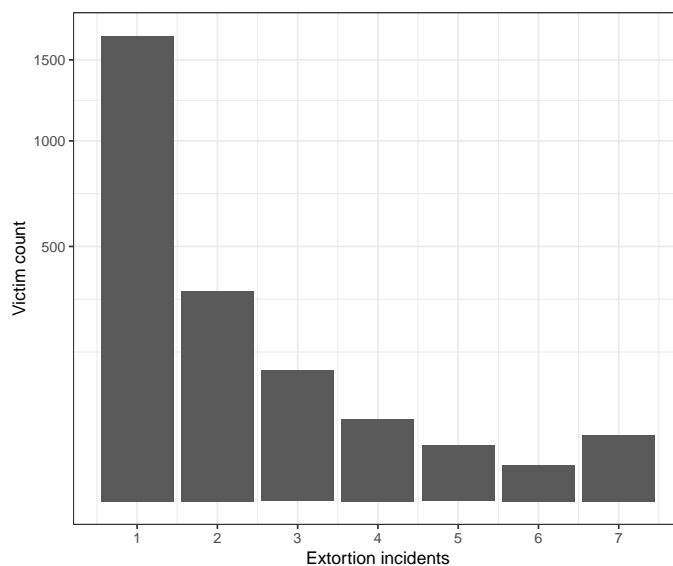
Figure 6.1: Distribution of extortion incidents. Scale of y axis was square-root transformed.

nature of the data. As seen in Figure 6.1, most victims experienced only one inci-
dent, thus there was not enough variance at level 1 (i.e., within victims) to estimate a
multilevel logistic model. Thus, to mitigate this violation, clustered standard errors
(Berger, Graham, & Zeileis, 2017; Zeileis, 2006) considering victim- and state-level
clusters were used.

6.5   Results

Results of a logistic model incorporating all independent variables can be found in
Table 6.3 (Model 1). A stepwise model-selection algorithm based on the Akaike
Information Criterion (AIC), detailed by Hastie and Pregibon (1992) and Venables
and Ripley (2002), indicated that an alternative specification (Model 2 in Table 6.3)
is more parsimonious. While a Wald test indicated that both models are signifi-
cantly different from a null model containing only the intercept, a Wald test between

model 1 and model 2 ($X^2 = 5.76$, $df = 11$, $p = 0.88$) confirmed that the excluded variables—size, age, rule of law, competitiveness, population and number of surveyed businesses—offer no improvement in model fit. Furthermore, the accuracy rate for Model 2 is 89.6%, whereas Model 1 offers a negligible improvement of 0.3 percentage points (89.9%). In contrast, Model 2 offers an improvement of 2.2 percentage points over the naive guess (87.4%).[17] Thus, only estimates from model 2 are discussed in detail. Generalised variance-inflation factors (Fox & Monette, 1992) indicated that multicollinearity was not present.

6.5.1 Effect sizes

As coefficient estimates are in the log-odds scale, interpretation of the exponentiated coefficients (e^B), also known as odds-ratios, is more straightforward. The odds-ratio is interpreted as the multiplicative effect on the odds of observing 1 in the dependent variable, for a one-unit increase in the independent-variable. For categorical independent variables, the odds-ratio is the multiplicative change in the odds in reference to a base category.

In what follows, the partial effect of each variable are described, thus the effect sizes refer to the expected change in the dependent variable after controlling for all other variables. The odds-ratios for extortion type categories were significant at the 99.9% confidence level and greater than 1, suggesting that in-person extortion incidents are more likely to involve compliance than remote extortion (the reference category). Street and in-premises extortion incidents were 7.67 and 8.33 times more likely to involve compliance than remote extortion incidents. Similarly, *cobro de piso* incidents were 16 times more likely to lead to compliance than remote extortion incidents.

The effect of the other incident-level variables appears to be more muted, though still relevant. When compared to incidents with only one offender, incidents with 2 and 4 or more offenders were 2.08 and 1.88 times more likely to involve compliance (significant at the 99% confidence level). In contrast, incidents with 3 offenders and in the dk/da category showed no statistically significant differences in the likelihood of compliance. When compared to incidents with no weapons, the presence of a weapon increases the likelihood of observing compliance by 2.76 ($p < 0.001$).

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[17]The accuracy rate corresponds to the percentage of correctly classified observations based on the conditional predictions of the model. The naive guess corresponds to the percentage of correctly classified observations assuming all observations have the same likelihood of observing the response variable, given by the unconditional rate of compliance.

Table 6.3: Extortion compliance: Results from the full and restricted model.

DV: Compliance	Model 1			Model 2		
	B	(SE)	OR	B	(SE)	OR
Intercept	-2.53***	(0.39)	0.08	-2.65***	(0.19)	0.07
Extortion type (Remote)						
Street	1.98***	(0.34)	7.23	2.04***	(0.34)	7.67
Premises	2.09***	(0.23)	8.10	2.12***	(0.23)	8.31
Cobro de piso	2.77***	(0.25)	16.00	2.76***	(0.26)	15.81
Num. offenders (1)						
2	0.73**	(0.27)	2.08	0.73**	(0.26)	2.08
3	0.61	(0.45)	1.85	0.60	(0.47)	1.83
4+	0.64**	(0.23)	1.91	0.63**	(0.23)	1.87
dk/da	-0.22	(0.30)	0.81	-0.22	(0.31)	0.80
Had weapon (No)						
Yes	1.00***	(0.20)	2.72	1.02***	(0.19)	2.78
dk/da	0.25	(0.23)	1.28	0.26	(0.23)	1.29
Business-level						
Business type (Retail)						
Hotels, Rest, Bar	-0.26	(0.25)	0.77	-0.24	(0.21)	0.79
Transport	0.82	(0.47)	2.28	0.86	(0.49)	2.36
Other services	-0.45*	(0.19)	0.63	-0.44*	(0.21)	0.64
Manufacturing	-0.45*	(0.19)	0.64	-0.45*	(0.18)	0.63
Other industry	-0.48	(0.35)	0.62	-0.44	(0.30)	0.64
Wholesale	-0.09	(0.28)	0.92	-0.09	(0.25)	0.91
Size (Large)						
Medium	-0.25	(0.34)	0.79			
Small	-0.04	(0.33)	0.96			
Micro	-0.13	(0.27)	0.88			
Years in business (0 to 5)						
6 to 9	0.03	(0.18)	1.03			
10 to 14	0.12	(0.30)	1.13			
15 to 23	-0.29	(0.23)	0.75			
24 to 212	0.12	(0.24)	1.13			
log(Extortions)	-0.56***	(0.16)	0.95	-0.55***	(0.16)	0.95
log(Corruption)†	0.53***	(0.12)	1.05	0.53***	(0.12)	1.05
State-level						
Rule of law	-0.01	(0.01)	0.99			
log(Weapon crimes)	0.37*	(0.18)	1.04	0.46**	(0.17)	1.04
log(Drug crimes)	-0.13	(0.13)	0.99	-0.14	(0.15)	0.99
log(Corruption preval.)	-0.34	(0.22)	0.97	-0.29	(0.16)	0.97
Competitiveness	0.01	(0.01)	1.01			
log(Population)	0.07	(0.19)	1.01			
log(N businesses)	0.23	(0.41)	1.02			
Log-lik	-868.22			-872.29		
Wald X^2(df)	42185*** (31)			2125.3*** (20)		
AIC	1800.4			1786.6		
n	3369			3369		

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, $^\dagger log(x+1)$; clustered standard errors were used.

The effect sizes of business-level variables were considerably smaller. Among business type categories, only the manufacturing and other services categories presented significant effects at the 95% confidence level. When compared to retailers (the reference category), manufacturers and other service firms were 37% and 36% less likely to comply with an extortion incident.[18] Business size and age were insignificant, meaning that the likelihood of compliance was not affected by these variables.

The amount of extortion incidents suffered by businesses was negatively associated with the likelihood of complying with an extortion incident ($p < 0.001$). However, the effect was relatively modest: a 10% increase[19] in the amount of extortion concentration experienced by a business was associated with a 5% decrease in the likelihood of complying. In contrast, corruption incidence was positively associated with the likelihood of observing compliance ($p < 0.001$). A 10% increase in the amount of bribes a business is solicited to pay was associated with a 5% increase in the likelihood of complying with an extortion incident.

State-level variables were mostly insignificant. Only the amount of weapon-related crimes showed a significant association with extortion compliance ($p < 0.001$). A 10% increase in the state-level amount of weapon-related crimes was associated with a 4% increase in the likelihood of compliance. While the amount of drug crimes and the state-level prevalence of corruption contributed to improving model fit, their partial effects on the likelihood of compliance was indistinguishable from 0. Similarly, the strength of the rule of law, competitiveness, population, and the number of surveyed businesses were also insignificant.

6.5.2 Predicted probabilities

The substantive interpretation of effect sizes can be refined by using predicted probabilities. The baseline predicted probability for compliance is given by the intercept. In model 2, the baseline probability was 6.6%, and it represents the likelihood of compliance when all dependent variables are zero or at their reference level. Regarding extortion type, the baseline represents the likelihood of compliance in remote extortion incidents.

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[18]Percentage change on the odds of observing the outcome can be calculated from odds-ratios by subtracting 1 and multiplying by 100 $((OR - 1) * 100\%)$

[19]When the independent variable has been log-transformed, exponentiating the coefficient would give the change in the odds of observing the outcome for a 2.72 change in the independent variable. Thus, to facilitate interpretation, the odds-ratios for log-transformed variables can be instead calculated for a more familiar change, such as 10%. This is given by 1.10^B.
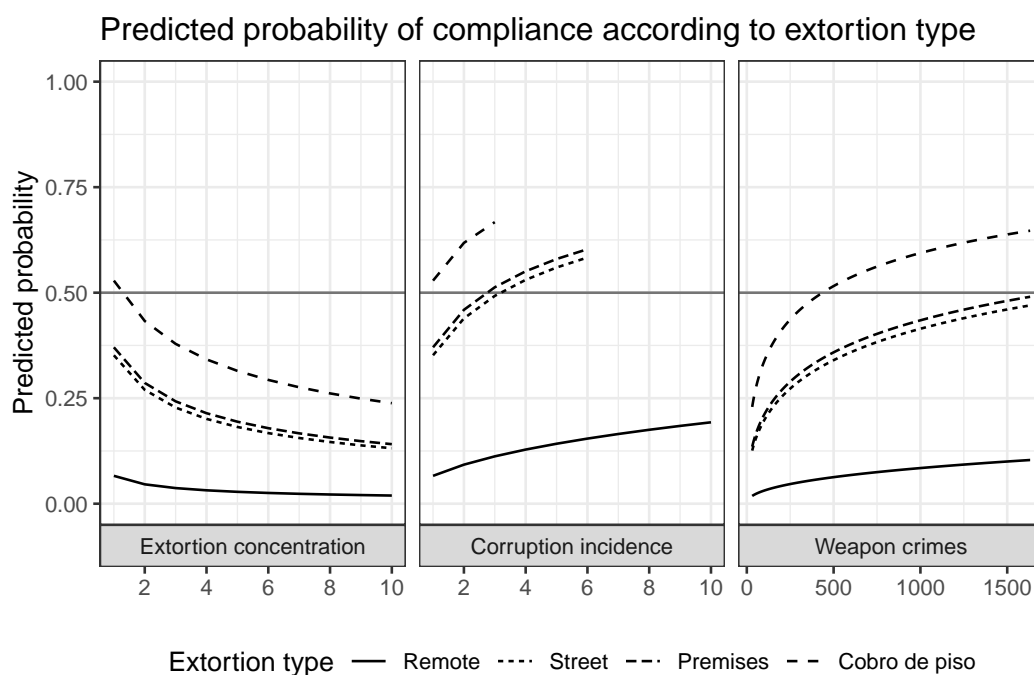
Figure 6.2: Predicted probabilities of extortion compliance according to extortion type and observed values of significant continuous variables. Estimates are based on model 2.

In contrast, the probability of compliance changed dramatically for in-person extortion incidents. Street and in-premises extortions were estimated to generate a 35.2% and 37.1% probability of compliance, holding all else constant. In contrast, *cobro de piso* extortions predicted a probability of 52.9%, all else being equal. This suggests that compliance was more likely than non-compliance only in *cobro de piso* incidents, as the predicted probability of compliance was greater than 50%, all else equal.

The presence of 2 and 4 or more offenders increased the baseline to 12.8% and 11.7%, respectively and holding all else equal. Similarly, the presence of a weapon increased the likelihood of compliance by around 9.8 percentage points, to 16.4% when compared to the reference incident.

In contrast, manufacturing and other services businesses were predicted to comply in only 4.3% and 4.4% of the cases, respectively and holding all else constant.

While the marginal effects for the continuous variables extortion concentration, corruption incidence and weapon related crimes were small, predicted probabilities suggested more drastic effects. Figure 6.2 presents predicted probability curves for

these variables according to each of the extortion type categories.[20] Regarding extortion concentration, the curves suggest notable reductions in the likelihood of compliance. In the case of *cobro de piso* extortions, the predicted probability decreased to 23.8% for businesses that experienced 10 extortions, and to 13.1% and 14.1% for street and in-premises incidents, respectively. The probability of compliance in remote extortions when victims suffered 10 extortions was 1.9%.

In contrast, increasing corruption incidence to the maximum value observed for *cobro de piso* incidents (3) increased the predicted probability of compliance to 66.7% in that type of incidents. In street and in-premises extortions, experiencing the maximum observed corruption incidence (6) increased compliance probability to 58.3% and 60.3%, respectively. In remote extortion incidents, increasing corruption incidence to 10 increased compliance probability to 19.3%.

The model predicts that incidents in states with the lowest amount of weapon-related crimes would lead to compliance in 1.8% of the cases of remote extortion, 12.6% and 13.1% respectively for street and in-premises incidents, and 22.9% for *cobro de piso* extortion. However, incidents in states that experienced the highest amount of weapon-related crimes would lead to compliance in 10.4% of the cases of remote extortion, 47% and 49% in street and in-premises incidents respectively, and 64.7% of the cases of *cobro de piso* incidents.

6.6 Discussion

This chapter sought to identify the determinants of extortion compliance. Using incident-level data from Mexico's commercial victimisation survey—one of the largest exercises of its kind—the study tested whether situational-, victim-, and area-level factors influenced victims' decision to comply, using multiple logistic regression.

The first hypothesis tested was that the likelihood of compliance with extortion demands would be higher in cases of in-person extortion, when compared to remote extortion incidents, as it was assumed that threats conveyed by richer media channels (in-person extortion) would be more believable than those conveyed via leaner channels (remote extortion). The findings strongly support this hypothesis, as all in-person extortion categories (street, in-premises and *cobro de piso*) were associated with substantially higher likelihoods of compliance when compared with cases

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[20]There were no statistically significant interactions between extortion type and extortion concentration (Wald $X^2(3) = 5.54$, $p = 0.136$), corruption incidence (Wald $X^2(3) = 5.87$, $p = 0.118$), or state weapon crimes (Wald $X^2(3) = 1.65$, $p = 0.649$). Interaction terms with categorical independent variables were ruled out due to complete and quasi complete separation.

of remote extortion. It is unclear what specific characteristics distinguish *cobro de piso* incidents from street and in-premises incidents, as the survey does not provide a precise definition. However, the fact that effect sizes for *cobro de piso* incidents were much larger than those of street and in-premises incidents—which were of similar magnitudes—suggests that the distinction is relevant and should be considered further.

Hypotheses 2.a and 2.b tested whether power asymmetries that favours the offender (operationalised as the presence of weapons and multiple offenders) increased the likelihood of observing compliance. The findings supported both hypotheses: the presence of a weapon, and incidents with 2 or 4 and more offenders (though not incidents with only 3 offenders) substantially increased the likelihood of observing compliance. This suggests that after controlling for threat believability as captured by the in-person/remote distinction, additional markers of power asymmetry can have a substantive effect on a victim's decision to comply with an extortion demand.

Hypotheses 3.a, 3b, and 3.c tested contextual factors that speak to the perceived costs of violence in the area where extortion incidents took place—the assumption being that compliance would be more likely in areas where the costs of violence are lower. The findings did not support hypotheses 3.a and 3.c: I failed to find any relationship between extortion compliance and the strength of the rule of law (H3.a), or the amount of drug crimes (H3.c). In contrast, the findings supported hypothesis 3.b: incidents in areas with more weapon-related crimes, and hence organised crime groups with more demonstrated readiness to use violence, were more likely to lead to compliance. Though the marginal effect was small, the relatively broad range in the prevalence of weapon-related crimes implies that the likelihood of compliance can vary dramatically between an area with a low prevalence of weapon-related crimes and one with a high prevalence.

Hypotheses 4.a, 4.b, and 4.c related to whether business characteristics were associated with extortion compliance, under the assumption that some businesses are more inherently vulnerable to intimidation. The findings suggested that most business types (4.a) have the same likelihood of complying with extortion demands, with the exception of businesses in the manufacturing or service sectors—though excluding hotels, restaurants and bars, and transportation—which were less likely to comply. Furthermore, there was no evidence of a relationship between extortion compliance and business size (H4.b) or business age (H4.c).

On the other hand, hypotheses 5.a and 5.b related to whether dynamic characteristics that speak to business vulnerability—extortion concentration and corruption

incidence—had an effect on extortion compliance. In contrast to what was predicted, the more extortion incidents a victim experienced, the less likely they were to comply.

Given the cross-sectional nature of the data, it is not possible to establish the direction of the causal effect; it may be that suffering more extortion incidents helps victims properly assess risks and avoid complying, or it could reflect repeated attempts by offenders to harass victims into compliance after being refused. However, establishing the direction of the effect would require longitudinal data that are not readily available (though see Chapter 8).

Consistent with what was expected, the amount of bribes that victims were asked to pay was positively associated with the likelihood of compliance. While the marginal effect was small, predicted probabilities suggested more drastic effects.

There are additional limitations to the findings reported here. Extortion against businesses is notoriously difficult to measure: on the one hand statistics based on crimes reported to the police rarely disaggregate crimes by victim type; on the other, extortion incidents are usually underreported, as victims fear reprisals.

While, commercial victimisation surveys can overcome such limitations to an extent (for a review, see Mugellini, 2013b), the estimates and patterns captured by surveys suffer from well-known limitations involving memory decay, telescoping effects and victims' reticence to report certain experiences (Mugellini, 2013c; Skogan, 1986b; UNODC/UNECE, 2010).

Due to these limitations, Mugellini (2013c) notes that victimisation estimates tend to underestimate the 'true' prevalence and incidence of crimes, though they do represent an improvement over other crime statistics. However, such underestimates notwithstanding, the large sample size and high response rate help assuage fears of any systematic biases affecting the reliability of the patterns observed.

The sampling frame employed presents additional limitations. Insofar as only permanent business establishment with fixed addresses were sampled, the study does not examine extortion compliance patterns of informal, temporary, and itinerant businesses.

Considering that such informal businesses are more exposed and less likely to turn to law enforcement for recourse, it is plausible that they are more vulnerable to extortion demands. Thus, it is likely that the compliance patterns observed are more acute in the informal sector, though there is currently no data available to test this assertion. Further studies focused specifically on the extortion experiences of informal businesses would thus be needed.

6.7 Chapter conclusion

The chapter has important academic and practical implications. Academically, it contributes to the literature on organised crime by going beyond contextual factors and identifying situational determinants of extortion compliance. Furthermore, it contributes to the literature on decision theory by empirically testing theoretical predictions and experimental findings regarding the role of threat believability. Additionally, it introduces the use of media richness theory to explain the influence of the communication channel used to convey extortion threats.

Practically, the findings contribute to refining our understanding of extortion. In particular, they highlight the need to consider in-person and remote extortion incidents as separate offence classes, given their divergent effects on compliance. Furthermore, the relevance of the communication medium points towards potential pinch points suitable for disruption: by reducing the opportunities for offenders to approach victims, the extortion script may be successfully interrupted.

Nonetheless, the chapter also highlighted areas where further research is needed. In particular, the need to examine the effects of past compliance behaviours on future extortion victimisation risk using longitudinal data, as well as clarifying the distinctions between *cobro de piso* and other in-person incidents. The following chapters will attempt to address some of these issues.

Chapter 7

Extortion victimisation: A crime specific approach

This chapter aims to answer the third research question presented in Chapter 2: Do victimisation patterns and mechanisms vary according to the type of extortion suffered? The motivation for this question stems from the findings presented in Chapter 5—which suggested that repeat extortion victimisation was the product of two distinct mechanisms—and the findings presented in Chapter 6—which suggested that extortion patterns may differ greatly according to the type of extortion suffered (i.e. remote, in-person or *cobro de piso*). This study thus aims to synthesise these previous findings applying the methodological approach employed in Chapter 5 to extortion figures classified according to the type of extortion suffered.

7.1 Background

Research presented in Chapter 5 suggested that extortion against businesses exhibits patterns of repeat victimisation that exceed chance expectation. Furthermore, quantitative analysis indicated that extortion victimisation follows a hurdle model, meaning that the mechanisms affecting prevalence—the likelihood of becoming a victim (Johnson, 2008)—are distinct from those affecting concentration—the amount of incidents suffered by victims (Johnson, 2008). In particular, the study found that business and area characteristics were relevant for predicting prevalence, whereas most business characteristics, and all observed area characteristics, were not significant for predicting extortion concentration. However, the study reported

in Chapter 5 did not take into account differences in the type of extortion suffered by businesses.

According to previous research (see Locks, 2015; Mugellini, 2013a; ONC, 2014; Pérez Morales et al., 2015), extortion in Mexico can broadly refer to three types of incidents. First, there are 'remote' extortion incidents in which threats are made over the telephone or the internet. Second, there are in-person extortion incidents for which threats are made face-to-face on the business's premises or on the street. Third, the literature also distinguishes *cobro de piso* incidents, which also take place in person but are believed to involve periodic payments at regular intervals. It is quite likely that remote, in-person, and *cobro de piso* extortion incidents are affected by different factors, as the opportunity structures to commit such crimes will likely differ. Recall from Chapter 2 that repeat victimisation is thought to be driven by two processes: risk heterogeneity and event dependence (Johnson, 2008).

Risk heterogeneity refers to characteristics of the business or its environment that could increase or decrease the likelihood of being targeted for an extortion. Considering that remote extortions do not require direct contact between victims and extorters, it is plausible that victim characteristics that speak to their vulnerability and accessibility (for example) may not be relevant for remote extortion, as they are for in-person and *cobro de piso* extortions. Similarly, as in-person and *cobro de piso* extortions are generally considered to be associated with organised crime groups, whereas remote extortions are considered to be committed by more 'opportunistic' criminals, area measures of organised crime presence might be more relevant to in-person and *cobro de piso* extortions than remote extortion incidents.

On the other hand, event dependence suggests that victimisation risk is dynamic, with the risk of subsequent victimisations being affected by past victimisation experiences. Event dependence is likely to have a significant impact on crime concentration when the outcome of a previous event informs the risk and effort of a subsequent one (Farrell et al., 1995, p. 396). In the case of extortion, this could mean that complying with an extortion demand could beget further victimisations. Considering that the research presented in Chapter 6 suggests that compliance rates vary widely according to the type of extortion suffered—in-person and *cobro de piso* extortions were, respectively, 8 and 16 times more likely to lead to compliance than remote extortions—it is plausible that the role of event dependence would similarly vary according to extortion type.

Given these potential differences between remote, in-person and *cobro de piso* extortions, it is not unreasonable to expect victimisation patterns would to vary

according to extortion type. As noted in Chapter 5, identifying the effect of event dependence requires longitudinal data, which is not readily available for measurements of Mexican extortion (see Chapter 8 for an exploration of event dependence using cross-sectional data). Nonetheless, the potential role of event dependence could be inferred by employing the type of hurdle model used in Chapter 5, by comparing whether the predictors for prevalence are consistent predictors for concentration. Thus, this chapter aims to replicate the analytical approach employed in Chapter 5 using measures of extortion disaggregated by type as the dependent variable(s).

Refining the analysis of victimisation patterns is important for at least two reasons. One, ignoring relevant differences between extortion types can lead to spurious inferences, as the patterns revealed by analyses may only be relevant for one type of extortion, but not others. Similarly, combining crime types could obscure potential associations lost through aggregation. Two, from a practical perspective, crime prevention is most successful when it is focused on very specific forms of crime (Clarke, 2009, p. 264); thus, refining our understanding of extortion by identifying the different opportunity structures underpinning different forms of extortion can help expand the knowledge base from which crime prevention interventions can be devised (Ekblom, 2002).

The chapter is structured as follows. The next section discusses the relevance of being crime specific in the context of crime analysis and crime prevention. This is followed by a discussion of the differences between extortion types and their potential opportunity structures. Next, the data and analytical approach are described. This is followed by the results and discussion.

7.2 The importance of being crime specific

Analysing various crime types aggregated as a single measure essentially assumes that the different crime types share the same underlying causes (Copes, 1999, p. 126). However, as Roberts and Block (2013, p. 446) note 'opportunity-based theories argue that each type of crime has a different opportunity structure', which means that different crime types are likely to be influenced by different causal mechanisms—and by extension require different solutions (Clarke, 2009, p. 264).

Opportunity-based theories of crime—which also serve as the theoretical underpinnings of the situational approach (see Chapter 2)—consider that opportunities for crimes occur when a motivated offender meets a suitable target, absent a capable guardian (Felson, 2011). However, a crucial aspect of the opportunity approach is

that target suitability cannot be defined in a general way, as it depends on the type of crime being committed, and on the offender's capabilities. According to the opportunity approach, this is because an offender's choice of target is affected by the objectives they aim to achieve, as well as by 'choice-structuring properties' (Cornish & Clarke, 1987, p. 935)—target and situation characteristics—that inform the perceived risks, effort and potential rewards of particular crime opportunities, given an offender's capabilities (Clarke, 1999; Cornish & Clarke, 1985).

Thus, as different offence types involve different levels of risk, effort, and rewards, they also reflect different choice-structuring properties. This not only means that crimes should be analysed using broad distinctions (e.g. street crimes vs violent crimes), but that 'the opportunity for crime must be evaluated for very specific categories of offence. . . robbery of post offices, banks, people on the street or in stairwells of council housing, are all different crimes from the standpoint of crime opportunity theory' (Felson & Clarke, 1998, p. 14).

For example, the literature on 'car theft' has identified that distinct categories of car thefts—e.g. theft for joyriding and transportation, theft for scrapping parts, theft for illicit export markets (e.g. Clarke & Harris, 1992a, 1992b; Copes, 1999; Light, Nee, & Ingham, 1993)—are associated with different opportunity structures. For instance, Clarke and Harris (1992b) found that midlevel sport cars were more susceptible to temporary thefts (associated with amateur thieves who steal cars for joyriding), whereas luxury European cars were more susceptible to permanent thefts (associated with professional car thieves who steal for parts and export markets).

Similarly, Tremblay, Clermont, and Cusson (1994) and Roberts and Block (2013) analysed temporary and permanent car thefts using multiple regression methods, and found that the two car theft categories were associated with different opportunity structures regarding the availability of suitable targets and the presence of motivated offenders, as well as measures of the potential markets in stolen cars. Further evidence of the differences in the opportunity structures for permanent and temporary car theft is provided by Farrell et al. (2011), who note that increases in the quantity and quality of security in cars has produced major reductions in temporary car thefts, while the decrease in permanent thefts has been comparatively smaller.

The crime specific approach has been further applied for other crime types such as burglary (Poyner, 2013; Tilley et al., 2015), sexual homicide (Beauregard & Martineau, 2015), rape (Rebocho & Silva, 2014), and corruption (Gorta, 1998), among others.

From an analytical perspective, being more crime specific is crucial to properly

identify the potential causal mechanisms underpinning crime problems. However, the crime specific approach is also important due to its practical implications, as a more precise understanding of the opportunity structures of specific crime types can inform more effective crime prevention strategies.

7.3 A crime specific approach to extortion victimisation

Thus far, the literature on extortion in Mexico has been primarily concerned with its relationship with organised crime violence in the context of the 'drug war' (e.g. Guerrero-Gutiérrez, 2012; Locks, 2015; ONC, 2014; Pérez Morales et al., 2015). The study presented in Chapter 5 represents the first systematic attempt to identify the opportunity structure underpinning specific extortion incidents. However, as noted earlier, that study did not take into account potential differences in extortion type that may be associated with different opportunity structures.

As noted in Chapter 6, extortion in Mexico can be broadly classified into three types of incidents: remote extortion, in-person extortion, and *cobro de piso* incidents. A straightforward distinction between these types is that remote extortion does not involve direct contact between offenders and victims. Instead, in these type of incidents, victims are primarily contacted by phone, though other electronic means can also be used (ONC, 2014, p. 32).

In contrast, it is generally considered that both in-person and *cobro de piso* incidents involve direct contact (i.e. face-to-face threats) (INEGI, 2014a; ONC, 2014). In turn, the main distinction between in-person extortion and *cobro de piso* incidents, is that the latter purportedly involve regular payments (e.g. monthly, weekly) (INEGI, 2014c; ONC, 2014).

7.3.1 Remote extortions

The modus operandi of remote extortion incidents is closer to a fraud or scam than to the shakedowns one associates with organised crime extortion. To commit a remote extortion, offenders cold-call potential victims and attempt to convince them to pay an amount into a financial account or to a mobile phone number. The methods used to convince victims to pay up range from trickery to threats (Locks, 2015; ONC, 2014). A common approach is to claim that a family member has been kidnapped and threaten to kill them if victims refuse to pay a ransom. However, in practice no kidnapping has taken place—hence these incidents are called fake or virtual kidnappings (Moor & Remijnse, 2008, p. 8). In virtual kidnappings:

> The extortionists usually have a recording of a child or woman crying
> and, sometimes, the shocked victim says a family member's name. With
> this information, the extortionists make the victim believe that their
> family member is in imminent danger and demand an immediate payment
> (Locks, 2015, p. 72).

Virtual kidnappings can also involve elaborate 'live' performances of abuse situations, with fellow offenders acting as the purportedly kidnapped victims pleading for help while the extortion victim is on the phone (Moor & Remijnse, 2008, p. 8).

Furthermore, ONC (2014) reports that some virtual kidnappings can be more elaborate, involving simultaneous calls to the extorted party and to the purportedly kidnapped family member. In these incidents, offenders call a person while pretending to be the police or other figure of authority, warn them of imminent danger at their home and convince them to go to a hotel or some other location, while holding them on the line. Throughout the call, the offenders harvest as much information as possible from the unsuspecting recipient. Simultaneously, an accomplice calls a family member and tells them that they have kidnapped person one and ask for ransom. The offenders use the knowledge gleaned from the first call to make the kidnapping believable, and the fact that person one is not home and not answering their phone further makes it appear as a real kidnapping (ONC, 2014, p. 30).

While virtual kidnappings can appear to be real to victims, and cause heightened fear and anxiety, they are not usually associated with any real threats or physical harms to the victim or the supposedly kidnapped person.

Remote extortions can also involve other types of scams. For example, offenders can attempt advanced-fee scams, where extortionists claim the victim has won a prize from a contest or raffle, but requires them to pay a sum before receiving the reward (ONC, 2014, p. 30). Similarly, extortionists can pretend to be calling from a bank in order to steal financial details that can be used to then draw resources from victims' accounts.

Lastly, remote extortions can take the form of direct threats. In these incidents, extortionists claim to be members of a well-known organised crime group—especially one known to engage in extortion rackets, such as the Zetas (see Chapter 3)—and demand money from victims (Mugellini, 2013a, p. 34; ONC, 2014, p. 30-31). A variation of this approach—which has some overlaps with virtual kidnapping—is for extortionists to claim they are government officials and threaten to arrest an acquaintance or family member unless they pay a 'bribe' (ONC, 2014, p. 30). Yet,

as in other forms of remote extortion, threats are usually empty and normally do not lead to harms for non-compliance.

7.3.2 In-person and *cobro de piso* extortions

In contrast, the modus operandi of in-person and *cobro de piso* extortions appears to be more straightforward: one or several extortionists approach a business, ask to speak with the owner or manager and demand an amount of money in exchange for not damaging the business or killing its owners and/or employees (Locks, 2015, p. 72). However, some variations in how these incidents take place have been noted.

First, if in-person extortion occurs regularly, it is often called *cobro de piso* (ONC, 2014). Furthermore, Mugellini (2013a, p. 34) notes that *cobro de piso* incidents can also include the 'sale' of 'protection services', whereby the extorting party would purportedly offer extorted businesses protection from other criminals. Given its recurrent incidence, and the associated offers of protection, *cobro de piso* incidents could be interpreted as the racketeering phenomenon described by Savona and Zanella (2010). From an illicit-governance perspective, *cobro de piso* incidents are also considered to be part of a parallel (illicit) tax system imposed by criminal groups in the territories they control (ONC, 2014, p. 31).

Second, in-person extortions are assumed to be committed by members of organised crime groups—especially in cases of *cobro de piso*—though it is not always entirely clear if this is the case. As in remote extortion incidents, offenders could still be spuriously benefiting from an organised crime group's reputation—what Gambetta (1994) calls 'pirates', and A. Smith and Varese (2001) refer to as 'fakers'. However, this strategy is certainly riskier for offenders in the case of in-person extortion, as it exposes them to retaliation by 'true' members of the organised crime group in question, whereas remote extortion incidents offer a degree of anonymity.

Regarding the demands imposed on victims, Locks (2015) notes that these can take the form of straightforward payments, or they can be more complex requests, such as forcing businesses to purchase goods from the criminal group—e.g. stolen petrol—or to hand over deeds of business properties. Locks (2015) also notes that when payments are requested, some groups have been reported to conduct reconnaissance to estimate how much money can be demanded. For example, criminals can stand outside a popular restaurant and count the number of customers per hour to estimate the restaurant's revenues, they can recruit employees to provide intelligence on the companies' finances, or employ economists to track international commodities

prices to vary their demands accordingly (Locks, 2015). Nonetheless, it is unclear if these accounts reflect generalised practice, as they are mostly based on anecdote.

7.3.3   Potential differences in opportunity structures

The descriptions presented above suggest that remote and in-person extortion incidents are quite distinct, and thus are likely to be associated with different opportunity structures. However, in the case of in-person and *cobro de piso* extortion, it is not quite clear if there are any major differences in the micro-level opportunity structures for these incidents. Perhaps the differences in the opportunity structure for these events are to be found at the higher level of 'territory' suggested by Kleemans (2018).

The results presented in Chapter 6 suggest that the probability of being successful (from the criminal perspective) is much higher for in-person—especially *cobro de piso*—incidents than in remote extortions. Yet, despite this, remote extortions are overwhelmingly more common than any other type of extortion incidents.

A potential explanation for this disparity is that the modus operandi of remote extortion represents much less risk and effort for offenders. In-person and *cobro de piso* extortion requires offenders to interact with their prospective victims, which, all else being equal, leads to a higher risk of detection by law enforcement or by rival criminal groups.[1] In contrast, offenders carrying out remote extortion reveal only their voices (which can be purposefully or electronically modified) and their phone numbers (which can be obscured, spoofed, or discarded with ease).

This distinction also impacts the pool of suitable targets that offenders can attempt to extort. In the case of in-person and *cobro de piso* extortions, offenders are limited by physical space, and can thus only extort businesses operating in their area of operations. Such areas of operations are likely to be constrained by offenders' awareness spaces (Brantingham & Brantingham, 2011), further reducing the number of targets suitable for predation (Hepenstal & Johnson, 2010). Furthermore, some businesses within reach of extorters may be harder to access (e.g. an office in a high-rise building would be comparatively harder to access than a similar office at street level), or may involve higher exposure risks (e.g. perhaps businesses clustered

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[1]It may be that in territories controlled by organised crime groups, such exposure does not significantly affect the risks of capture. However, considering that Mexico has, for the most part, functional government institutions, as well as a complex law enforcement environment (with police forces at the municipal, state and federal level, as well as the presence of the army and navy), such territorial control is unlikely to be impervious to some government interference. Thus it would make sense that criminal groups would prefer to minimise their exposure.

in a purpose-built commercial building have better security features than those occupying street-facing repurposed residential premises). Some businesses may also be more inherently vulnerable to intimidation than others given their type, size and age (e.g. Broadhurst et al., 2011; Broadhurst, Bouhours, & Bouhours, 2013; Chin et al., 1992; Schelling, 1971).

In contrast, remote extortionists have access to a much larger pool of suitable targets. Offenders committing remote extortion are not limited by physical space and can attempt to extort victims far removed from their location. A remote extortionist can target victims in other cities, other states, and even other countries. There is evidence of the transnational reach of remote extortionists. Recently the FBI (2017) warned that virtual kidnapping calls from Mexico were increasingly targeting homes in the US (see also Green, 2018). The seemingly limitless reach of remote extortion also means that there are few constraints on the type of location from which offenders can operate. It is widely assumed that a sizeable proportion of remote extortion incidents originate from prisons (FBI, 2017; Locks, 2015; ONC, 2014), where offenders operate in makeshift call-centres cold-calling victims around the clock using smartphones provided by corrupt prison personnel (Redacción Excelsior, 2017).

Nonetheless, the lack of geographical restraints on the target pool does not mean that all businesses are equally accessible or vulnerable to remote extortion. While most businesses will likely have public phone numbers that can be easily exploited by offenders, calling some businesses may involve circumventing additional obstacles before reaching a business's owner or manager who can be extorted.

For example, larger businesses may employ receptionists or automated answering systems to receive and direct calls to the appropriate persons. It is possible that the additional effort involved in clearing such hurdles may not be worth the offenders' time, given that calling other (smaller) businesses may not involve such barriers.

On the other hand, as offenders are known to gather information on prospective victims, public-facing businesses are likely to be more accessible and vulnerable, as more of their details are likely to be available through public channels (as opposed to businesses dealing primarily with other businesses).

The different modus operandi associated with remote and in-person extortion also suggest that the offences have different logistical requirements for their commission. Regarding tools, remote extortions require access to a phone—preferably one that supports blocking the outgoing number to the recipient's caller id. Furthermore, given that phone numbers known to engage in remote extortion can be blacklisted

by operators, remote extortionists need access to a steady supply of new phone numbers, a relatively trivial affair given the ubiquity of pre-paid mobile phones. Access to the internet is possibly useful (to identify suitable victims and to obtain personal details useful to leverage the extortive threats), though it does not appear to be essential.

As opposed to in-person extortions where payments can be made in cash, remote extortions rely on electronic transfers, which can be provided by the banking system or specialist providers (especially in the case of transnational transfers). However, these systems also pose risks to offenders as transactions can be more easily traced if they arouse suspicions (financial providers must comply with money laundering regulations). Thus, other methods to transfer money electronically have been devised,[2] such as transferring pre-paid mobile phone credits (which criminals can sell or use to extort more victims) (Locks, 2015; ONC, 2014).

In contrast, it is not immediately clear if in-person and *cobro de piso* extortions require any specific tools. Nonetheless, given that the presence of weapons increases the likelihood of victim compliance (see Chapter 6), it would make sense for offenders committing these types of incidents to carry weapons. It is also possible that offenders use vehicles to more effectively move around and approach victims, though it is not a specific requirement.

Regarding skills, both remote and in-person extortions require some theatrical abilities to convince victims to comply with demands. However, the dramatic skills required for remote extortions appear to be more extensive, as offenders sometimes act in different voices and mount elaborate ruses. In contrast, in-person and *cobro de piso* extortions require the ability to present credible threats face-to-face, and to carry out the respective violent punishments for non-compliance. While both remote and in-person extortion events can benefit from the ability to obtain information that can be leveraged to threaten victims, this appears to be far more important for remote extortion, where offenders use social engineering[3] techniques commonly used in computer hacking (Applegate, 2009; Mitnick & Simon, 2002).

Furthermore, the different incident types appear to involve different levels of co-offending. While co-offenders do not appear to be strictly necessary for any of the

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[2]Thus far, there are not many reports of the use of electronic cryptocurrencies such as bitcoin for the payment of remote or in-person extortion; though they are widely used in 'ransomware' extortion (Darrel, 2013, 'ransomware').

[3]Social engineering is the term used in information and computer security to refer to the techniques used to manipulate and deceive people so that they divulge sensitive or confidential information, or perform actions that compromise the security of a system (Applegate, 2009; Mitnick & Simon, 2002).

extortion variations, they do appear to be relevant in some cases. For instance, if offenders engaging in remote extortion are working from prison, accomplices are usually needed outside prison to collect payments from banks or wire transfer services. Similarly, the presence of more than one co-offender is associated with higher likelihood of compliance with extortion demands, thus it is likely that offenders may prefer to operate together. Lastly, while in-person and *cobro de piso* extortions can be carried out by sole extortionists, these types of incidents are traditionally associated with organised crime groups, thus co-offending would appear to be likely.

The above discussion suggests that there are sufficient grounds to assume that remote, in-person and *cobro de piso* extortion are associated with different opportunity structures. Nonetheless, there are also some potential overlaps between extortion types. For example, Felbab-Brown (2011b, p. 13) reports that offenders engaged in *cobro de piso* extortions would resort to calling their victims by phone to demand payments if approaching the premises became too risky due to police presence. Similarly, ONC (2014, p. 33) notes that some businesses subjected to *cobro de piso* extortions are simply given a phone number they should call to 'settle their bill'. These incidents could be catalogued as remote extortion, despite being closer to *cobro de piso* extortion. Thus, it is necessary to empirically assess if there are differences in the opportunity structures. In the context of victimisation, such differences would be evident in the explanatory variables associated with the incidence of each type of extortion incident. Consequently, the main hypothesis in this chapter is:

- **H1**: The predictor variables that explain the risk of victimisation are different for remote, in-person and *cobro de piso* extortion.

As illustrated in Chapter 5, incidence may not be an ideal measure of the extortion victimisation phenomenon as it obscures the fact that the variables affecting the prevalence of extortion might not be the same as those that explain the concentration of extortion—possibly due to the role of event-dependence. Thus, it is also important to determine whether there are differences across the components of the model for each of the extortion types:

- **H2**: For remote, in-person and *cobro de piso* extortions, the predictors that explain prevalence are distinct from those that explain concentration.

7.4 Data and measures

As in previous chapters, this study uses the 2014 sweep of Mexico's commercial victimisation survey, ENVE (see Section 4.2.2 for more detail). As is common in other victimisation surveys (e.g. UNODC/UNECE, 2010), the instrument is divided in two parts: a screening questionnaire that records the prevalence and incidence of crimes experienced by respondents, and a victim form used only for victimised businesses to capture the details of each victimisation incident experienced, though there is a cap of 7 incidents per crime type per business (INEGI, 2014c).

In Chapter 5, the measures of extortion used came from the screening questionnaire. While these measures are useful because they provide a readily available uncapped summary of victimisation experiences (Farrell & Pease, 1993; Trickett et al., 1992), they are not disaggregated by the type of extortion suffered, and therefore they are not useful for the purposes of this chapter. To obtain suitable measures of extortion disaggregated by type, measures had to be constructed from the victimisation experiences reported in the victim forms.

7.4.1 Dependent variables

The chapter has three dependent variables measuring the incidence of extortion per type. For each extortion incident reported by a victim (up to a maximum of 7), the victim form records extortion type in 5 categories: 'telephone extortion', 'by internet/email', 'on the street', 'on the premises', '*cobro de piso*', and 'other'. Following the approach used in Chapter 6, incidents in the 'other' category (9, 0.3%) were excluded, while incidents categorised as 'by internet/email' (8, 0.2%) were merged with the 'telephone extortion' category into a new 'remote' extortion category. Given the very similar compliance patterns found in Chapter 6, 'on the street' and 'on the premises' categories were combined in an 'in-person' extortion category. As '*cobro de piso*' exhibited a much higher likelihood of compliance than other 'in-person' extortions, it was considered better to keep the former category unchanged. Thus, to construct incidence measures for 'remote', 'in-person', and '*cobro de piso*' extortions, victim forms were analysed to count the number of incidents per extortion type per unit. Units that did not experience any incidents of a particular category were given a value of zero for that extortion type.

Given the capping practices used in victim forms, the maximum number of incidents that could be registered per unit was seven. However, as the survey considers the different extortion types to be sub-types of the 'extortion' umbrella term, if a

Table 7.1: Descriptive statistics of the dependent variables used in the study.

	Remote	In person	*Cobro de piso*
Mean	0.101	0.015	0.003
Variance	0.224	0.023	–
Ratio (Var./Mean)	2.21	1.56	–
Range	[0,7]	[0,6]	[0,1]
Prevalence rate[†]	670.79	122.51	33.02
Incidence rate[†]	1013.10	150.21	33.02
Concentration	1.51	1.23	1.00
Percentage repeats	33.79	18.44	0.00
n	28161	28161	28161

[†]Rates per 10,000 units.

unit suffered more than one extortion type, the amount of incidents suffered in one category would necessarily reduce the maximum number of incidents that could be reported for another type.

Nonetheless, the amount of multiple victimisation across extortion types was relatively rare. Among the 1,889 victims of remote extortion, only 2.4% suffered an in-person incident, and only 0.74% experienced *cobro de piso*. Among the 345 victims of in-person extortion, only 13.3% experienced remote extortion, and 3.5% experienced *cobro de piso*. Lastly, among the 93 victims of *cobro de piso*, 15.1% experienced remote extortion, and 13.2% experienced in-person extortion. Overall, only 4 victims experienced the three types of extortion; these victims represented 0.2% of remote extortion victims, 1.2% of in-person extortion victims, and 4.3% of *cobro de piso* extortion victims.

Multiple victimisation is unlikely to have affected the counts of remote extortion, though it may have been more relevant in constraining the estimates of in-person and *cobro de piso* extortion. For these reasons, the estimates presented herein— particularly for in-person and *cobro de piso* extortion—should be considered to be underestimates of the true incidence of extortion.

The descriptive statistics in Table 7.1 provide an overview of the extent of victimisation according to extortion type. Both remote and in-person extortion exhibited overdispersion, as their variances were larger than their means—2.21 and 1.56 times respectively—which suggests the presence of a repeat victimisation phenomenon. In contrast, there were no repeat *cobro de piso* extortions, as the maximum number of incidents observed for this extortion type was 1. Regarding prevalence, there were

670.79 victims of remote extortion, 122.51 victims of in-person extortion, and 33.02 victims of *cobro de piso* extortion per 10,000 businesses.

Regarding incidence, there were 1,013.1 incidents of remote extortion, 150.21 incidents of in-person extortion, and 33.02 incidents of *cobro de piso* extortion per 10,000 businesses. These figures suggest a concentration rate of 1.51 incidents of remote extortion per remote extortion victim, 1.23 incidents of in-person extortion per in-person extortion victim, and one incident per victim in the case of *cobro de piso*. Thus, not only is remote extortion more likely, but it also appears to be associated with higher rates of repeat victimisation than in-person extortion—33.8% of remote extortions were repeat incidents, while only 18.4% of in-person extortions were repeats.

7.4.1.1   The extent of remote extortion concentration

The summary statistics presented above can obscure the true extent of crime concentration. To fully capture the extent of the phenomenon, it is necessary to examine the distribution presented in Table 7.2. According to the table, only 1.8% of businesses (27% of remote extortion victims) suffered repeat remote extortion victimisation, however, they accounted for 52% of all remote extortion incidents. Given the capping practices implemented in the ENVE, the extent of concentration is likely to be underestimated.

However, given that repeat victimisation can also occur due to chance, it is important to compare the distribution observed to that expected if victimisation were

Table 7.2: Distribution of remote extortion victimisation. Non-cumulative percentages.

Events	Prevalence	Incidence	Repeats	Target %	Victim %	Incident %
0	26272	–	–	93.292	–	–
1	1381	1381	–	4.904	73.107	48.405
2	285	570	285	1.012	15.087	19.979
3	117	351	234	0.415	6.194	12.303
4	46	184	138	0.163	2.435	6.449
5	21	105	84	0.075	1.112	3.680
6	11	66	55	0.039	0.582	2.313
7	28	196	168	0.099	1.482	6.870
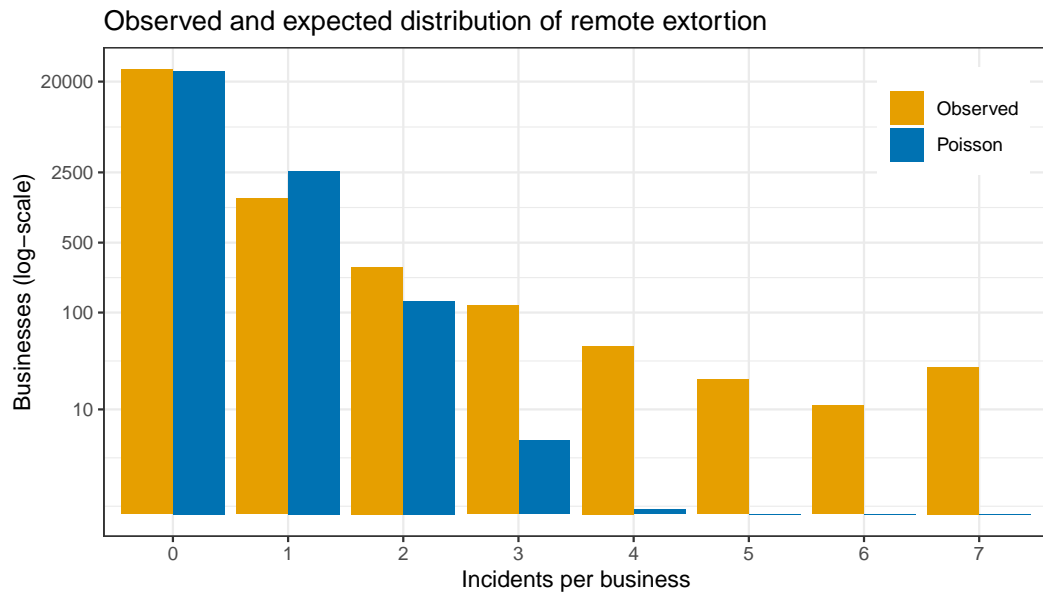
Figure 7.1: Observed and expected (Poisson) distribution of remote extortion victimisation.

a random process. The latter can be represented by a Poisson[4] process. Figure 7.1 and Table 7.3 compare the observed distribution to that expected if remote extortion victimisations were the product of a Poisson process. As can be seen, the observed distribution is overdispersed, which strongly suggests that it is the product of a non-random process consistent with the repeat victimisation expectation.

Crucially, a Kolmogorov-Smirnov test[5] (KS test, Upton & Cook, 2014b) comparing the observed distribution to 2,000 simulated Poisson distributions suggested that the observed distribution is significantly different from the Poisson expectation ($D_{sim} = 0.029$, $p < 0.001$). Similarly, a Chi-squared test comparing the observed counts with the those expected[6] under a Poisson process (see Table 7.3), also indicated that the observed distribution was not likely to be the product of chance ($X^2 = 11315$, $df = 3$ $p < 0.001$).

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[4]Events generated by a Poisson process are *random* and *independent* insofar as they occur at a constant rate (μ) not affected by past events (Sparks, 1981a). The Poisson counts were calculated estimating the expected Poisson density given the observed rate, times the number of observations.

[5]To estimate the KS test statistic, the implementation for discrete distributions implemented by Dimitrova, Kaishev, and Tan (2017) was used.

[6]Observations were aggregated to ensure that expected counts met the assumptions of the Chi-squared test.

Table 7.3: Observed and expected (Poisson) distribution of remote extortion victimisation. Observations were aggregated to ensure expected counts met the assumptions of the Chi-squared test.

Incidents	Observed	Poisson
0	26272	25447.76
1	1381	2578.12
2	285	130.60
3+	223	4.52

7.4.1.2 The extent of in-person extortion concentration

The distribution of in-person extortion is shown in Table 7.4. It displays much lower prevalence and incidence rates than remote extortion, and there was less evidence of repeat victimisation—only 18.4% of all in-person extortions were repeats. Nonetheless, the distribution did exhibit high levels of concentration: while repeat in-person extortion victims constituted 0.18% of units (15% of in-person extortion victims) they accounted for 30.7% of all in-person extortion incidents experienced in the country in 2013. However, as in remote extortions, capping is similarly likely to lead to underestimates of concentration.

Figure 7.2 and Table 7.5 compare the observed distribution of in-person extortion with that expected assuming a Poisson process. As in the case of remote extortions, in-person extortions also appear to exhibit more overdispersion than chance expectation, which suggests the presence of a non-random process of repeat victimisation. However, evidence of the differences between the observed and expected distributions is mixed. On the one hand, a KS test comparing the observed distribution to 2,000 simulated Poisson distributions did not provide sufficient evidence to reject the null hypothesis that the observed distribution was produced by a random process ($D_{sim} = 0.0027$, $p = 0.951$).

Table 7.4: Distribution of in-person extortion victimisation. Non-cumulative percentages.

Events	Prevalence	Incidence	Repeats	Target %	Victim %	Incident %
0	27816	–	–	98.775	–	–
1	293	293	–	1.040	84.928	69.267
2	36	72	36	0.128	10.435	17.021
3	11	33	22	0.039	3.188	7.801
4	2	8	6	0.007	0.580	1.891
5	1	5	4	0.004	0.290	1.182
6	2	12	10	0.007	0.580	2.837
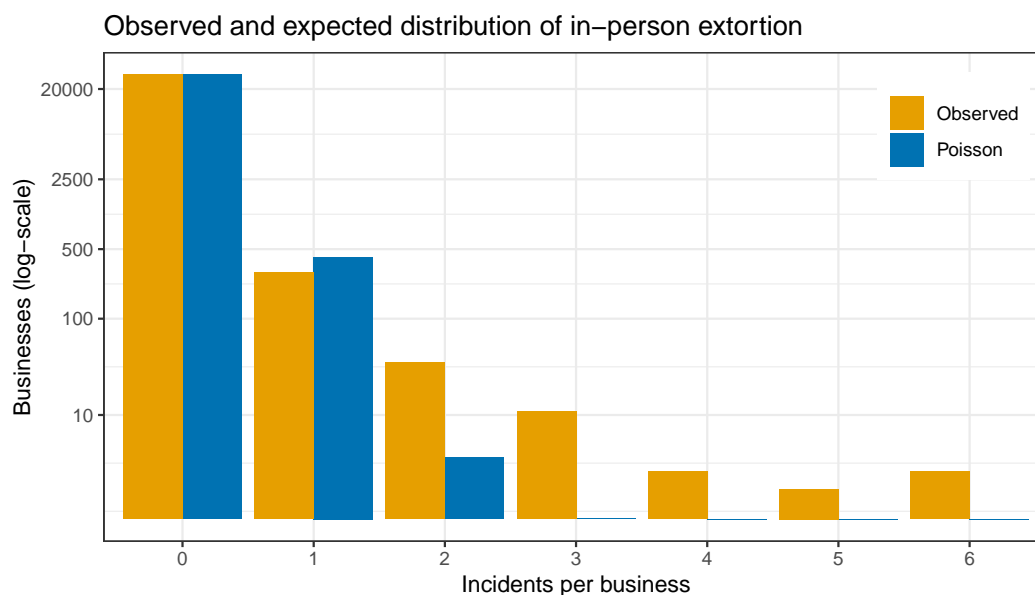
Figure 7.2: Observed and expected (Poisson) distribution of in-person extortion victimisation.

On the other hand, a Chi-squared test[7] comparing the observed counts of in-person extortion to those expected under a Poisson process (see Table 7.5) indicated that the observed distribution was not likely to be the product of chance ($X^2 = 16627$, $p_{sim} < 0.001$). The discrepancy can be explained by differences between the tests. The KS test is not as sensitive to discrepancies in the tail of the distribution, while the main contribution to the Chi-squared statistic came precisely from the right-hand tail of the distribution—note how the Poisson counts drop near 0 at 3 or more events, while the observed distribution still presents counts there. Thus, it is likely that the observed distribution is not the product of chance, though it remains important to test this assertion when choosing an appropriate modelling approach.

Table 7.5: Observed and expected (Poisson) distribution of in-person extortion victimisation.

Incidents	Observed	Poisson
0	27816	27741.16
1	293	416.69
2	36	3.13
3+	16	0.02

[7]Given that even after aggregation, the expected counts were below the conventional value required for Chi-squared tests, the p-value was estimated using a simulation with 2,000 replicates.

7.4.1.3   Why is there no repeat *cobro de piso* extortion?

The lack of repeat *cobro de piso* victimisations is surprising. On the one hand, one possibility for the lack of repeats is that the measurements are correct and there were no repeat *cobro de piso* incidents in the reference year. Assuming that the distribution of *cobro de piso* extortions follows a Poisson distribution with $\mu = 0.003$, there is approximately an 86% chance that the distribution would contain no repeats,[8] though the true likelihood of repeats would certainly be higher if the underlying process generating the incidents does not conform to the Poisson assumptions—a likely scenario.

The figures reported in the screening questionnaire suggest that victims of *cobro de piso* experienced at most 15 extortion incidents in the reference year (which is notably lower than the 40 and 24 incidents that victims of remote and in-person extortion respectively experienced). However, as these figures aggregate all types of extortion, and as around 23% victims of *cobro de piso* also reported experiencing at least one other type of extortion, it cannot be assumed that the figures reported in the screening questionnaire refer only to *cobro de piso*. Thus, I cannot reject the possibility that there were no repeat *cobro de piso* incidents.

On the other hand, though the survey documentation does not actually provide an operational definition of *cobro de piso*, it is broadly assumed that a defining feature of this type of extortions is repetition. In the ENVE documentation, INEGI (2014c) notes that if a victim is involved in a *cobro de piso* scheme with weekly payments, the survey would record 52 incidents in the year for that victim (p. 29). While it appears that this refers to the measurements captured in the screening questionnaire, the documentation does not specify what procedure should be followed in these cases in the second part of the survey (the victim forms). Thus, another possibility for the lack of repeat *cobro de piso* incidents is that only one incident for each *cobro de piso* 'series' was recorded in the victim forms. Such an approach would be somewhat consistent with recording practices in other victimisation surveys.

For example, the US National Crime Victimization Survey (NCVS) implements a protocol that identifies crime series as six or more similar incidents suffered by a victim during the reference period for which the respondent is unable to recall details of each incident (Rennison & Rand, 2006, p. 42). In crime series, only one victim form

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[8]The probability of repeats was calculated by simulating a Poisson distribution with $\mu = 0.003$ and 28,161 observations. Only in 14% of the 2000 replicates did the distribution present at least one unit with more than one incident (and never more than 2). The probability can also be calculated by estimating the density of a Poisson distribution with $\mu = 0.003$ at the value 2. The second approach produces nearly identical results.

is used to record details of the most recent incident in the series, though the total incidence is recorded as well (Rennison & Rand, 2006, p. 42; Planty, 2006, p. 156). The protocol is only used as a last resort (Rennison & Rand, 2006, p. 42), and its goal is to ease the cognitive burden on respondents, who 'must not only remember and report details of numerous crime events, but they also must not confuse aspects of different events and even treat continuous events as if they were discrete' (Planty, 2006, p. 156). While INEGI (2014c) notes that it has identified crime series in the ENVE, in which victims experience the same crime multiple times, in similar circumstances, and possibly by the same offenders (p. 29), it does not mention if a specific protocol is used to deal with such crime series.

Thus, it is possible that the lack of repeat *cobro de piso* incidents is due to an 'informal' recording practice applied to highly repetitive crime series, such as a *cobro de piso* scheme where victims are asked to pay once a week. If this is the case, it would represent a grave flaw of the ENVE, and would mean that the true incidence and concentration (though not necessarily the prevalence) of *cobro de piso* may be gravely underestimated.

As noted by Farrell and Pease (2007), the amount of crimes suffered by crime series victims can account for a disproportionate proportion of total crime incidence in a year; thus it is of paramount importance to accurately capture their extent. As illustrated by the NCVS, there may be genuine reasons to implement specific recording protocols for highly repetitive crime series; however, such protocols should be clearly indicated, and the actual estimated incidence for each series should still be recorded even if the particular details of each incident in the series is not.

At this stage, it is not possible to determine which of the two scenarios is more likely to explain the absence of repeats (or indeed if there is another scenario not currently considered). Thus, the analysis on *cobro de piso* presented herein will be limited to examining prevalence.

7.4.2 Independent variables

This chapter uses the same independent variables as those used in Chapter 5 but a different set of dependent variables. This allows an explicit comparison of the estimated effects of covariates across the different extortion types. The variables are:

- Unit level

- *Corruption incidence*: Number of times businesses were asked to pay a bribe to government officials in 2013.[9]
- *Years in business*: Number of years in operation by 2013, in quintiles.
- *Business type*: The categories used had to be collapsed, as some business type categories used in Chapter 5 exhibited complete or quasi-complete separation[10] with the dependent variables used in this study. Categories with very few observations were aggregated to the higher-level classification in the North American Industrial Classification System (INEGI, 2007). The final categories used here are: *Retail*, *Wholesale*, *Industry*, *Hotels, restaurants and bars*, and *Other services.*
- *Business size*: Categorical variable (micro, small, medium, large) based on the number of employees (see Chapter 5).

- State level

  - *Rule of law*: Modified IMCO (2016) index measuring strength of rule of law at state level (see Chapter 5, footnote 9); centred around the national mean.
  - *Corruption prevalence*: Number of businesses that were asked to pay a bribe in each state in 2013; log-transformed and centred around the log of the national mean.
  - *Drug-related crimes*: Number of drug-related crimes per state in 2013 (SESNSP, 2015); log-transformed and centred around the log of the national mean.
  - *Weapon-related crimes*: Number of crimes related to the possession of forbidden firearms per state in 2013 (SESNSP, 2015); log-transformed and centred around the log of the national mean.

- Controls

  - *Economic competitiveness*: Modified IMCO (2016) index measuring economic competitiveness (see Chapter 5, footnote 8); centred around the national mean.

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[9]In Chapter 5, corruption incidence was used untransformed, while in Chapter 6 the log-transformation was found to be a better fit to explain extortion compliance. In this chapter, several functional forms were tested (log-transformation and polynomials). Ultimately, the best-fitting functional form for each extortion type was used.

[10]As noted in Chapter 6, complete and quasi-complete separation occur when a categorical variable perfectly (or almost perfectly) predicts the value of the dependent variable (e.g. when all or nearly all observations for the dependent variable of a particular category are 0). The presence of complete and quasi-complete separation can lead to estimation failures in logit and count models.

- *Population*: Number of people living in each state in 2013 (CONAPO, 2012); log-transformed and centred around the log of the national mean.
- *Number of businesses*: Number of businesses surveyed by the ENVE 2014 per state; log-transformed and centred around the log of the national mean.

Descriptive statistics for the independent variables can be found in Table 5.2 in Chapter 5.

7.5 Analytical approach

As Pease and Tseloni (2014) note, understanding the factors that are associated with micro-level risks of victimisation requires the use of a modelling approach. In particular, given the overdispersed nature of crime counts and the clustering of potential targets in larger areas, Pease and Tseloni (2014) recommend using the multilevel negative binomial model. However, using this type of model assumes that the factors that explain prevalence are the same as those that explain concentration due to repeat victimisation. While this assertion may be true for some crime types, in Chapter 5 I show that this is not the case for extortion victimisation. Thus, I proposed an alternative approach using a two-part modelling strategy: the multilevel negative binomial-logit hurdle model.[11]

The modelling approach[12] followed in this study can be summarised as follows. First, a count model was used to estimate the incidence of a type of extortion. Then the two components of the hurdle were estimated: a logit model was used to estimate the prevalence of extortion, and a truncated count model was fit to the counts of extortion experienced among the victimised subset.

Given that there were no repeat *cobro de piso* incidents, the approach described above is not suitable for this crime type. Instead, only a logit model was estimated for this extortion type.

To assess the hypotheses, the predictors were compared across the different types of extortion, and across the hurdle components. If there were differences in the significance and effect size of the associations between the independent variables and risk of victimisation across different extortion types, then the null hypothesis

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[11]In this chapter, models were fit using the glmmTMB (Bolker, 2017; Brooks et al., 2017) and glmmADMB (Bolker et al., 2012; Fournier et al., 2012) packages in R (R Core Development Team, 2015).

[12]The specific statistical definitions of the models used can be found in Chapter 5.

was rejected (H1). Similarly, for remote and in-person extortion, the null hypothesis (H2) was rejected if the predictors of prevalence were distinct from those that explain concentration.

To interpret coefficient effect sizes, these need to be transformed into a more convenient scale (as they are estimated in the log-scale in count models, or log-odds scale in logit models). In the case of count models, exponentiating the coefficient (e^β) transforms the coefficients into incidence rate ratios (IRR, Hilbe, 2014, p. 60), whereas in the case of logit models, exponentiation transforms the coefficients into odds ratios (OR, Weisburd & Britt, 2014, p. 568). The exponentiated coefficients represent the multiplicative effect on the expected counts (or on the expected odds) of the dependent variable, for a one-unit increase in the independent variable.[13] In the case of categorical variables, the effect is in reference to the expected count (or odds) of the base category. Lastly, IRRs (ORs) can also be interpreted as the percentage change in the dependent variable (given by $IRR - 1$ and $OR - 1$).

7.6 Results

The results of the statistical models are presented in Tables 7.6 to 7.8. All models were found to be statistically significant when compared to null models containing only the intercept, as indicated by likelihood ratio tests (LRT). Similarly, in all models, the multilevel specifications were found to be significant improvements over models with single-level specifications, similarly tested using LRT. For the count models, the negative binomial specification was significantly better than the Poisson for the incidence models for remote and in-person extortion, and in the concentration model for remote extortions. In contrast, the truncated negative binomial specification was not significant in the concentration model for in-person extortions, thus the truncated Poisson was used instead ($LRT(1) = 0.098$, $p = 0.754$).

The hurdle specifications were found to improve model fit. In remote extortions, the hurdle components had a joint Akaike information criteria (AIC, Cameron & Trivedi, 2013, p. 197) of 16656.2, 148.3 units smaller than the AIC of the standard negative binomial model. Similarly, the in-person hurdle components had an AIC of 3847.7, which was 27.1 units smaller than the standard negative binomial model.

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[13]When the independent variable has been log-transformed, the IRR (OR) represents change for a 2.72 multiplicative increase in the independent variable. To facilitate interpretation, the IRR (OR) of log-transformed variables can be calculated for a 10% increase in the independent variable (given by 1.10^β).

Thus, the interpretation of the coefficient estimates will focus only on the results of the hurdle components.

Multicollinearity was not deemed to be a problem, as all generalised variance-inflation factors (Fox & Monette, 1992) were well below any threshold suggesting its presence (O'Brien, 2007).

7.6.1 Remote extortion

As expected, the significance and magnitude of estimated coefficients for remote extortion (see Table 7.6) varies greatly between models of prevalence (logit) and concentration (truncated negative binomial).

In the prevalence model, the intercept represents the baseline probability of being the victim of remote extortion when all continuous dependent variables are valued at zero[14] and all categorical variables are at the base category. In this case, the odds of experiencing a remote extortion in 2013 were 0.04 (given by $e^{-3.12}$, $p < 0.001$).

The coefficients represent the partial effect (i.e. holding all else constant) of a change in the independent variable. A 10% increase in the number of bribes[15] a business is asked to pay was associated with an 8.44% increase in the odds of suffering a remote extortion (given by $1.10^{0.85}$, $p < 0.001$). All businesses with more than 5 years of operation were more likely to suffer a remote extortion. The odds were 36.3% higher for businesses with 6 to 9 years of operation ($e^{0.31}$, $p < 0.001$); 43.3% higher for 10 to 14 years ($e^{0.36}$, $p < 0.001$); 69% higher for 15 to 23 years ($e^{0.53}$, $p < 0.001$); and 46.2% higher for businesses with 24 or more years of operation ($e^{0.38}$, $p < 0.001$).

Regarding business type, only hotels, restaurants and bars had significantly different odds of experiencing a remote extortion when compared to the base category (retailers): Restaurants, hotels and bars were 50.7% more likely to become victims of remote extortion ($e^{0.41}$, $p < 0.001$). Business size was also a significant variable. Medium and small businesses were 29.7% and 41.9% more likely to experience a remote extortion than large businesses (given by $e^{0.26}$, $p < 0.01$, and $e^{0.35}$, $p < 0.001$, respectively). In contrast, the smallest of businesses—micro-sized businesses with 10 employees or fewer—were 32.3% less likely to become victims of remote extortion than large businesses ($e^{-0.39}$, $p < 0.001$).

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[14]Recall that all state level variables centred were around the national mean, thus the intercept captures the value at the national mean for these variables.

[15]Corruption incidence was log transformed (using the $log(x + 1)$ function as the original values contain 0) as this functional form was found to be a better fit than un-transformed and second-order polynomial specifications (the AIC of the log-transformed specification was 90.6 and 58.6 units smaller, respectively).

Table 7.6: Model estimates (log and log-odds scale) for remote extortions.

| Remote extortions | Neg. Bin. | *Hurdle* | |
		Logit	Trunc. Neg. Bin.
Intercept	$-2.79\ (0.12)^{***}$	$-3.12\ (0.12)^{***}$	$-5.11\ (0.23)^{***}$
Business-level variables			
log(Corruption incidence)†	$0.88\ (0.09)^{***}$	$0.85\ (0.07)^{***}$	$0.23\ (0.12)$
Years (0 to 5)			
6 to 9	$0.31\ (0.08)^{***}$	$0.31\ (0.08)^{***}$	$0.11\ (0.18)$
10 to 14	$0.41\ (0.09)^{***}$	$0.36\ (0.08)^{***}$	$0.17\ (0.18)$
15 to 23	$0.50\ (0.08)^{***}$	$0.53\ (0.08)^{***}$	$0.15\ (0.17)$
24 to 212	$0.45\ (0.09)^{***}$	$0.38\ (0.08)^{***}$	$0.34\ (0.18)$
Business type (Retail)			
Wholesale	$0.07\ (0.11)$	$0.04\ (0.10)$	$0.12\ (0.20)$
Industry	$-0.03\ (0.08)$	$-0.10\ (0.08)$	$0.13\ (0.17)$
Hotels, rest. & bars	$0.47\ (0.09)^{***}$	$0.41\ (0.08)^{***}$	$0.53\ (0.17)^{**}$
Other serv.	$0.10\ (0.07)$	$0.04\ (0.06)$	$0.11\ (0.14)$
Business size (Large)			
Medium	$0.24\ (0.10)^{*}$	$0.26\ (0.09)^{**}$	$-0.11\ (0.19)$
Small	$0.21\ (0.09)^{*}$	$0.35\ (0.09)^{***}$	$-0.29\ (0.18)$
Micro	$-0.53\ (0.09)^{***}$	$-0.39\ (0.09)^{***}$	$-0.52\ (0.17)^{**}$
State-level variables			
Rule of law	$-0.00\ (0.01)$	$-0.00\ (0.01)$	$0.00\ (0.01)$
log(Corruption prevalence)	$0.35\ (0.17)^{*}$	$0.43\ (0.18)^{*}$	$-0.16\ (0.24)$
log(Weapon crimes)	$0.41\ (0.11)^{***}$	$0.40\ (0.12)^{***}$	$0.16\ (0.16)$
log(Drug crimes)	$-0.24\ (0.08)^{**}$	$-0.21\ (0.09)^{*}$	$-0.23\ (0.13)$
Competitiveness	$-0.02\ (0.01)^{***}$	$-0.02\ (0.01)^{*}$	$-0.02\ (0.01)$
log(Population)	$-0.23\ (0.11)^{*}$	$-0.24\ (0.12)^{*}$	$0.03\ (0.17)$
log(N businesses)	$-0.45\ (0.29)$	$-0.45\ (0.31)$	$-0.02\ (0.44)$
Log-lik.	-8380.23	-6541.89	-1743.21
LRT (df)	$661.54^{***}(20)$	$772.32^{***}(20)$	$70.36^{***}(20)$
AIC	16804.50	13125.80	3530.40
α	7.22^{***}		148.41^{***}
σ^2	0.07^{***}	0.09^{***}	0.12^{***}
Groups	32	32	32
n	28161	28161	1889

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}log(x+1)$ was used. Standard errors in parentheses.

Regarding state-level coefficients, only corruption prevalence, the incidence of weapon-related and drug-related crimes, economic competitiveness and the state population were found to be statistically significant. A 10% increase in the prevalence of corruption at the state level was associated with a 4.18% increase in the odds of suffering a remote extortion ($1.10^{0.43}$, $p < 0.05$). Similarly, a 10% increase in the incidence of weapon-related crimes at the state level was associated with a 3.89% increase in the odds of a business becoming the victim of remote extortion ($1.10^{0.40}$, $p < 0.001$). In contrast, a 10% increase in the incidence of drug-related crimes at the state level were associated with a 1.98% decrease in the odds of experiencing a remote extortion ($1.10^{-0.21}$, $p < 0.05$). Increasing a state's economic competitiveness by 10 points was associated with an 18.1% decrease in the odds of becoming a victim of remote extortion ($e^{-0.02 \times 10}$, $p < 0.05$), while a 10% increase in a state's population was associated with a 2.26% decrease in the odds of becoming a victim of remote extortion ($1.10^{-0.24}$, $p < 0.05$).

In contrast, in the concentration model, most coefficients were not statistically significant. Restaurants, hotels and bars experienced 69.6% more remote extortion concentration than retailers ($e^{0.53}$, $p < 0.01$), while micro-sized businesses experienced 40.5% less remote extortion concentration than large businesses ($e^{-0.52}$, $p < 0.01$).

The models present two measures of unobserved heterogeneity (Osborn & Tseloni, 1998; Pease & Tseloni, 2014). The concentration model indicates a high level of between-businesses unobserved heterogeneity[16] (as captured by α), which suggests that repeat remote extortions may be largely driven by such unobserved differences at the micro level. Similarly, unobserved differences between states (captured by σ^2) suggest that such unmeasured state-level differences may play a more prominent role in explaining concentration than in explaining prevalence.

7.6.2 In-person extortion

The models for in-person extortion (see Table 7.7) also suggest that the risk factors associated with prevalence (logit) are somewhat distinct from those associated with concentration (truncated Poisson).

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[16]The fact that the estimates for alpha presented in Chapter 5 are the same value as that presented here suggests that the estimates are at the limit of the parameter space that can be calculated by the statistical package used. Thus, they likely represent an underestimate of the true amount of unobserved heterogeneity.

Table 7.7: Model estimates (log and log-odds scale) for in-person extortions.

		Hurdle	
In-person extortions	Neg. Bin.	Logit	Trunc. Poisson
Intercept	−4.70 (0.27)***	−4.97 (0.25)***	−0.72 (0.52)
Business-level variables			
Corruption incidence	1.67 (0.19)***	1.65 (0.16)***	0.32 (0.28)
Corruption incidence^2	−0.24 (0.05)***	−0.24 (0.04)***	−0.05 (0.06)
Years (0 to 5)			
6 to 9	0.36 (0.17)*	0.42 (0.17)*	−0.12 (0.36)
10 to 14	0.25 (0.19)	0.30 (0.18)	−0.28 (0.40)
15 to 23	−0.09 (0.20)	−0.03 (0.19)	−0.52 (0.45)
24 to 212	0.34 (0.19)	0.26 (0.18)	0.30 (0.36)
Business type (Retail)			
Wholesale	−0.11 (0.24)	−0.19 (0.23)	−0.10 (0.47)
Industry	−0.28 (0.18)	−0.31 (0.17)	−0.18 (0.33)
Hotels, rest. & bars	0.08 (0.20)	0.10 (0.19)	−0.90 (0.46)
Other serv.	−0.39 (0.15)**	−0.25 (0.14)	−1.18 (0.37)**
Business size (Large)			
Medium	−0.20 (0.24)	−0.05 (0.22)	−0.84 (0.49)
Small	0.22 (0.21)	0.26 (0.20)	−0.09 (0.42)
Micro	−0.09 (0.20)	0.04 (0.19)	−0.56 (0.39)
State-level variables			
Rule of law	−0.01 (0.01)	−0.01 (0.01)	0.02 (0.02)
log(Corruption prevalence)	0.05 (0.32)	0.11 (0.30)	−0.18 (0.62)
log(Weapon crimes)	0.48 (0.21)*	0.54 (0.21)**	−0.10 (0.38)
log(Drug crimes)	−0.40 (0.16)*	−0.39 (0.15)*	−0.32 (0.33)
Competitiveness	−0.01 (0.01)	−0.00 (0.01)	−0.03 (0.02)
log(Population)	0.34 (0.21)	0.32 (0.20)	0.38 (0.42)
log(N businesses)	−0.12 (0.56)	−0.22 (0.53)	0.21 (1.09)
Log-lik.	−1914.42	−1694.73	−185.09
LRT (df)	291.24***(21)	333.78***(21)	53.03***(21)
AIC	3874.80	3433.50	414.20
α	11.74***		
σ^2	0.22***	0.18***	0.52***
Groups	32	32	32
n	28161	28161	345

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Standard errors in parentheses.

The baseline odds of in-person extortion prevalence were 0.007 (given by $e^{-4.97}$, $p < 0.001$), which suggests that the conditional risk of becoming a victim of in-person extortion in 2013 was less than 1%.

Most coefficients for prevalence were not statistically significant. The association between the number of bribes a business was asked to pay and the risk of in-person extortion was statistically significant ($p < 0.001$), but the functional form suggests the relationship was non-linear and was approximated by a second-order polynomial.[17] The signs of the polynomial coefficients suggest the relationship between corruption incidence and the likelihood of suffering an in-person extortion follow an inverted parabola, with the risk increasing when corruption incidence increases from zero, but then decreasing when corruption incidence reaches higher levels. The fitted probabilities in Figure 7.4 suggest that businesses that experienced 3 corruption incidents faced a 10% chance of suffering an in-person extortion, while those that experienced 6 corruption incidents faced a lower 2% risk of in-person extortion victimisation, all else being equal.

In addition to corruption incidence, only years in operation had a statistically significant relationship with the prevalence of in-person extortion at the business-level. Businesses with between 6 and 9 years of operation were 52.2% more likely to experience an in-person extortion than businesses with 5 or fewer years in operation ($e^{0.42}$, $p < 0.05$).

Regarding state-level variables, only the incidence of weapon-related and drug-related crimes were significantly associated with in-person extortion prevalence. A 10% increase in a state's incidence of weapon-related crimes was associated with a 5.28% increase in the odds of a business becoming a victim of in-person extortion ($1.10^{0.54}$, $p < 0.01$). In contrast, a 10% increase in the number of drug-related crimes in a state was associated with a 3.65% decrease in the odds of a business becoming a victim of in-person extortion ($1.10^{-0.39}$, $p < 0.05$). However, the lack of significant associations between other state-level variables and in-person extortion does not imply that state-level differences did not affect in-person extortion prevalence, as unobserved state-level heterogeneity was relatively high.

In the concentration model, only one coefficient was found to be significantly associated with in-person extortion concentration. Businesses in the services sector

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[17]Several functional forms were tested to capture the association between corruption incidence and in-person extortions. Ultimately, a second-order polynomial was found to be a better fit than a linear and log-transformed relationships. The AIC of the model with the polynomial relationship was 56.8 units smaller than the log-transformed model, and 137.8 units smaller than the linear relationship.

(other than restaurants, hotels and bars) experienced -69.3% less in-person extortion concentration than retailers ($e^{-1.18}$, $p < 0.01$), while all other businesses experienced the same rate of in-person repeats. A relevant finding from the concentration model is that there was no unobserved heterogeneity at the business-level, as the truncated negative binomial specification was not significantly different from a truncated Poisson model.

This suggests that, once a businesses has been a victim of in-person extortion, the rate at which in-person extortions occur appears to be a somewhat random process. However, this rate is likely to vary significantly depending on the state in which the business is located, as the concentration model presented a large amount of unobserved state-level heterogeneity, given by the σ^2 parameter (0.52).

7.6.3   Cobro de piso

As noted earlier, there were no repeat *cobro de piso* incidents, thus only a model for prevalence (logit) was estimated for this crime type (see Table 7.8).

The intercept of the prevalence model suggests that the baseline odds for becoming a victim of *cobro de piso* extortion in 2013 were approximately 0.0005 ($e^{-7.68}$, $p < 0.001$). In percentage terms that translates into a 0.05% odds. Most coefficients were not statistically significant, with the exception of corruption incidence, business size, and the incidence of drug-related crimes. A 10% increase in the number of bribes a businesses was asked to pay[18] was associated with a 6.59% increase in the odds of becoming a victim of *cobro de piso* extortion ($1.10^{0.67}$, $p < 0.05$). Only small businesses experienced a different prevalence risk, as these were 3.42 times more likely to experience a *cobro de piso* extortion than large businesses ($e^{1.23}$, $p < 0.05$). In contrast, all other business size categories faced the same odds as large businesses.

Regarding state-level variables, increasing a state's economic competitiveness by 10 points was associated with a 45.1% decrease in the likelihood of experiencing a *cobro de piso* extortion ($e^{-0.06 \times 10}$, $p < 0.05$). While all other state-level variables were not significant, unobserved state-level heterogeneity (captured by σ^2) indicated that unmeasured state-level differences contributed significantly to the observed differences in *cobro de piso* prevalence risk.

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[18]As in the models for remote extortion, corruption incidence was log transformed in the model for *cobro de piso* extortion. The AIC for this functional form was 4 units smaller than for linear functional form. Similarly, a polynomial specification was not statistically significant.

Table 7.8: Model estimates (log-odds scale) for *cobro de piso* extortions.

Cobro de piso extortions	Logit
Intercept	$-7.68\ (0.64)^{***}$
Business-level variables	
log(Corruption incidence)†	$0.67\ (0.27)^{*}$
Years (0 to 5)	
6 to 9	$0.55\ (0.31)$
10 to 14	$0.30\ (0.35)$
15 to 23	$0.31\ (0.35)$
24 to 212	$0.28\ (0.36)$
Business type (Retail)	
Wholesale	$0.51\ (0.38)$
Industry	$-0.17\ (0.34)$
Hotels, rest. & bars	$0.24\ (0.33)$
Other serv.	$-0.29\ (0.28)$
Business size (Large)	
Medium	$0.73\ (0.59)$
Small	$1.23\ (0.55)^{*}$
Micro	$0.91\ (0.54)$
State-level variables	
Rule of law	$-0.03\ (0.02)$
log(Corruption prevalence)	$-0.22\ (0.56)$
log(Weapon crimes)	$0.26\ (0.37)$
log(Drug crimes)	$-0.30\ (0.31)$
Competitiveness	$-0.06\ (0.02)^{**}$
log(Population)	$0.60\ (0.38)$
log(N businesses)	$1.09\ (0.98)$
Log-lik.	-546.18
LRT (df)	$155.97^{***}(20)$
AIC	1134.40
α	
σ^2	0.41^{**}
Groups	32
n	28161

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}log(x+1)$ was used. Standard errors in parentheses.

7.6.4   Comparisons between extortion types

Figure 7.3 presents forest plots to facilitate comparisons between the estimated models. Comparing estimates for prevalence suggests that the predictors associated with the risks of becoming a victim were very different across the three types of extortion. Most of the coefficients that were significant predictors for the prevalence of remote extortion, for example, were not significant predictors of in-person or *cobro de piso* extortion. These inconsistencies suggest that the different types of extortion are possibly fuelled by different causes.
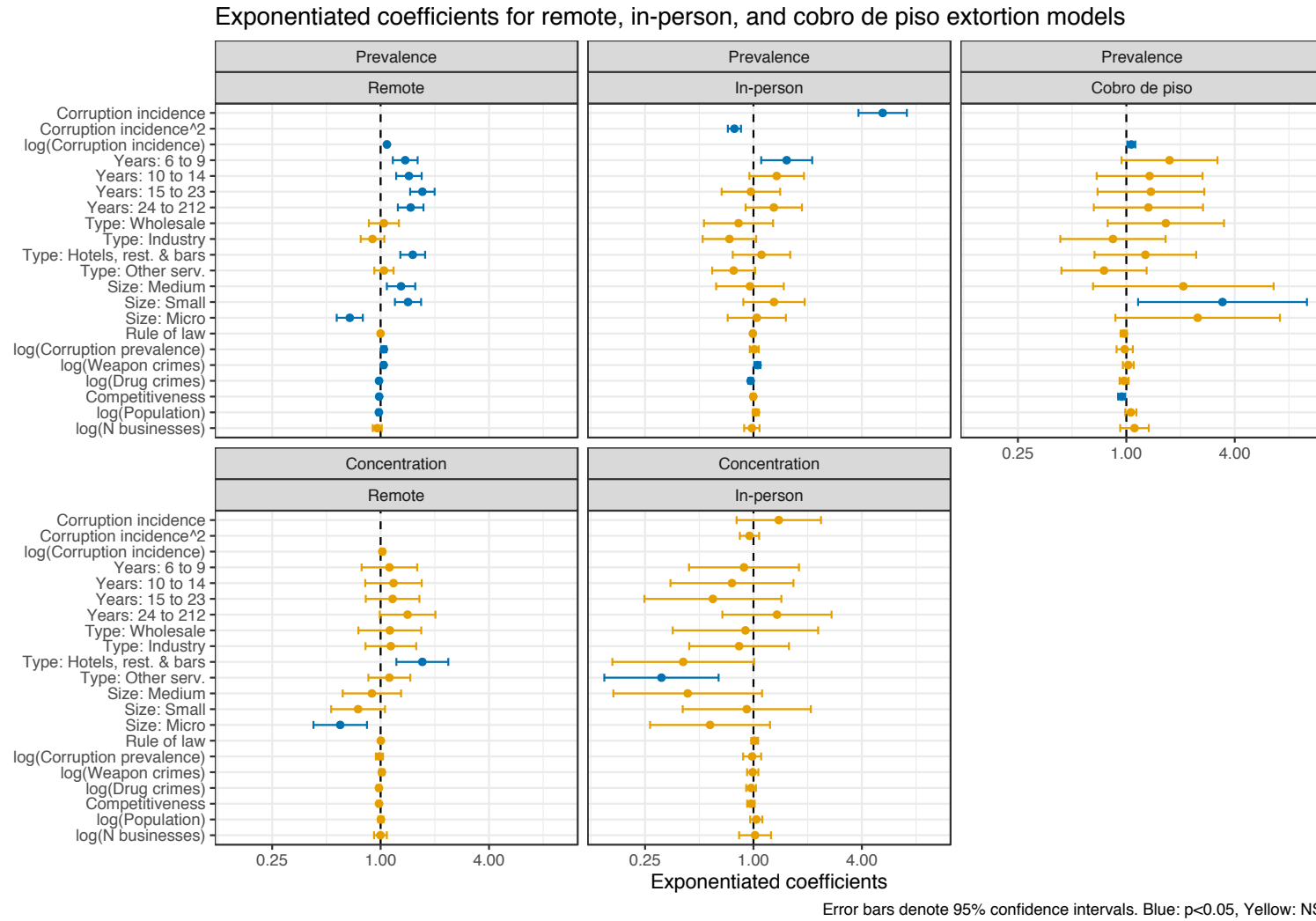
Figure 7.3: Forest plots comparing the exponentiated estimated coefficients (log scale x-axis) from prevalence and concentration models for remote, in-person and *cobro de piso* extortion. Log-transformed dependent variables represent change for a 10% increase, given by 1.10^{β}.

Corruption incidence is the only variable that was significantly associated across the three types of extortion. However as Figure 7.4 shows, the nature of the relationship is different across the extortion types.

In remote extortions, the relationship is always positive, whereas in in-person extortions the relationship varies: it begins as positive and then switches direction and becomes negative (with more incidents of corruption). In *cobro de piso* extortions, the relationship is also positive, but the baseline odds are so small that increases in the predicted probabilities are negligible.

Among the coefficients for years in operation, only the category '6 to 9' years was consistently associated with higher prevalence risks in remote and in-person extortions, though the association was not significant in *cobro de piso* extortions.

Business type was not significant for in-person and *cobro de piso*, though there were significant associations between business type categories and remote extortions. Business size did not play a role in in-person prevalence, but was significant for remote and *cobro de piso*. However, the associations were not consistent. Only the coefficient for small-sized businesses was significant for *cobro de piso* victimisation, whereas all business size categories were significant for remote extortions.

Regarding state-level variables, the incidence of weapon-related and drug-related crimes had similar effects (in significance, direction and magnitude) for the prevalence of remote and in-person extortions, though they had no effect on the prevalence of *cobro de piso*.

Similarly, economic competitiveness was negatively associated with prevalence risks for remote and *cobro de piso* extortions, though it had no effect on the prevalence of in-person extortions. Unobserved state-heterogeneity (σ^2) was highest for *cobro de piso*, followed by in-person extortions, and lowest for remote extortions.

On the other hand, there were no consistent associations between any of the predictors used and the amount of remote and in-person extortion concentration. Most predictors were not significant for either crime type, with the exception of hotels, restaurants and bars—which experienced more remote extortion—the 'other services' category—which experienced fewer in-person incidents—and micro-sized businesses—which experienced fewer remote extortions.

Unobserved state-level heterogeneity was far more relevant for in-person concentration than for remote extortion concentration. In contrast, remote extortion concentration had significant levels of unobserved business-level heterogeneity, whereas in-person concentration did not.

Predicted probability of extortion victimisation

By extortion type and corruption incidence
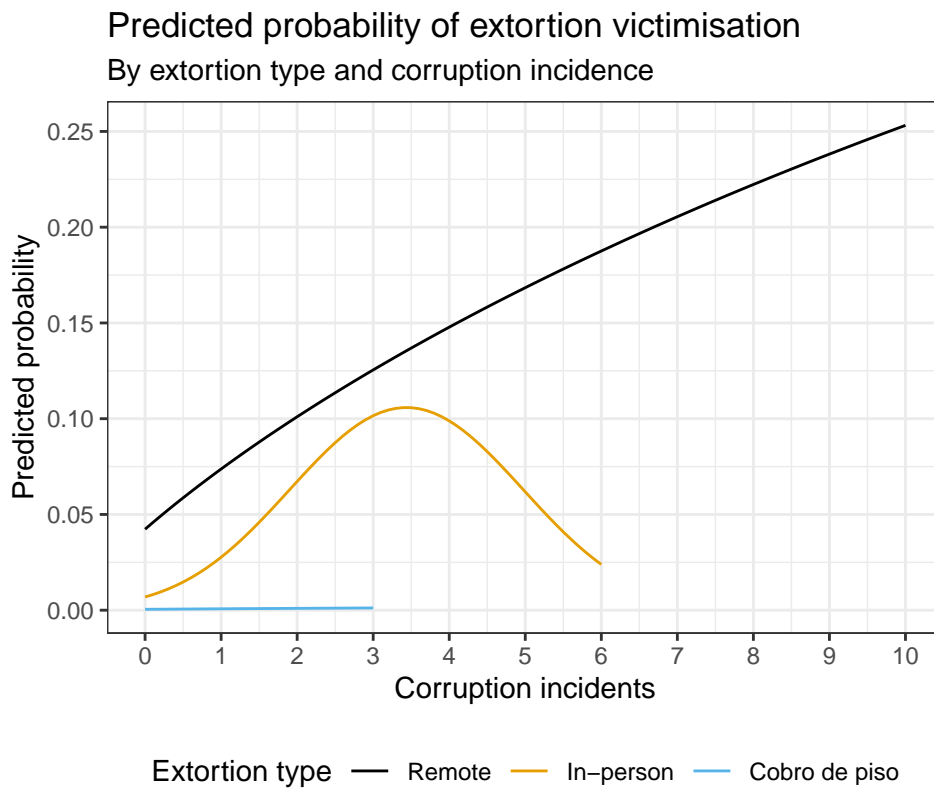
Figure 7.4: Predicted probabilities of extortion victimisation per type for different values of corruption incidence. Based on estimates from logit models.

7.6.5 Comparisons between prevalence and concentration

Overall, there was little consistency in the predictors across hurdle components for remote and in-person extortion. In the case of remote extortions, the only consistent associations were the predictors for hotels, restaurants and bars—which predicted higher prevalence and concentration of remote extortion—and for micro-sized businesses—which predicted lower prevalence and concentration of remote extortion. In contrast, there was no consistency in predictors for in-person extortion across the hurdle components.

7.7 Discussion

This chapter sought to determine whether victimisation patterns and mechanisms vary according to the type of extortion suffered. The study was motivated by findings presented in Chapter 5, which indicated that repeat extortion victimisation was

probably caused by two distinct processes, and in Chapter 6, which suggested that the different extortion types experienced by Mexican businesses (remote, in-person and *cobro de piso* extortion) were in fact different crimes, rather than variations of the same crime type.

I had hypothesised that the predictors for extortion risks would be different for each extortion type (H1). This hypothesis was motivated by the fact that the different extortion types (particularly remote and in-person extortions) would have different opportunity structures, as their modus operandi are very different. Using data from Mexico's commercial victimisation survey, I found evidence to support H1. Very few predictors were significant for two or more of the different extortion types, and most times the associations identified were in different directions and differing magnitudes.

Consistent associations across extortion types were only observed in the prevalence components of the models, which suggests a minor overlap in the opportunity structures for these crimes. Lastly, the varying levels of business- and state-level unobserved heterogeneity suggest that such unmeasured variables play a more prominent role for in-person and *cobro de piso*, but less so for remote extortions.

The more prominent role of state-level unobserved heterogeneity for in-person and *cobro de piso* extortion supports Kleemans's (2018) observations regarding the concentration of extortion racketeering, which he suggests clusters at the level of territories, rather than at the micro-level of places (p. 874). It may be that such unobserved state-level differences refer to the level of territorial control exerted by criminal groups, even after accounting for weapon- and drug-related crimes, which are thought to be associated to organised crime activity. Future research that examines the relationship between explicit measures of organised crime governance and the risks of in-person and *cobro de piso* extortion would appear to be a fruitful avenue to explore this further, though no such measures are reliably available.

I also hypothesised that the predictors that explained prevalence would be distinct from those that explain concentration for each crime type (H2). This was true for remote and in-person extortion, which suggests that the factors affecting repeat extortion victimisation may be unrelated to the risk factors affecting prevalence, and vary for each crime type. As noted in Chapter 5, I believe that event dependence may feature as a relevant factor to explain concentration, though I was not able to test this explicitly. Further research that explores the potential role of event dependence to explain extortion concentration is needed.

There are some important limitations to be mentioned. The first concerns the

operationalisation and recording of *cobro de piso* incidents. It was surprising that there were no repeat *cobro de piso* incidents, as it was assumed that the defining feature of this crime type was repetition. Two explanations were proposed: either the measures are correct and no repeat *cobro de piso* extortions occurred—a statistically plausible scenario—or the lack of repeats is due to an informal recording practice for highly repetitive 'crime series' (Rennison & Rand, 2006, p. 42; Planty, 2006, p. 156), whereby only one *cobro de piso* incident is recorded per victim reporting a series. These potential situations suggest that urgent revisions to the ENVE are needed; on the one hand it is necessary to properly define what a *cobro de piso* incident is (as it is not currently defined), and on the other, it may be necessary to adopt a crime series protocol akin to that implemented in other crime surveys (Rennison & Rand, 2006, p. 42; Planty, 2006, p. 156).

Second, the extent to which capping practices affect the estimates presented herein is unclear. Capping affects the estimates in two ways. First, by reducing the maximum number of incidents that any business can report, it artificially reduced both the mean and variance of the distributions observed. Thus, the estimated values presented in the models are likely to be underestimates of both the conditional means, and the amount of overdispersion captured by the models. Second, the number of incidents reported for one crime type also reduces the number of incidents of another type that the same victim can report.

While such cases of multiple victimisation were unlikely to affect the patterns of remote extortion (as they represented proportionally very few cases), the phenomenon was likely more prominent for in-person and *cobro de piso*, where multiple victimisation was proportionally higher. Thus, it is likely that the estimates for these crime types may be more widely affected by capping than remote extortion. Nonetheless, the direction and significance of the associations observed (particularly in the case of prevalence) are unlikely to be much affected.

7.8   Chapter conclusion

The results of this chapter suggest that remote, in-person and *cobro de piso* extortions are indeed different crime types, rather than variations of the same crime. Such differences stem from very different modus operandi, with remote extortions sharing more in common with frauds or some forms of cyber-crime, than with the prototypical extortion one associates with organised crime. In contrast, in-person and *cobro de piso* have modus operandi that more closely resemble the extortion rackets that are

considered quintessential to organise crime groups. The statistical analyses presented in the chapter strongly suggest that such crime types are indeed distinct, as they appear to be associated with different opportunity structures.

The differences between the three extortion types have three main implications:

1. Measurement of extortion victimisation should consider such distinctions from the onset, rather than presenting extortions counts that aggregate the crime types. Aggregation implies assuming the crimes are fuelled by the same causes; an assumption that is questioned by these results. Furthermore, aggregation aggravates the effects of capping, particularly for less frequent crime types. Thus, the measurement of extortion could be improved if future ENVE surveys are revised to properly reflect the differences between remote, in-person and *cobro de piso* extortions. Such revision should also consider the possibility of implementing a series protocol to properly capture the incidence of highly repetitive crime series, as is assumed to occur in *cobro de piso*.

2. The differences between extortion types should inform crime prevention practice, whereas current policy in Mexico tends not to make such distinctions. Though the research presented here identifies that there are probably significant differences in the opportunity structures underpinning such crimes, more research is needed to specifically understand these opportunity structures and thus devise appropriate crime prevention interventions.

3. Further research that studies extortion in Mexico should try to incorporate the differences in extortion type, or at the bare minimum it should be clear what type of extortion is under study, as other crime data sources (e.g. SESNSP, 2015) do not distinguish between extortion types. In particular, there appears to be an important gap in studying the potential role of event dependence to victimisation patterns for the different types of extortion.

Chapter 8

Event dependence in repeat extortion victimisation

This chapter presents the last empirical study in this thesis and aims to further elaborate on the fourth research question presented in Chapter 2: Do victimisation patterns and mechanisms vary according to the type of extortion suffered? In Chapter 7, I found that the concentration of extortion varied according to the type of extortion suffered. In that study, I also found that concentration was not explained by the same factors that explained the risk of becoming a victim of extortion. It was thus assumed that repeat extortion victimisation could be explained by a process of event dependence. This study elaborates on the findings presented thus far and attempts to model the effect of event dependence on extortion victimisation.

8.1 Background

Repeat victimisation is broadly thought to be the product of two mechanisms: risk heterogeneity and event dependence (Johnson, 2008). Risk heterogeneity considers that the risk of victimisation is not equal for the entire population of potential targets because specific characteristics make some targets more suitable than others (Johnson, 2008; Pease, 1998). On the other hand, event dependence considers that victimisation is dynamic, with previous victimisations increasing—at least temporarily (Johnson et al., 1997)—the likelihood of experiencing a repeated incident (Pease, 1998; Sagovsky & Johnson, 2007).

Evidence for the former includes the fact that target and context characteristics have been found to be associated with higher risks of victimisation in household

(e.g. Bowers et al., 2005; Trickett et al., 1992; Tseloni et al., 2004) and personal crimes (Lauritsen, 2010; Lauritsen & Rezey, 2018; Miethe & McDowall, 1993; Miethe & Meier, 1990). In contrast, evidence for the latter mechanism comes from the distinctive 'time-course' of repeat victimisation (Polvi, Looman, Humphries, & Pease, 1991)—which suggests that the risks of subsequent victimisations decay exponentially as time progresses following an initial event (Johnson et al., 1997; Spelman, 1995)—and from longitudinal studies that have found that victimisations suffered in previous periods increase the risk of suffering crimes in the future, even after controlling for stable risk factors (e.g. Lauritsen & Davis Quinet, 1995; Lynch et al., 1998; Tseloni & Pease, 2003, 2004).

While the precise role that each mechanism plays in generating repeat patterns is a source of academic discussion (e.g. Farrell et al., 1995; Hope, 2015; Johnson, 2008; Kleemans, 2001; Tseloni & Pease, 2003), experimental (e.g. Johnson, 2008; Pitcher & Johnson, 2011) and observational studies (e.g. Ellingworth, Hope, Osborn, Trickett, & Pease, 1997; Lauritsen & Davis Quinet, 1995; Lynch et al., 1998; Osborn & Tseloni, 1998; Tseloni & Farrell, 2002; Tseloni & Pease, 2003, 2004; Wittebrood & Nieuwbeerta, 2000) suggest that both mechanisms contribute to generate the patterns of repeat victimisation observed. A parsimonious explanation of how these mechanisms interact is offered by Johnson (2008), who notes that risk heterogeneity is likely to contribute to determining the prevalence of victimisation (i.e. the likelihood of becoming a victim), whereas concentration (i.e. the number of crimes experienced by victims) is likely to be caused by event dependence, especially when repeats occur swiftly (p. 235).

Nonetheless, it is important to note that the relative contribution of each mechanism is likely to vary considerably across crime types (Johnson, 2008, p. 236). Of particular relevance to extortion, Farrell et al. (1995) note that event dependence may play a bigger role when the effort and likely risk of a subsequent offence is clarified by victim response to a first offence (e.g. complying with an extortion demand may entice a repeated event), and when the crime implies higher degrees of co-offending, as in organised crimes (p. 396).

Research presented in Chapter 7 (see also Chapter 5) suggested that extortion against businesses exhibits patterns of repeat victimisation that exceed chance expectation, and that the patterns observed vary by the type of extortion suffered (i.e., remote, in-person and *cobro de piso* extortion). Furthermore, the study attempted to examine event dependence implicitly by modelling victimisation in two steps. First, a model examined the prevalence of extortion using variables primarily thought to

be associated with risk heterogeneity. Next, a second model examined whether the predictors of risk heterogeneity could also explain the number of repeats that victims experienced (i.e. concentration). The fact that the predictors of prevalence were, for the most part, not significant predictors of concentration (particularly in the case of remote extortion, and to a lesser extent in in-person extortions[1]), was taken as an indication of the presence of an unobserved mechanism of event dependence driving repeat extortion victimisation. However, the research design used did not enable explicitly examining the presence of event dependence.

Explicitly examining event dependence generally requires the use of longitudinal data (i.e. repeated measures of the same unit). Longitudinal data allow estimation of whether victimisations experienced in one period are significantly associated with the risk of (repeat) victimisation in later periods, while controlling for time-variant and time-invariant victim characteristics (Lynch et al., 1998, p. 15). Police-recorded crime data are a good source of such longitudinal measures (e.g. Johnson et al., 1997).However they are of little use in the case of extortion against businesses, as the crime suffers from extensive underreporting (see Chapter 4). In contrast, victim surveys offer more reliable measurements, though most surveys employ cross-sectional designs (Lynch, 2006, p. 249; Mayhew & van Dijk, 2014, p. 2604)—with the notable exception of the US National Crime Victimization Survey (NCVS, Lynch et al., 1998; Rennison & Rand, 2006).

Nonetheless, cross-sectional surveys can provide an approximate measure of event dependence by asking respondents about prior victimisation experiences suffered before the reference period. Using such measures, Ellingworth et al. (1997), Osborn and Tseloni (1998), and Tseloni and Farrell (2002), were able to (tentatively) examine the potential role of event dependence by examining whether prior victimisation was associated with future victimisation risks (and they found that it mostly was).

The data source used in this thesis, the Mexican commercial victimisation survey (ENVE, INEGI, 2014d), does not capture information on prior extortion victimisation experiences, thus event dependence could not be assessed in Chapters 5 and 7. However, in this study I attempt to tentatively assess the presence of event dependence by taking advantage of the information provided about the month of occurrence for each extortion reported. First, I examine whether repeat incidents follow the characteristic time-course of repeat victimisation. Then, I create a 'synthetic' measure of prior victimisation by splitting the reference year into two periods

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[1]Surprisingly, there were no repeat *cobro de piso* incidents, thus only prevalence was studied for this crime type.

and use the measures of victimisation experienced in the first period as predictors of victimisation in the second.

Investigating event dependence is important for at least two reasons. From an academic perspective, it can help clarify what are the potential causal mechanisms associated with repeat victimisation—which is especially relevant in the case of crimes not often studied from the victimisation perspective, such as extortion against businesses. From a practical perspective, such understanding is crucial to expand the knowledge base that informs crime prevention practice (Ekblom, 2002, 2003). In particular, if repeat victimisation is primarily driven by event dependence, as opposed to being mainly a function of risk heterogeneity, crime prevention interventions may be more effective if they focus on victimised targets, rather than focusing only on those targets deemed at risk of victimisation.[2]

The chapter proceeds as follows. The next section provides a brief overview of event dependence. This is followed by a discussion on the potential role of event dependence in repeat extortion victimisation. Next, I describe the data and analytical approach. This is followed by the results and discussion.

8.2   Event dependence and repeat victimisation

The idea that the risk of subsequent victimisation is affected by past victimisation experience has long been discussed in crime and victimisation research. However, the prevailing notion initially held was that suffering a victimisation would lead to *lower* risks of future victimisation. In a seminal work, Hindelang et al. (1978) advanced the 'once bitten, twice shy' hypothesis, which stated that the experience of victimisation would prompt individuals to change their lifestyles to avoid suffering a repeat incident (see also Averdijk, 2011). On the other hand, the idea that previous victimisation would increase the risk of future victimisations was dismissed as farfetched by Sparks (1981a, p. 767).

Nonetheless, mounting empirical evidence soon tilted the view in the opposite direction (e.g. Farrell & Pease, 1993; Pease, 1998). Numerous studies have demonstrated not only that the likelihood of repeat victimisation is greater than that of suffering a first incident (e.g. Bowers et al., 2005; Ellingworth, Farrell, & Pease, 1995; Farrell & Pease, 1993; Osborn et al., 1996; Tseloni, 1995; Tseloni, Ntzoufras,

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[2]However, it should be noted that due to the existence of the phenomenon of near-repeat victimisation (see Morgan, 2001)—which sees an increase in risk following an initial event not just for the victimised target but for those in its vicinity as well—focusing preventive resources on victimised targets can also proactively protect non-victimised targets (Johnson & Bowers, 2004).

Nicolaou, & Pease, 2010), but also that the risk of repeat victimisation is dynamic, rising swiftly following an initial event and decaying exponentially as time progresses (e.g. Bowers et al., 2004; Johnson, 2008; Johnson et al., 1997; Polvi et al., 1991; Sagovsky & Johnson, 2007).

The precise mechanisms that drive event dependence have not always been clear. Lauritsen and Davis Quinet (1995, p. 147) hypothesised that event dependence could be caused by a mechanism of 'victim labelling', whereby the stigmatising label associated with victimhood could lead to further victimisation by heightening the perception of vulnerability, reducing guardianship due to increased social isolation, or by inducing riskier behaviours from victims. This interpretation fits with the view of event dependence as 'state dependence', whereby 'entering into the victim "state" carries a higher than normal risk that a similar victimisation will occur in the following period' (Lynch et al., 1998, p. 11).

However, the labelling and victim 'state' dependence hypotheses cannot easily account for the time-course of repeat victimisation (unless it is also assumed that the victim label would wear off quickly following an initial event). The existence of the near-repeat victimisation phenomenon (see Morgan, 2001) also casts doubt on the labelling mechanism, as it cannot explain why non-victimised targets would see increases in risk following a victimisation incident in their vicinity. Furthermore, a victim labelling mechanism would also seem insufficient to explain event dependence in non-personal victimisation, and especially that of business victimisation (e.g. Bowers et al., 1998; Dugato, 2014; Matthews et al., 2001).

In contrast, a parsimonious explanation for event dependence can be found in more nuanced understanding of offender behaviour and decision-making. Numerous studies have found that offenders often return to victimise past targets (Bernasco, 2008), as the choice of future targets appears to be influenced by previous experience (Bernasco, 2008; Johnson, 2014; Johnson, Summers, & Pease, 2009). This view of offending behaviour is underpinned by the rational choice perspective (Cornish & Clarke, 1985), which considers that offenders draw from their past experiences when making decisions about where and when to offend in the future. From this perspective, returning to victimise a past target could be seen as the result of a rational calculation.

Such an account can accommodate the presence of event dependence in a wide range of crimes. Furthermore, it also permits the effect of event dependence to vary between crime types. If offenders learn from past victimisation experiences, then it follows that event dependence may play a more prominent role in crime types where

the risks, effort and rewards of a subsequent offence are clarified by the outcome of a first offence (Farrell et al., 1995). Matthews et al. (2001) present empirical evidence of this, as they find that the probability of experiencing repeat bank robbery was positively associated with the amount taken in a prior incident.[3]

8.3 Event dependence and extortion victimisation

As noted in Chapter 7, extortion against businesses in Mexico can take the form of remote, in-person and *cobro de piso* extortion. The differences in modus operandi between these extortion types suggested that the opportunity structures underpinning such crimes would vary for each type, an assumption that was supported by the analysis presented in Chapter 7. However, that study mostly tested variables related to risk heterogeneity, though the findings suggested the presence of event dependence in remote and in-person extortions. *Cobro de piso* extortions did not exhibit patterns of repeat victimisation, thus they will not be considered further in this study.

As numerous studies have shown, event dependence is often evident in the time-course of repeat victimisation, exhibiting a characteristic 'boost' to crime risk immediately following an initial event and a subsequent exponential decay as time progresses. However, to determine if the patterns observed indicate the presence of event dependence, the time course must first be demonstrated to be different from that expected under chance:

- **H1**: The distribution of time intervals between repeat extortion victimisation incidents is distinct from that expected by chance.

Second, the effect of event dependence must be disentangled from the confounding effect of risk heterogeneity. As the overall risk of victimisation can be affected by stable victim characteristics, examining event dependence in isolation could lead to spurious inferences. Thus, a second hypothesis needs to examine the partial effect of prior victimisation after controlling for potential risk heterogeneity confounders:

- **H2**: The risk of suffering a repeat extortion victimisation, after controlling for risk heterogeneity, is positively associated with prior victimisation.

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[3]On the other hand, Dugato's (2014) analysis of bank robbery in Italy provides inconsistent findings in this regard, as he found that the rate of success of bank robbery was positively associated with the risk of repeats, but the average haul was not.

Considering that victim responses can clarify the risk, effort and rewards of subsequent victimisations, examining the amount of prior victimisation may be an insufficient approach to examine the role of event dependence. In particular, acquiescence with extortion demands could entice further victimisations, as victims would be known to be profitable. Thus, the third hypothesis in this study is:

- **H3**: The risk of suffering a repeat extortion victimisation, after controlling for risk heterogeneity, is higher for victims who complied with prior extortion demands than for victims who did not.

8.4 Data and measures

As in previous chapters, this study used the 2014 sweep of Mexico's commercial victimisation survey, ENVE (see Chapter 4 for more detail). As is common in other victimisation surveys (e.g. UNODC/UNECE, 2010), the instrument is divided in two parts: a screening questionnaire that records the prevalence and incidence of crimes experienced by respondents, and a victim form used only with victimised businesses to capture the details of each victimisation incident experienced, though there is a cap of 7 incidents per crime type per business (INEGI, 2014c).

In this chapter, measurements of the time-course of repeat victimisation came from the victim forms, as these capture the month of occurrence of each incident. Similarly, these measurements were then used to divide the reference year into two periods (Jan–June, and Jul–Dec, 2013). The study used the same measurements of risk heterogeneity[4] as Chapter 7, though in this study risk heterogeneity coefficients are not reported, as they were merely used as controls. Throughout the study, all measurements of extortion were disaggregated into two types: 'remote' and 'in-person' extortion (see Chapter 7 for details).

8.4.1 Dependent Variables

As the study involves two types of analysis (see Section 8.5), two types of dependent variables were used. For the time-course analysis, the dependent variable is the number of months elapsed between successive extortion events against the same business. Thirteen businesses could not recall the month on which the reported incidents occurred, thus they were excluded from the data set.

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[4]The business size variable had to be changed slightly, as the categories used in Chapter 7 lead to complete separation. To overcome this, the 'medium' and 'small' categories were combined into one category.

The second analysis examines the association between previous and future victimisation. To construct the dependent variable used in this analysis, extortion events per respondent were classified into two semesters: January until June 2013 (inclusive) as semester 1; and July to December 2013 (inclusive) as semester 2. Then, the number of events per business (per extortion type) were aggregated per semester. The counts in semester 2 were used as the dependent variable, and those in semester 1 were used as an independent variable. Businesses that did not experience incidents in a semester were given a value of 0.

8.4.2   Independent variables

The main independent variable used is the number of extortion events per business (per extortion type) in semester one. However, as the capping practices used in the ENVE can affect the maximum number of events that can be reported in semester one if a businesses is also victimised in semester two, all businesses that experienced 7 incidents (in aggregate) in either of the semesters were excluded from the analysis. This led to the exclusion of data from a further 33 businesses. This ensured that there were no 'artificial' zeroes in either semester due to the capping of counts of extortion.

Furthermore, in addition to using raw counts, a categorical variable for previous victimisation was also used. Observations per business (per extortion type) in semester 1 were classified as 'Not a victim' if a business experienced 0 incidents that semester, as 'Victim, not complied' if a business experienced 1 or more incidents that semester, but did not comply in any of them, or as 'Victim, complied' if a business complied with at least one extortion incident (of a particular type) in semester one.

8.5   Analytical approach

The time-course of repeat victimisation is usually analysed by plotting the distribution of the time elapsed between subsequent events. Such plots usually show that the risk of suffering a subsequent victimisation tends to be highest immediately following an initial event, and decay rapidly following an exponential trend (e.g. Johnson et al., 1997).

However, it is important to determine if the observed time-course is distinct from that expected under chance, as the distribution of waiting times between events in a Poisson process also follows an exponential distribution. As Short, D'Orsogna, Brantingham, and Tita (2009) note, the probability density function (pdf) for waiting

times, t, in a Poisson process with rate per unit-time, λ, is given by:

$$p(t) = \lambda e^{-\lambda t} \tag{8.1}$$

which results in a monotonically decreasing function. This means that it is more likely to observe shorter waiting times than longer ones, with $t = 0$ having the highest density, as $\lambda e^{-\lambda \times 0} = \lambda$.

Before comparing the observed time course to that expected, a suitable rate parameter must be chosen. The findings reported in Chapter 7 suggested that repeat extortion victimisations were fuelled by a distinct process from that which explains extortion prevalence. Thus, the population incidence rate would be unsuitable to estimate the expected time-course of repeat extortion victimisations (as it considers victims and non-victims alike). Thus, I used the concentration rates for remote and in-person extortions reported in Table 7.1 (Chapter 7), which—after being divided by 12—provided estimates of the monthly rates of repeat victimisation expected for each crime type.

After defining the monthly rates to be used, the observed waiting time counts were compared to those expected using a univariate Chi-squared test, with the probabilities[5] for expected counts obtained using Equation (8.1).

However, the time-course curve is likely to be confounded by the time window effect (Johnson et al., 1997, p. 235-236), as repeats that occurred later in the reference period (in this case the 12 months of 2013) have longer maximum time spans than repeats that occurred early in the period. For example, if a repeat occurred in December, the maximum time span possible is 11 months, whereas if the event occurred in February, the maximum time span is one month. Thus, the observed time-course could simply be a statistical artefact caused by the fact that even if events at the same location occur on random dates, there is a higher likelihood of observing pairs of events that are closer in time (there are simply more 1 month intervals, for example, in a year than there are 12 month intervals).

To mitigate this, the analysis was repeated using a moving time window to calculate a 'corrected' time-course (as suggested by Johnson et al., 1997). The moving time window (in this case 6 months) ensured that all repeats had the same number of retrospective months from which to obtain a time span. To calculate the corrected time-course, only repeats that occurred during the second semester of 2013 (July to December, inclusive) were used, while observations from the first semester were

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[5]As required by the univariate Chi-squared test, the expected probabilities were rescaled so that the sum of probabilities equaled 1.

used as historical data from which to draw the time spans. For example, if a repeat occurred in July, a time window from January to July was used; if a repeat occurred in August, the time window was moved to the period between February and August; and so on so that events that occurred in December used the period between July and December as the time window.

After calculating the corrected time-course, the expected time-course was compared to that expected[6] using the same Chi-squared test as described above.

The second analysis involved the use of statistical modelling to determine if extortion victimisation experiences in semester 1 were associated with extortion victimisation in semester 2, holding all else equal. Considering the results presented in Chapter 7, which suggested that a hurdle model approach was preferred over a standard count model, this study used only the hurdle approach. Thus, the following modelling strategy[7] was used. First, a logit model was fit to estimate the prevalence of extortion victimisation in semester 2, conditional on extortion victimisation experienced in semester 1 and risk heterogeneity controls. Then, a truncated count model was fit to estimate the concentration of extortion among victimised businesses in semester 2, conditional on extortion victimisation experienced in semester 1 and risk heterogeneity controls. The models were estimated twice, once for remote extortions and once for in-person incidents.

The interpretation of coefficient effect sizes is similar to that presented in Chapter 7. However, given that the main interest in this study is to evaluate the potential association between prior extortion experiences and future extortion risks, only the coefficients for prior victimisation will be interpreted.

In logit models, exponentiating the coefficient for raw counts (e^β) transforms the estimate into the odds-ratio (OR) scale, and represents the multiplicative effect on the odds of becoming a victim of extortion in semester 2, for a one unit increase in the amount of extortion suffered in semester 1. In the case of the categorical version of extortion experiences in semester 1, the OR represents the multiplicative change in comparison to the reference category ('Not a victim'). The interpretation for the truncated count models is similar, with the difference being that the exponentiated coefficients are known as Incidence Rate Ratios (IRR), and represent the multiplica-

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[6]Unfortunately, the rates used to estimate the expected time-course could not be recalculated using the moving time window approach. Thus, true rates may be slightly smaller than observed, leading to a more conservative expected distribution.

[7]The specific statistical definitions of the hurdle models used can be found in Chapter 5. Models were fit using the glmmTMB (Bolker, 2017; Brooks et al., 2017) and glmmADMB (Bolker et al., 2012; Fournier et al., 2012) packages in R (R Core Development Team, 2015).

Extortion incidents (monthly)
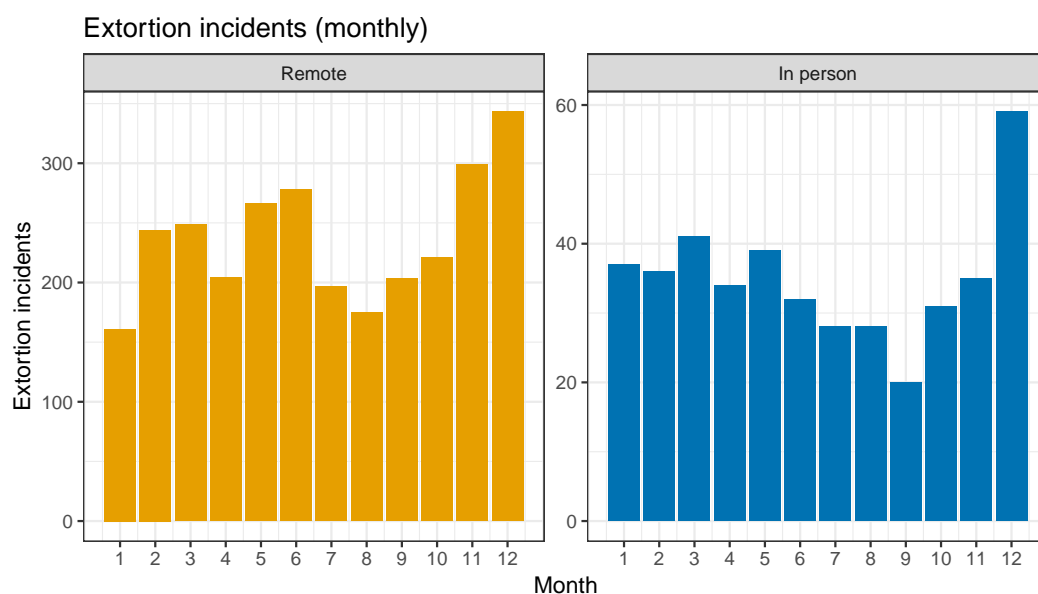
Figure 8.1: Monthly counts of extortion incidents for 2013, by type of extortion.

tive effect on the concentration of extortion in semester 2 for a one unit increase in extortion in semester 1, or in comparison with the reference category. Lastly, ORs (IRRs) can also be interpreted as the percentage change in the dependent variable (given by $OR - 1$ and $IRR - 1$).

8.6 Results

Before presenting the results of the analyses, exploratory descriptive statistics are presented.

Figure 8.1 presents the monthly counts of extortion incidents per type for the observed period. The plots suggest that both types of extortion were more likely towards the end of the year, particularly in December. During the earlier part of the year, remote extortions appear to fluctuate with no obvious trend, whereas in-person extortions do appear to be trending downwards between January and September. Chi-squared tests of association suggested that the variations in extortion counts between months was not due to random chance (Remote: $X^2 = 133.16$, $df = 11$, $p < 0.001$, In-person: $X^2 = 28.06$, $df = 11$, $p < 0.01$).

It is not clear why such variations occur. A potential explanation may be that monthly variations simply reflect seasonal fluctuations, as previous research has found that most crime rates exhibit seasonal variation (e.g. Farrell & Pease, 1994;

Table 8.1: Counts and proportions of extortion incidence per type per semester.

	Jan.–Jun.	Jul.–Dec.	Total
Remote	1402 (49.4%)	1438 (50.6%)	2840 (100%)
In-person	219 (52.1%)	201 (47.9%)	420 (100%)

McDowall, Loftin, & Pate, 2012). The relatively short period observed here precludes determining whether extortion patterns exhibit seasonality, though the issue would appear to be an important avenue for future research.

Nonetheless, the peaks observed in the latter months of the year could also be explained by increased extortion incidents associated with end-of-year festivities, as Kelly et al. (2000) found that extortion by Chinese gangs in New York Chinatown tends to peak around the Chinese New Year. On the other hand, the pattern could also be an artefact of the measurement instrument. When answering the ENVE's victim forms, respondents are instructed to report the most recent incidents first. Thus, as incidents latter in the year would be the first to be reported, it may be that incidents against repeat victims in the early portion of the year are not reported due to capping restrictions, or due to respondent fatigue.

Table 8.2: Summary statistics of extortion by type and semester.

	Remote		In-person	
	Jan.–Jun.	Jul.–Dec.	Jan.–Jun.	Jul.–Dec.
Mean	0.050	0.048	0.007	0.008
Variance	0.083	0.079	0.009	0.011
Ratio (Mean/Var.)	1.660	1.646	1.286	1.375
Range	[0,6]	[0,6]	[0,4]	[0,5]
Prevalence rate[†]	380.30	374.25	61.13	66.11
Incidence rate[†]	499.72	483.37	67.88	77.48
Concentration	1.31	1.29	1.11	1.17
Percentage repeats	23.90	22.57	9.95	14.68
n	28136	28136	28136	28136

[†]Rates per 10,000 units.

Nonetheless, once the extortion counts were aggregated into semesters (see Table 8.1) there were no statistically significant differences in the amount of extortion incidents experienced in each semester (Remote: $X^2 = 0.46$, $df = 1$, $p = 0.50$, In-person: $X^2 = 0.77$, $df = 1$, $p = 0.38$), which assuages concerns relating to the effects of capping on the temporal patterns observed. The descriptive statistics in Table 8.2
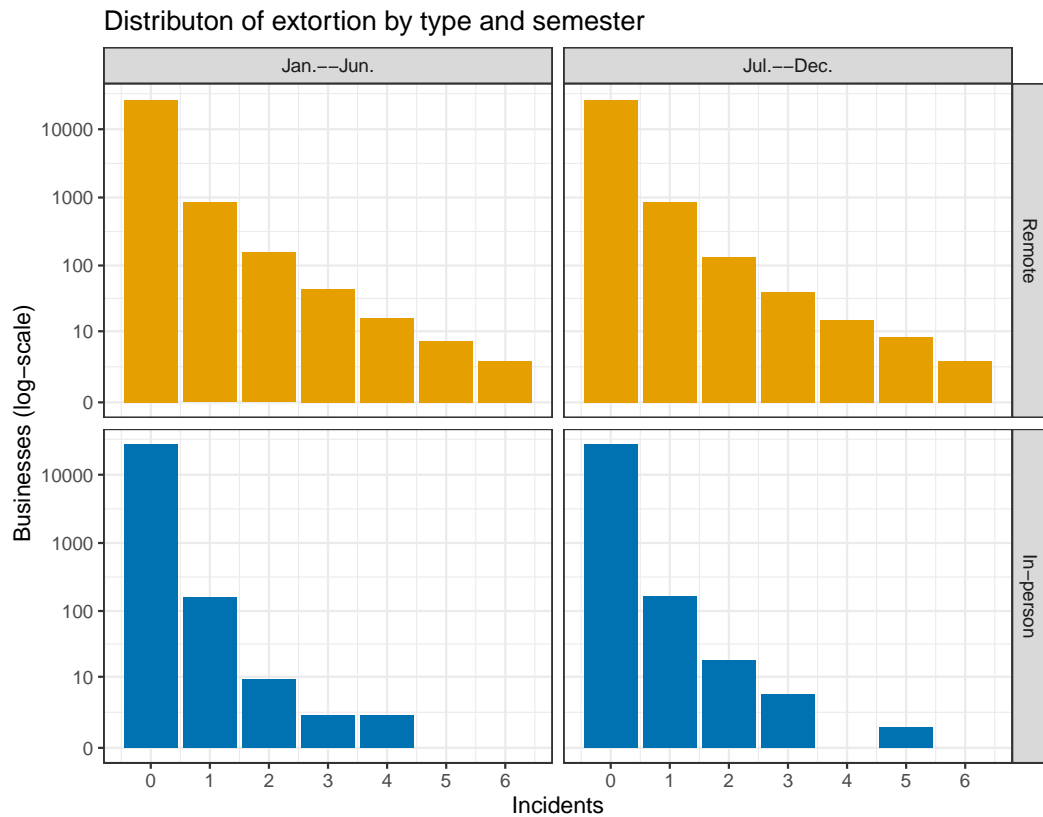
Figure 8.2: Distribution of extortion incidents by type and semester.

and the histograms in Figure 8.2 further illustrate the similarities in extortion victimisation across the semesters.

8.6.1 Time-course

The time-course curves for the entire observation period are presented in Figure 8.3. Both curves for remote and in-person extortion suggest that the risk of repeat victimisation is highest one month after an initial event, and second highest during the same month of the initial event. The plots also suggest that the observed risk was higher than that expected for about the first three months, and lower than that expected thereafter. Chi-squared tests[8] suggested that the time-course for both crime types was significantly different from that expected by chance (Remote: $X^2 = 354.85$, $df = 11$, $p < 0.001$, In-person: $X^2 = 46.11$, $p_{sim.} < 0.001$).

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[8] As some expected counts for in-person extortion were small, the test was conducted using a Monte Carlo simulation with 2000 replicates.
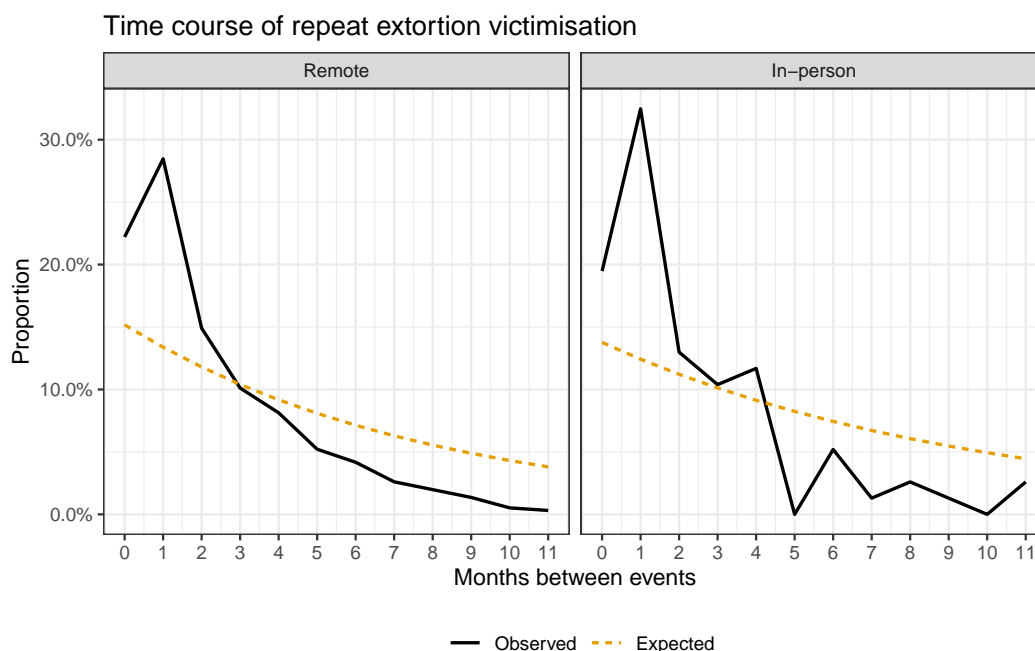
Figure 8.3: Time-course for repeat extortion victimisation by type, entire period.

The standardised residuals of the Chi-squared tests, presented in Table 8.3, permit a closer scrutiny of the deviations from the expected counts. For remote extortions, they suggest that the risk of suffering a repeat was significantly higher than expected during months 0 to 2, was not significantly different from that expected for months 3 and 4, and was significantly lower than expected from month 5 onwards. In contrast, for in-person extortions, only the peak observed at month 1 represents a significantly higher risk of repeat extortion than that expected. The risk of repeats for all other months was not significantly different from that expected, with the exception of months 5 and 10, which presented lower risks (as they had no observations). The differences in significance levels between the crime types are partly due to the fact that in-person extortions are not as common as remote extortions, thus analyses involving the former have less statistical power.

However, as stated earlier, using the entire period to examine the time-course can lead to spurious inferences due to the time window effect. Thus, Figure 8.4 present the time-course curves using a 6 month time window. The observed curves also exhibit a notable spike at the first month, followed by a decaying trend. Chi-squared tests similarly suggested that the time-course for both crime types was significantly

Table 8.3: Standardised residuals of time-course analysis.

Months	Remote	In-person
0	6.07***	1.46
1	13.72***	5.33***
2	2.99***	0.49
3	−0.29	0.08
4	−1.12	0.78
5	−3.27***	−2.63***
6	−3.56***	−0.75
7	−4.70***	−1.90
8	−4.82***	−1.27
9	−5.08***	−1.61
10	−5.78***	−2.00*
11	−5.65***	−0.79
$X^2_{(11)}$	354.85***	46.11***†

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

†simulated p-value

different from that expected by chance, though the differences were smaller (Remote: $X^2 = 43.92$, $df = 6$, $p < 0.001$, In-person: $X^2 = 12.56$, $p_{sim.} < 0.05$).

Standardised residuals shown in Table 8.4 suggest that deviations from the expected counts were smaller. Interestingly, for both extortion types, only the peak observed at month 1 presented a significantly higher risk of extortion victimisation than expected. For remote extortions, months 5 and 6 presented less risk than that expected; whereas for in-person extortion, only month 5 presented less risk than expected. All other months presented no significant differences with the expected time-course for both crime types.

8.6.2 Remote extortions

Estimates of the effects of prior victimisation on remote extortion can be found in Table 8.5.[9] All models for remote extortion were statistically significant when compared to null models containing only the intercept, as indicated by likelihood ratio tests (LRT).

The multilevel specification was only significant in prevalence (logit) models. In the truncated count models estimating concentration, the (truncated) negative binomial specification was not significant, thus the truncated Poisson was used. Mul-

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[9]See Section 8.9 for tables containing results for all covariates used.

Figure 8.4: Time-course for repeat extortion victimisation by type, using a 6 month time window

Table 8.4: Standardised residuals of time-course analysis using a six-month time window.

Months	Remote	In-person
0	1.46	-0.66
1	5.70***	2.78***
2	-1.38	-0.46
3	-1.37	0.24
4	-0.79	0.53
5	-2.35**	-2.43**
6	-2.74***	-0.36
$X^2_{(6)}$	43.92***	12.56*†

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

†simulated p-value

ticollinearity was not deemed to be a problem, as variance-inflation factors (VIF) were small.

Table 8.5: Event dependence model estimates (log-odds and log scale) for remote extortion.

Remote extortions	Logit				Truncated Poisson			
	ED	ED + RH	ED	ED + RH	ED	ED + RH	ED	ED + RH
Intercept	−3.50***	−3.80***	−3.54***	−3.86***	−0.79***	−0.56*	−0.83***	−0.64**
	(0.09)	(0.16)	(0.08)	(0.15)	(0.07)	(0.23)	(0.07)	(0.23)
Prior victimisations	1.38***	1.26***			0.35***	0.34***		
	(0.06)	(0.06)			(0.06)	(0.06)		
Prior victimisations (cat.)								
Victim, not complied			2.19***	2.00***			0.57***	0.57***
			(0.09)	(0.09)			(0.12)	(0.12)
Victim, complied			1.48***	1.32***			1.29***	1.37***
(*base: Not a victim*)			(0.38)	(0.39)			(0.33)	(0.34)
Log-lik.	−4182.14	−4049.35	−4156.32	−4026.71	−719.63	−694.47	−718.23	−692.30
LRT	593.30***	858.87***	644.92***	904.14***	26.47***	76.79***	29.27***	81.12***
LRT df	2	20	3	21	1	19	2	20
AIC	8370.30	8140.70	8320.60	8097.40	1443.30	1428.90	1442.50	1426.60
σ^2		0.19***	0.09***	0.17***	0.08***			

ED: Event dependence covariates only. ED + RH: Event dependence and risk heterogeneity covariates. ***$p < 0.001$,
**$p < 0.01$, *$p < 0.05$. Standard errors in parentheses. Groups for multilevel specifications: 32. Logit obs.: 28,115,
Truncated Poisson obs.: 1,049.

The estimates of prevalence (logit) models are interpreted first. The coefficients for the continuous version of prior victimisation were significant ($p < 0.001$) in both the bivariate specification (ED) and after controlling for risk heterogeneity covariates (ED + RH). Furthermore, adding the variable of prior victimisation significantly improved fit when compared to a model containing only risk heterogeneity controls ($LRT(1) = 364.25$, $p < 0.001$), while the risk heterogeneity controls were also found to improve model fit when compared to a model containing only prior victimisation ($LRT(18) = 265.58$, $p < 0.001$). In the ED model, suffering an additional remote extortion incident in semester one increased the risk of becoming a victim of remote extortion in the second semester by 3.97 times ($e^{1.38}$). After controlling for risk heterogeneity covariates, the effect size decreased to 3.52 ($e^{1.26}$).

The coefficients for the categorical version of prior victimisation were similarly significant ($p < 0.001$) in both the bivariate specification (ED) and after controlling for risk heterogeneity covariates (ED + RH). Adding the categorical covariates significantly improved model fit when compared to a model containing only risk heterogeneity controls ($LRT(2) = 409.51$, $p < 0.001$), and the risk heterogeneity controls were also found to be significant against a model containing only the prior victimisation categories ($LRT(18) = 259.22$, $p < 0.001$).

In the ED model, being a non-compliant victim of remote extortion in semester one increased the likelihood of becoming a victim of remote extortion in semester two by 8.94 times ($e^{2.19}$), when compared to businesses that were not victimised in semester one. In contrast, complying with a remote extortion incident in semester one was associated with 4.39 ($e^{1.48}$) higher odds of becoming a victim of remote extortion in semester two, when compared to businesses that were not victimised in semester one. Controlling for risk heterogeneity covariates did not substantively alter the associations observed though the effect sizes were smaller (Non-compliant victim: $e^{2.0} = 7.39$, Compliant victim: $e^{1.38} = 3.97$). This would suggest that although prior victimisation was associated with higher risks of subsequent victimisation overall, non-compliant victims faced higher risks of subsequent victimisation. However, the confidence intervals for the estimates suggest there are overlaps in the true effects (see Figure 8.5).

Overall, models fit using the categorical version of prior victimisation appear to be better than models fit using the continuous version, as the AIC of these models was smaller. Furthermore, the former models captured a marginally larger share of state-level unobserved heterogeneity (σ^2), which also indicates a better fit.

Regarding the estimates for concentrated (truncated Poisson) models, the coef-

ficients for the continuous version of prior victimisation were significant ($p < 0.001$) in both the bivariate specification (ED) and after controlling for risk heterogeneity covariates (ED + RH). However, the effect size was smaller than for prevalence, as suffering an additional remote extortion incident in semester one increased the amount of remote extortion incidents suffered by victims in semester two by 42% ($e^{0.35} = 1.42$) in the ED model, and by 40% ($e^{0.34} = 1.40$) after controlling for risk heterogeneity covariates (ED + RH). Nonetheless, models including the continuous variable of prior victimisation were significantly better than models containing only risk heterogeneity controls ($LRT(1) = 25.49$, $p < 0.001$), and similarly, risk heterogeneity controls also improved model fit over the sole prior victimisation covariate ($LRT(18) = 50.32$, $p < 0.001$).

The categorical version of prior victimisation suggested that compliance with prior victimisation had a somewhat different effect on concentration from the effects observed for prevalence. Both prior victimisation categories were significant ($p < 0.001$) in ED and ED + RH models, and their inclusion improved model fit when compared to a model controlling for risk heterogeneity ($LRT(2) = 29.83$, $p < 0.001$).[10]

While in the prevalence models, being a non-compliant victim of remote extortion in semester one was associated with higher likelihoods of being a victim of remote extortion in semester 2, in the concentration model, compliant victims experienced higher rates of repeat remote extortion victimisation. In the ED model, being a non-compliant victim of remote extortion in semester one was associated with 1.77 ($e^{0.57}$) more remote extortions suffered by victims in semester two, when compared with businesses not victimised during semester one. In contrast, complying with a remote extortion incident in semester one was associated with 3.63 ($e^{1.29}$) more remote extortions in semester 2, when compared with businesses not victimised during semester one. Controlling for risk heterogeneity covariates had no effect on the coefficient for non-compliant victims, while it increased the effect size of compliant victims ($e^{1.37} = 3.94$). However, as in the prevalence models, the confidence intervals of the estimates (see Figure 8.5) suggest that the true effect sizes may overlap.

As with the prevalence models, the use of the categorical version of prior victimisation produced a better fit, as judged by its smaller AIC values, though the difference was quite small.

The effect sizes can also be used to calculate predicted values. Figure 8.5 presents

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[10]The risk heterogeneity covariates were similarly found to improve model fit when compared to a model containing only the prior victimisation categories ($LRT(18) = 51.86$, $p < 0.001$).

Remote extortion: Partial effects of prior victimisation
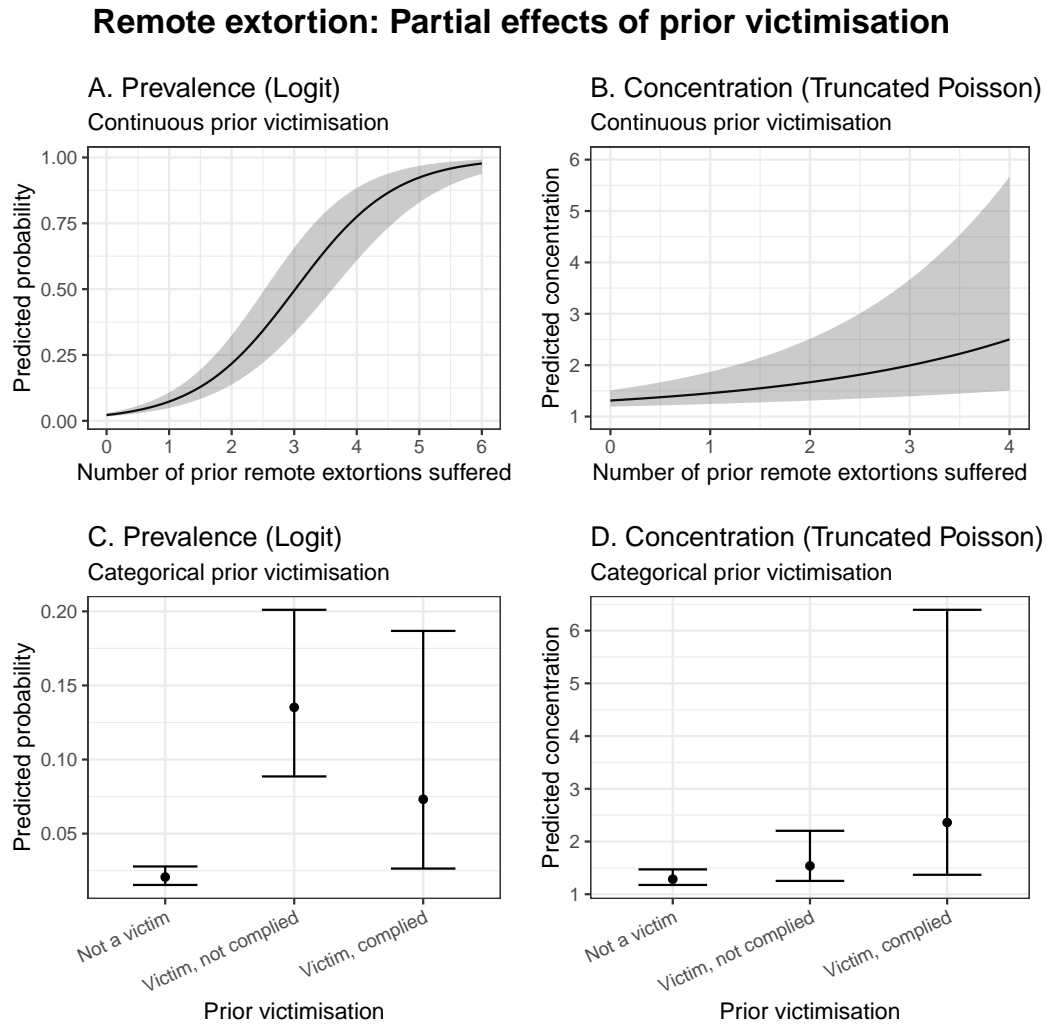
Figure 8.5: Predicted effects of prior (remote) victimisation on remote extortion victimisation in semester two. Estimates from ED + RH models in Table 8.5. Shaded areas and error bars denote 95% confidence intervals.

four plots with the predicted values[11] of the prevalence and concentration of remote extortion, according to the partial effects of prior victimisation (after controlling for risk heterogeneity covariates).

Panel A shows how the likelihood of becoming a victim of remote extortion in semester 2 increases as the number of remote extortions suffered in semester one increases. At around 3 prior remote extortions, the likelihood of suffering at least one remote extortion in semester two is higher than 50%. Panel B shows the partial effect of the continuous version of prior victimisation on the concentration of remote extortion among semester 2 victims. While the amount of concentration increases relatively slowly with each successive prior incident, the higher estimate given by the 95% confidence interval quickly reaches the upper limits imposed by the capping practices. Panels C and D show the predicted values for prevalence and concentration using the categorical version of prior victimisation. Notably, the estimates also serve to highlight the amount of uncertainty regarding the true estimates (given by the 95% confidence intervals). Such uncertainty is highest for compliant victims when predicting the amount of concentration of remote extortion.

8.6.3 In-person extortions

Table 8.6 presents estimates of the effects of prior victimisation on in-person extortion. All prevalence (logit) models for in-person extortion were significant when compared to null models containing only the intercept, as indicated by the LRT. In contrast, only one of the models for in-person concentration was found to be statistically significant when compared to a null model. As in remote extortion models, the multilevel specification was significant for prevalence models, though not for concentration models. Also as in remote extortion models, the truncated Poisson was used to estimate concentration, as the negative binomial specification was not significant. Multicollinearity was not deemed to be a problem, as variance-inflation factors (VIF) were small.

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[11]Predicted counts for truncated Poisson models are calculated using the following equation (Rodríguez, 2019):

$$E[y|y > 0, x] = \frac{\mu}{1 - e^{-\mu}}$$

where μ is the estimated count from the 'untruncated' model, $E[y|x] = \mu = e^{\beta_0 + X\beta}$, for a dependent variable y, and independent variables X.

Table 8.6: Event dependence model estimates (log-odds and log scale) for in-person extortions.

In-person extortions	Logit				Truncated Poisson			
	ED	ED + RH	ED	ED + RH	ED	ED + RH	ED	ED + RH
Intercept	−5.43***	−5.54***	−3.35***	−5.54***	−1.78***	−3.00*	−1.80***	−3.30*
	(0.17)	(0.34)	(0.09)	(0.34)	(0.27)	(1.49)	(0.27)	(1.59)
Prior victimisations	1.44***	1.19***			0.55	2.08*		
	(0.20)	(0.20)			(0.56)	(0.89)		
Prior victimisations (cat.)								
Victim, not complied			0.80*	2.67***			0.92	2.75*
			(0.40)	(0.40)			(0.74)	(1.23)
Victim, complied			−0.41	1.73***			0.37	1.82
(*base: Not a victim*)			(0.59)	(0.41)			(1.02)	(1.39)
Log-lik.	−996.78	−948.54	−4402.27	−939.81	−55.57	−40.24	−55.32	−39.85
LRT	82.23***	178.69***	153.03***	196.10***	0.79	31.44*	1.30	32.22
LRT df	2	21	3	22	1	20	2	21
AIC	1999.60	1941.10	8812.50	1925.60	115.10	122.50	116.60	123.70
σ^2		0.54***	0.22***	0.22***	0.20***			

ED: Event dependence covariates only. ED + RH: Event dependence and risk heterogeneity covariates.***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Standard errors in parentheses. Groups for multilevel specifications: 32. Logit obs.: 28,115, Truncated Poisson obs.: 170.

The estimates of prevalence (logit) models are interpreted first. The coefficients for the continuous version of prior victimisation were significant ($p < 0.001$) in both the bivariate specification (ED) and after controlling for risk heterogeneity covariates (ED + RH). Furthermore, adding the variable of prior victimisation significantly improved fit when compared to a model containing only risk heterogeneity controls ($LRT(1) = 22.08$, $p < 0.001$), while the risk heterogeneity controls were also found to improve model fit when compared to a model containing only prior victimisation ($LRT(19) = 96.47$, $p < 0.001$). In the ED model, suffering an additional in-person extortion incident in semester one increased the risk of becoming a victim of in-person extortion in the second semester by 4.22 times ($e^{1.44}$). However, after controlling for risk heterogeneity covariates, the effect size decreased to 3.29 ($e^{1.19}$).

The coefficients for the categorical version of prior victimisation suggested the presence of a strong confounding effect with risk heterogeneity. In the bivariate specification (ED), only the coefficient for non-compliant victims was significant ($p < 0.05$). Its effect size suggested that being a non-compliant victim of in-person extortion in semester one increases the risk of becoming a victim of in-person extortion in semester two by 2.23 times ($e^{0.80}$), when compared to businesses not victimised in semester one.

Nonetheless, after controlling for risk heterogeneity covariates (ED + RH), both prior victimisation categories were significant ($p < 0.001$), and effect sizes increased markedly. Compared to businesses not victimised in semester one, non-compliant victims were 14.4 times ($e^{2.67}$) more likely to become a victim of in-person extortion in semester two, while compliant victims were 5.64 times ($e^{1.73}$) more likely to be victimised in semester two. Furthermore, the inclusion of the prior victimisation categories significantly improved model fit ($LRT(2) = 39.55$, $p < 0.001$), something also seen after the inclusion of the risk heterogeneity controls ($LRT(19) = 6924.9$, $p < 0.001$). As in remote extortion prevalence models, the confidence intervals for these estimates suggest that the true effect sizes may overlap (see Figure 8.6).

Overall, models controlling for both risk heterogeneity and event dependence (and in particular the categorical version of prior victimisation) were found to be better fits to explain the prevalence of in-person extortion in semester two, as indicated by the AIC values. Unobserved state-level heterogeneity (σ^2), was generally higher than for remote extortions, though the inclusion of covariates managed to reduce the amount substantially.

Regarding models for in-person concentration (truncated Poisson), only the ED + RH model using the continuous version of prior extortion was significantly better

than a model containing only the intercept, as indicated by LRTs. After controlling for risk heterogeneity covariates, suffering an additional in-person extortion incident in semester one increased the amount of in-person extortion suffered by victims in semester two by 8.0 times ($e^{2.08}$, $p < 0.05$). While the coefficient for non-compliant victims was significant in the ED + RH model ($p < 0.05$), the model itself was not significantly better than a null model. However, as in the case of the time-course analysis for in-person extortion, the estimates for in-person concentration models may have been affected by the fact that there were (comparatively) very few victims of in-person extortion. This would mean that the models have less statistical power (than the concentration models for remote extortion).

Figure 8.6 presents four plots with the predicted values of the prevalence and concentration of in-person extortion in semester two, according to the partial effects of prior victimisation (after controlling for risk heterogeneity covariates). Panel A shows how the likelihood of becoming a victim of in-person extortion in semester 2 increases as the number of in-person extortions suffered in semester one increases. The likelihood of suffering at least one remote extortion in semester two exceeds 50% when businesses experienced close to 5 prior in-person incidents in semester one. However, the amount of uncertainty in the estimate is quite large, as indicated by the 95% confidence interval.

Panel B shows the partial effect of the continuous version of prior victimisation on the concentration of in-person extortion among semester 2 victims. The amount of concentration increases sharply after two prior events, and quickly exceeds the upper limits of the cap. Furthermore, while the coefficient was found to be significant, the amount of uncertainty surrounding the estimate is extremely large. Panels C and D show the predicted values for prevalence and concentration of in-person extortion using the categorical version of prior victimisation. Notably, the estimates also serve to highlight the amount of uncertainty regarding the true estimates (given by the 95% confidence intervals).

To facilitate the comparison across extortion types, Figure 8.7 presents forest plots of the prior victimisation coefficient estimates for remote and in-person models. Overall, in logit models for both crime types, the amount of extortions suffered in semester one was positively associated with the likelihood of becoming a victim of extortion in semester two. The coefficients for the categorical version of prior victimisation suggested that victims that did not comply in semester one were more likely to experience either type of extortion in semester two, while victims that complied tended see less pronounced increases in the risk of semester two victimisation.
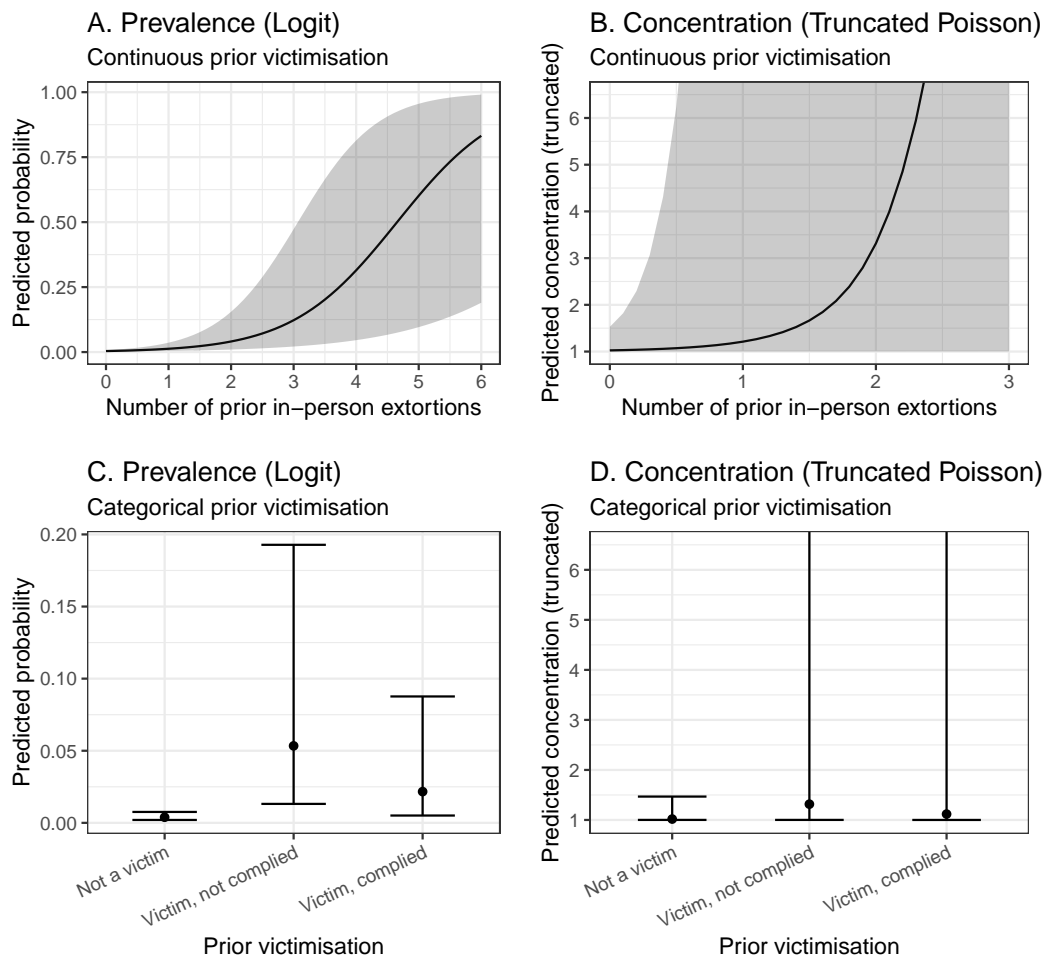
Figure 8.6: Predicted effects of prior (in-person) victimisation on in-person extortion victimisation in semester two. Estimates from ED + RH models in Table 8.6. Shaded areas and error bars denote 95% confidence intervals.
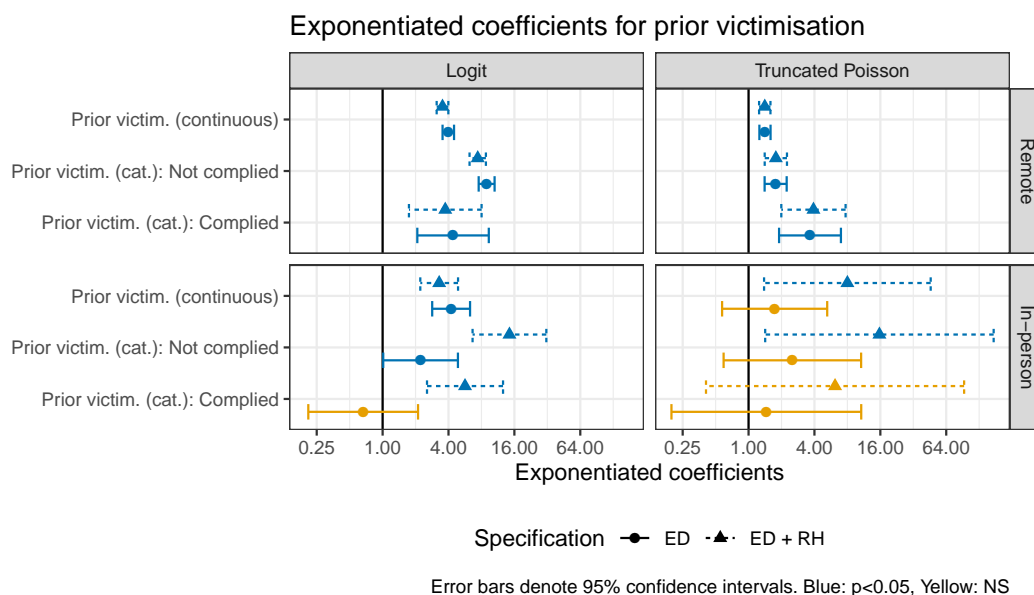
Figure 8.7: Forest plots comparing estimates of prior victimisation for remote and in-person extortion models

However, the categorical coefficients for prior victimisation experienced more confounding with risk heterogeneity covariates in the case of in-person extortion. Estimates for truncated Poisson models also suggested a positive association between the amount of prior extortion in semester one and the amount of extortion suffered by victims in semester two, though the estimates were much more uncertain for in-person extortion (and similarly showed signs of confounding). While complying with extortion demands in semester one had a stronger effect than not complying on semester two remote extortion concentration, compliance had no effect on the concentration of in-person extortion.

8.7 Discussion

This chapter sought to examine whether the patterns and mechanisms of extortion victimisation vary by type of extortion, with particular attention to the event dependence mechanism. The study was motivated by findings presented in Chapters 5 and 7, which suggested that the concentration of extortion could not be explained by the same factors that explained its prevalence, and by the literature on repeat victimisation, which suggested that event dependence would likely play a bigger role

in crime types where victim response to an initial event could alter the opportunity structure of future incidents.

Properly analysing the effect of event dependence requires the use of longitudinal data, which is not generally available for extortion measurements. Thus, as an attempt to investigate the matter, this study relied on measurements from a cross-sectional victimisation survey, using the information captured on victim forms to build a pseudo-longitudinal data set.

The study employed two analytical approaches. First, to test H1, the time-course of repeat extortion victimisation was analysed. The literature on repeat victimisation has consistently identified that, in the presence of event dependence, the risk of repeats is highest immediately after an initial event takes places and decays exponentially as time progresses. However, as the time-course expected under chance (assuming a Poisson process) also follows a monotonically decaying exponential function, the patterns observed had to be compared to those expected under chance, to determine if they were of theoretical importance.

The analysis presented herein suggested that the time-course patterns observed for remote and in-person extortion were distinct from those expected by chance. Furthermore, after accounting for the confounding effect of the time window, the risks of a repeat victimisation peaked to a level higher than that expected one month after an initial event. This finding stands in contrast with the majority of reported studies on the matter (e.g. Johnson et al., 1997; Sagovsky & Johnson, 2007), which find that the highest risk occurs the same month of occurrence as the initial event. On the one hand, such pattern could be consistent with an offender strategy whereby victims are extorted at regular intervals (e.g. every month). On the other, the pattern could also be a statistical artefact of the temporal units used (see below, third point).

The time-course analyses present important limitations. First, the length of the period used to study the time-course is quite short, thus, the time-course can only be analysed for a period of up to six months, while the effect of event dependence may be longer-lasting. Second, as the measurements were recorded retrospectively at a later cross-section, there is likely to be increased uncertainty regarding the precise period of occurrence of events.

Third, the temporal units used were relatively long (months), and can impose artificial lengths of time between events that may in fact be closer. For example, if a business experienced extortion events the first and last day of June, the time between events would be 0 months, while if another business experienced one event on the 30th of June, and another on the 1st of July, the time between events would

be 1 month, though the actual time elapsed in the first instance is longer than in the second (30 days vs 1 day). Thus, regarding the peaks observed at 1 month, it may be that many waiting times recorded as 1 month actually involved shorter periods. Also, the units can hide relevant within-month event dependence patterns that could be missed using this temporal aggregation unit.

Unfortunately, the present data do not allow for shorter temporal units to be analysed, nor for a longer period of analysis not affected by time-window confounding. This would appear to be a relevant area for further research, though given the dismal rates of reporting for extortion incidents, it is unlikely that better data will become available.

The second analysis used statistical modelling to examine whether prior extortion victimisation was associated with the risk of future extortion victimisation. For the statistical models, two periods were constructed. Measures of extortion during January–June 2013 were used as prior victimisations, while those during July–December 2013 were used as the dependent variable. Following the results presented in Chapter 7, two types of statistical models were fit. First, logistic models estimated the likelihood of a business becoming a victim of extortion during semester two. Then, a truncated Poisson model was used to estimate the concentration of extortion incidents among semester two victims.

There was support for H2, which predicted that the risks of repeat extortion victimisation would be associated with the amount of prior victimisation incidents suffered, after controlling for risk heterogeneity. Prevalence models (logits) consistently showed that the more extortion victimisations a business suffered in a previous period, the higher the likelihood of suffering a repeat in a subsequent period. The effects were highly consistent, even after controlling for a range of risk heterogeneity covariates used in Chapters 5 and 7, and were similar for remote and in-person extortions—though the magnitude and the uncertainty of the estimates varied by crime type.

In the case of concentration models (truncated Poisson), the amount of prior victimisations was similarly positively associated with extortion concentration in a subsequent period among semester two victims. However, the estimates for remote extortions appeared to be more robust than those of in-person extortion, which showed stronger confounding with risk heterogeneity covariates as well as much wider uncertainty around the estimate. Furthermore, the effect size for remote extortion concentration was comparatively smaller than for in-person extortion concentration.

H3 predicted a more complex relationship between prior victimisation and future

extortion risks, assuming that compliance with previous incidents would increase the risks in subsequent periods. Evidence for H3 was mixed. On the one hand, prevalence models did suggest that complying with extortion demands in semester one was associated with higher risks of extortion victimisation in semester two (for both crime types), when compared with businesses not victimised in semester one. However, not complying with prior extortion demands was consistently associated with higher likelihoods of extortion victimisation in semester two. On the other hand, compliant businesses experienced higher remote extortion concentration in semester two, than non-compliant victims (which did experience higher rates than non victims, though lower than compliant victims). In contrast, in-person concentration was not associated with compliance in previous extortion demands. As in the prevalence models, prior victimisation categories saw more confounding with risk heterogeneity for in-person extortion than for remote extortion.

While the findings appear to support the notion that event dependence plays an important role in repeat extortion victimisation, they are less clear on the precise mechanisms that explain how this occurs. A common explanation for event dependence is that offenders often return to victimise past targets (Bernasco, 2008; Johnson, 2014; Johnson, Summers, & Pease, 2009). The significant effect of past extortion compliance, particularly in remote extortion concentration, could be indicative of offenders returning to victimise victims that are known to be profitable. On the other hand, the higher likelihoods of victimisation for non-compliant victims would point in the opposite direction. However, it should also be noted that the uncertainty around the estimates for compliance categories suggested that there may be overlaps in the true effect sizes. In any case, the current dataset cannot be used to elucidate this matter further, as it does not contain information necessary to identify if repeats were committed by the same offenders.

An important limitation of the current study is that the measures of prior victimisation used are imperfect measures of event dependence. In the absence of true longitudinal data, the measures of prior victimisation used could be confounded with unmeasured sources of risk heterogeneity. Though the study controlled for relevant covariates of risk heterogeneity, these are by no means exhaustive—especially in the case of in-person extortion as the findings in Chapter 7 suggest. Thus, instead of 'true' event dependence, the association between in-person extortion and prior victimisation could be reflecting a relevant confounder not included in the model. For example, prior in-person victimisation could be an indicator of a business being

located in a territory controlled by organised crime groups (Kleemans, 2018), in a manner not adequately captured by the risk heterogeneity covariates used.

The only alternative to adequately capture event dependence is using true longitudinal data that permits fitting a two-way time and units fixed effect model. However, given that longitudinal commercial victimisation surveys are (extremely) rare, and that police reported statistics fail to adequately capture extortion measurements, such data are unlikely to be available in the near future. Thus, the approach presented here is probably the best possible, given the limitations of the data.

Other limitations are also relevant. The risk heterogeneity measures used do not account for differences between the two semesters, as it was not possible to disaggregate them. This does not affect time-invariant measures (such as business type), though it may be more relevant for time-variant measures (such as seasonal variation in area-level drug-related crimes). The length of the time periods used are also relevant limitations for the same reasons as mentioned in the limitations of the time-course analysis.

The capping practices are also likely to impose additional limitations. This is particularly true for estimates of prior victimisation for truncated models, as suffering more victimisations in semester one imposes artificial limits on the number of victimisations that are possible to report in semester two. The use of categorical measures of prior victimisation addresses this limitation to an extent, though uncapped measures would certainly be preferred.

Lastly, as in-person extortion is a relatively rare crime (compared to the more common remote extortion), analyses concerning this crime type may suffer from low statistical power—which means that the probability of wrongly failing to reject the null hypothesis is higher. This is particularly relevant for concentration models, which were estimated using only observations for victims of in-person extortion, and failed to reject the null on more occasions.

8.8 Chapter conclusion

The chapter presented the first (tentative) assessment of event dependence in extortion victimisation using pseudo-longitudinal measures constructed out of a cross-sectional survey.

The findings support the notion of event dependence as an important mechanism in extortion victimisation. Though further research into the matter would

be welcome, data limitations are likely to impede future efforts, unless appropriate longitudinal measures of extortion victimisation are created.

In terms of the practical implications, the tentative support for the event dependence mechanism points towards plausible intervention strategies to prevent repeat victimisation. Intervening soon after an initial event might help stop further repeats at a relatively low cost, given that the approach would be highly targeted.

In terms of academic implications, the study further highlights the differences between remote and in-person extortion, suggesting that future studies should consider the crime types as distinct offence classes. The study also highlights the limitations of the data available for investigating the mechanisms of repeat extortion victimisation. A potential avenue for future research might be to replicate the analyses presented here combining several sweeps of the ENVE survey, with an aim of increasing statistical power. The findings also add to the repeat victimisation literature by its innovative use of cross-sectional data to study a longitudinal problem, though the limitations of the approach are also noted.

8.9 Chapter appendix

For completeness, the results of the model estimates including all event dependence and risk heterogeneity covariates are presented below.

Table 8.7: Complete event dependence and risk heterogeneity prevalence model estimates (log-odds) for remote extortions.

			Logit		
Remote extortions	ED	ED + RH	ED	ED + RH	RH
Intercept	−3.50***	−3.80***	−3.54***	−3.86***	−3.73***
	(0.09)	(0.16)	(0.08)	(0.15)	(0.16)
Prior victimisations	1.38***	1.26***			
	(0.06)	(0.06)			
Prior victimisations (b: Non-vic.)					
Victim, not complied			2.19***	2.00***	
			(0.09)	(0.09)	
Victim, complied			1.48***	1.32***	
			(0.38)	(0.39)	
log(Corruption incidence)[†]		0.58***		0.56***	0.70***
		(0.09)		(0.09)	(0.08)
Years in business (b: 0 to 5)					
6 to 9		0.27*		0.25*	0.29**
		(0.11)		(0.11)	(0.11)
10, 14		0.38***		0.36**	0.38***
		(0.11)		(0.11)	(0.11)
15 to 23		0.47***		0.45***	0.52***
		(0.11)		(0.11)	(0.11)
24 to 212		0.40***		0.39***	0.41***
		(0.11)		(0.11)	(0.11)
Business type (b: Retail)					
Wholesale		0.01		0.01	0.01
		(0.13)		(0.13)	(0.13)
Industry		−0.19		−0.18	−0.17
		(0.10)		(0.10)	(0.10)
Hotels, rest. & bars		0.31**		0.32**	0.41***
		(0.11)		(0.11)	(0.11)
Other serv.		0.05		0.06	0.05
		(0.08)		(0.08)	(0.08)
Business size (b: Large)					
Small and Medium		0.31**		0.32**	0.37***
		(0.11)		(0.11)	(0.10)
Micro		−0.50***		−0.48***	−0.52***
		(0.11)		(0.11)	(0.11)
State level					
Rule of law		0.00		0.00	−0.00
		(0.01)		(0.01)	(0.01)
log(Corruption prevalence)		0.42*		0.39*	0.43*
		(0.19)		(0.18)	(0.19)
log(Weapon crimes)		0.37**		0.37**	0.41**
		(0.12)		(0.12)	(0.13)
log(Drug crimes)		−0.23*		−0.23*	−0.25*
		(0.10)		(0.09)	(0.10)
Competitiveness		−0.02*		−0.02*	−0.02*
		(0.01)		(0.01)	(0.01)
log(Population)		−0.21		−0.19	−0.23
		(0.13)		(0.12)	(0.13)
log(N businesses)		−0.52		−0.50	−0.53
		(0.33)		(0.32)	(0.34)
Log-lik.	−4182.14	−4049.35	−4156.32	−4026.71	−4231.50
LRT	593.30***	858.87***	644.92***	904.14***	494.62***
LRT df	2	20	3	21	19
AIC	8370.30	8140.70	8320.60	8097.40	8502.90
σ^2	0.19	0.09	0.17	0.08	0.09

ED: Event dependence covariates only. ED + RH: Event dependence and risk heterogeneity covariates. RH: Risk heterogeneity covariates only. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Standard errors in parentheses. [†]$log(x + 1)$ was used. Groups for multilevel specifications: 32. Logit obs.: 28,115.

Table 8.8: Complete event dependence and risk heterogeneity concentration model estimates (log scale) for remote extortions.

Remote extortions	*Truncated Poisson*				
	ED	ED + RH	ED	ED + RH	RH
Intercept	-0.79^{***}	-0.56^{*}	-0.83^{***}	-0.64^{**}	-0.49^{*}
	(0.07)	(0.23)	(0.07)	(0.23)	(0.23)
Prior victimisations	0.35^{***}	0.34^{***}			
	(0.06)	(0.06)			
Prior victimisations (b: Non-vic.)					
Victim, not complied			0.57^{***}	0.57^{***}	
			(0.12)	(0.12)	
Victim, complied			1.29^{***}	1.37^{***}	
			(0.33)	(0.34)	
log(Corruption incidence)†		0.29^{**}		0.30^{***}	0.29^{***}
		(0.09)		(0.09)	(0.09)
Years in business (b: 0 to 5)					
6 to 9		0.11		0.09	0.10
		(0.22)		(0.22)	(0.22)
10, 14		0.34		0.33	0.34
		(0.21)		(0.21)	(0.21)
15 to 23		0.08		0.07	0.12
		(0.21)		(0.21)	(0.21)
24 to 212		0.39		0.41^{*}	0.41^{*}
		(0.20)		(0.20)	(0.20)
Business type (b: Retail)					
Wholesale		-0.36		-0.33	-0.37
		(0.24)		(0.24)	(0.24)
Industry		-0.11		-0.09	-0.07
		(0.18)		(0.18)	(0.18)
Hotels, rest. & bars		0.13		0.19	0.18
		(0.17)		(0.17)	(0.17)
Other serv.		-0.18		-0.13	-0.16
		(0.15)		(0.15)	(0.15)
Business size (b: Large)					
Small and Medium		-0.46^{**}		-0.44^{**}	-0.41^{**}
		(0.15)		(0.15)	(0.15)
Micro		-0.65^{***}		-0.63^{***}	-0.62^{***}
		(0.17)		(0.17)	(0.17)
State level					
Rule of law		0.01		0.00	0.00
		(0.01)		(0.01)	(0.01)
log(Corruption prevalence)		0.24		0.23	0.18
		(0.17)		(0.17)	(0.17)
log(Weapon crimes)		-0.12		-0.16	-0.12
		(0.11)		(0.11)	(0.11)
log(Drug crimes)		0.05		0.05	0.05
		(0.09)		(0.09)	(0.09)
Competitiveness		-0.01		-0.01	-0.02^{*}
		(0.01)		(0.01)	(0.01)
log(Population)		-0.00		0.03	0.01
		(0.11)		(0.12)	(0.11)
log(N businesses)		-0.28		-0.24	-0.24
		(0.30)		(0.30)	(0.30)
Log-lik.	-719.63	-694.47	-718.23	-692.30	-707.22
LRT	26.47^{***}	76.79^{***}	29.27^{***}	81.12^{***}	51.29^{***}
LRT df	1	19	2	20	18
AIC	1443.30	1428.90	1442.50	1426.60	1452.40
σ^2					

ED: Event dependence covariates only. ED + RH: Event dependence and risk heterogeneity covariates. RH: Risk heterogeneity covariates only. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Standard errors in parentheses. $^{\dagger}log(x+1)$ was used. Groups for multilevel specifications: 32. Truncated Poisson obs.: 1049.

Table 8.9: Complete event dependence and risk heterogeneity Logit model estimates (log-odds) for in-person extortions.

	Logit				
In-person extortions	ED	ED + RH	ED	ED + RH	RH
Intercept	−5.43***	−5.54***	−3.35***	−5.54***	−5.55***
	(0.17)	(0.34)	(0.09)	(0.34)	(0.34)
Prior victimisations	1.44***	1.19***			
	(0.20)	(0.20)			
Prior victimisations (b: Non-vic.)					
Victim, not complied			0.80*	2.67***	
			(0.40)	(0.40)	
Victim, complied			−0.41	1.73***	
			(0.59)	(0.41)	
Corruption incidence		1.83***		1.80***	1.89***
		(0.25)		(0.26)	(0.25)
Corruption incidence^2		−0.35***		−0.35***	−0.35***
		(0.08)		(0.09)	(0.08)
Years in business (b: 0 to 5)					
6 to 9		0.44		0.45	0.47
		(0.24)		(0.24)	(0.24)
10, 14		0.30		0.31	0.33
		(0.26)		(0.26)	(0.26)
15 to 23		0.01		0.01	0.02
		(0.27)		(0.27)	(0.27)
24 to 212		0.34		0.34	0.36
		(0.26)		(0.26)	(0.26)
Business type (b: Retail)					
Wholesale		−0.34		−0.35	−0.37
		(0.33)		(0.33)	(0.33)
Industry		−0.30		−0.27	−0.30
		(0.24)		(0.24)	(0.24)
Hotels, rest. & bars		−0.13		−0.13	−0.13
		(0.29)		(0.29)	(0.28)
Other serv.		−0.20		−0.21	−0.21
		(0.20)		(0.20)	(0.19)
Business size (b: Large)					
Small and Medium		−0.06		−0.09	−0.05
		(0.25)		(0.25)	(0.24)
Micro		−0.31		−0.34	−0.28
		(0.25)		(0.25)	(0.25)
State level					
Rule of law		−0.00		−0.00	−0.00
		(0.01)		(0.01)	(0.01)
log(Corruption prevalence)		0.39		0.38	0.37
		(0.37)		(0.36)	(0.36)
log(Weapon crimes)		0.52*		0.52*	0.55*
		(0.25)		(0.25)	(0.25)
log(Drug crimes)		−0.46*		−0.45*	−0.48*
		(0.19)		(0.19)	(0.19)
Competitiveness		0.00		0.00	0.00
		(0.02)		(0.01)	(0.01)
log(Population)		0.15		0.12	0.18
		(0.25)		(0.24)	(0.24)
log(N businesses)		−0.19		−0.20	−0.23
		(0.65)		(0.64)	(0.64)
Log-lik.	−996.78	−948.54	−4402.27	−939.81	−959.58
LRT	82.23***	178.69***	153.03***	196.10***	156.61***
LRT df	2	21	3	22	20
AIC	1999.60	1941.10	8812.50	1925.60	1961.20
σ^2	0.54***	0.22***	0.22***	0.20***	0.21***

ED: Event dependence covariates only. ED + RH: Event dependence and risk heterogeneity covariates. RH: Risk heterogeneity covariates only. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Standard errors in parentheses. $^\dagger log(x + 1)$ was used. Groups for multilevel specifications: 32. Logit obs.: 28,115.

Table 8.10: Complete event dependence and risk heterogeneity concentration model estimates (log scale) for in-person extortions.

	Truncated Poisson				
In-person extortions	ED	ED + RH	ED	ED + RH	RH
Intercept	−1.78***	−3.00*	−1.80***	−3.30*	−2.30
	(0.27)	(1.49)	(0.27)	(1.59)	(1.33)
Prior victimisations	0.55	2.08*			
	(0.56)	(0.89)			
Prior victimisations (b: Non-vic.)					
Victim, not complied			0.92	2.75*	
			(0.74)	(1.23)	
Victim, complied			0.37	1.82	
			(1.02)	(1.39)	
Corruption incidence		−0.37		−0.46	−0.35
		(0.91)		(0.90)	(0.88)
Corruption incidence^2		0.07		0.11	0.07
		(0.28)		(0.28)	(0.26)
Years in business (b: 0 to 5)					
6 to 9		2.29		2.54	1.80
		(1.23)		(1.31)	(1.14)
10, 14		0.12		0.25	0.45
		(1.50)		(1.54)	(1.46)
15 to 23		2.11		2.31	1.72
		(1.20)		(1.26)	(1.13)
24 to 212		0.97		1.31	0.88
		(1.21)		(1.31)	(1.19)
Business type (b: Retail)					
Wholesale		0.33		−0.01	0.43
		(1.28)		(1.45)	(1.17)
Industry		0.28		0.33	0.49
		(0.69)		(0.72)	(0.63)
Hotels, rest. & bars		0.66		0.68	−0.02
		(1.28)		(1.28)	(1.21)
Other serv.		−1.24		−1.25	−1.22
		(0.84)		(0.85)	(0.83)
Business size (b: Large)					
Small and Medium		−1.80		−1.67	−1.31
		(0.93)		(0.95)	(0.82)
Micro		−1.96*		−1.88*	−1.78*
		(0.87)		(0.88)	(0.80)
State level					
Rule of law		−0.15*		−0.16*	−0.10
		(0.06)		(0.06)	(0.05)
log(Corruption prevalence)		−2.44		−2.56*	−1.86
		(1.29)		(1.31)	(1.09)
log(Weapon crimes)		−0.97		−1.06	−0.91
		(0.73)		(0.74)	(0.71)
log(Drug crimes)		0.73		0.91	0.58
		(0.67)		(0.71)	(0.63)
Competitiveness		−0.06		−0.05	−0.06
		(0.04)		(0.04)	(0.03)
log(Population)		1.33		1.32	1.30
		(0.91)		(0.93)	(0.77)
log(N businesses)		6.60*		6.93*	4.66
		(2.92)		(3.02)	(2.41)
Log-lik.	−55.57	−40.24	−55.32	−39.85	−42.66
LRT	0.79	31.44*	1.30	32.22	26.62
LRT df	1	20	2	21	19
AIC	115.10	122.50	116.60	123.70	26.61
σ^2					

ED: Event dependence covariates only. ED + RH: Event dependence and risk heterogeneity covariates. RH: Risk heterogeneity covariates only. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Standard errors in parentheses. $^\dagger log(x + 1)$ was used. Groups for multilevel specifications: 32. Truncated Poisson obs.: 170.

Chapter 9

Discussion

This chapter presents an overview of the main findings of the thesis. It begins by recapping the aims and motivation of the thesis. Then, it summarises the findings of each of the four empirical studies presented herein. The chapter then discusses the contributions to the literature. This is followed by the practical implications of the findings. Lastly, the general limitations and avenues for future research are discussed.

9.1 Overview of the study aims and motivation

This thesis was primarily concerned with understanding the patterns of extortion victimisation against businesses. Specifically, using data from Mexico's commercial victimisation survey (ENVE), the main aims were to examine the patterns of extortion experienced by Mexican businesses to determine if repeat victimisation occurred, and to identify the incident, victim and area level factors and mechanisms that could explain it.

By approaching an 'archetypal' organised crime such as extortion (Tilley & Hopkins, 2008, p. 450) from the repeat victimisation perspective, the thesis addressed two distinct literatures, one on organised crime, and the other on environmental criminology. To my knowledge, the thesis presented the first systematic and quantitative analysis of repeat extortion victimisation patterns.

My interest in researching repeat extortion victimisation in Mexico was mainly driven by two motivating factors. As Mexico has experienced a dramatic surge in organised crime-related violence since around 2007 (see Chapter 3), my first moti-

vation was the desire to produce knowledge that would have implications for crime prevention.

My second motivation stemmed from the fact that there is too little empirical research in non-western settings from an environmental criminology perspective (Sidebottom & Wortley, 2015, p. 174). Expanding the scope of repeat victimisation research (and by extension of environmental criminology) to a new geographical setting (Mexico) and to a previously unstudied crime type (extortion) is important for at least two reasons. First, it contributes to refining the theories that underpin environmental criminology. And second, it helps identify further avenues for research that could result in knowledge useful to prevent crimes in the world's most violent region (Latin America and the Caribbean).

9.2   Overview of main findings

Given the paucity of knowledge on micro-level extortion patterns in Mexico at the outset of this research, the studies presented in the thesis followed an 'organic' process of discovery, whereby studies sought to build on each other to refine our understanding of extortion. Ultimately, the goal was to tell the story of repeat extortion victimisation in Mexico as comprehensively as possible, given the constraints of a PhD research project.

9.2.1   Chapter 5 – A hurdle model of repeat extortion victimisation

The first study in the thesis was presented in Chapter 5. The study focused on two research questions. First, it asked whether the observed rate of repeat victimisation (concentration) was higher than would be expected by chance. The expected distribution was estimated by simulating a Poisson process 500 times—as events in a Poisson process are independent and occur at a constant rate. A comparison of the observed and expected distributions suggested that the level of concentration observed was higher than that expected by chance, suggesting the presence of repeat victimisation.

The second research question addressed by the study asks about the mechanisms that could explain repeat extortion victimisation. Recall from Chapter 2 that repeat victimisation is generally thought to be the product of two mechanisms. On the one hand, risk heterogeneity (e.g. Johnson, 2008) suggests that the risks of victimisation are uneven, as the characteristics and location of some targets make them more

attractive than others. On the other hand, event dependence (e.g. Johnson, 2008) suggests that the risks of (repeat) victimisation are dynamic, and that the risk of suffering a repeat in the near future tends to increase (albeit temporarily) after an initial incident.

As the data used in Chapter 5 are not longitudinal, event dependence could not be studied explicitly. However, the study attempted to identify the presence of event dependence (albeit implicitly) by using a novel modelling framework: the multilevel negative binomial-hurdle model. Most studies of repeat victimisation use a count model to estimate the incidence of victimisations, and previous studies have suggested that the factors that affect the prevalence of victimisation are usually the same as those that explain its concentration (see Pease & Tseloni, 2014).

However, these studies have focused on very different types of crime than that studied in this thesis. Here, I had hypothesised that event dependence could be particularly relevant to the risk of repeat extortions, as the outcome of previous extortion incidents could entice further attempts. Thus, in an attempt to identify the mechanisms at work in the case of repeat extortion victimisation, the second part of the study used the hurdle model to test whether the predictors of prevalence were the same as those for concentration.

The findings of the second analysis suggested that the hurdle framework was superior to the traditional count model approach. The hurdle model suggested that the predictors associated with the risk of becoming a victim of extortion (prevalence) were not the same as those that explained the amount of extortion suffered by victimised businesses (concentration). Specifically, some coefficients were inconsistent (e.g. increasing prevalence risk but not affecting concentration), while other predictors suggested contradictory effects (e.g. increasing prevalence risk but decreasing concentration). Additionally, the hurdle model suggested that unobserved heterogeneity (which captures micro-level variations in extortion risk not captured by the predictors used) was much greater in the concentration model than in the traditional incidence model. Overall, these findings suggested that prevalence and concentration were driven by distinct mechanisms, which was consistent with my hypothesis of event dependence as an important driver of repeat extortion victimisation.

Furthermore, the findings also suggested that the risks of extortion victimisation were mostly associated with differences between businesses, rather than with differences between areas. In particular, observed area-level variables were only relevant to predict the risk of extortion prevalence (though predictions did fit with theoretical expectations), whereas they had no effect on predicting extortion concentration.

On the other hand, the effects of business-level variables on extortion risks were in general consistent with the theoretical expectations based on the routine activity approach (Felson, 2017) and the rational choice perspective (Clarke & Cornish, 2017).

Nonetheless, the findings presented in Chapter 5 have important limitations. The main one being that the extortion measurements captured by the screening section combine incidents of 'remote' extortion with those of 'in-person' and '*cobro de piso*' extortion, and thus the study was unable to detect if the different crime types exhibit different victimisation patterns. The second limitation is that the models used cannot explicitly capture the effect of event dependence due to the cross-sectional nature of the data. Thus, the findings presented in the chapter must be taken as preliminary. While the specific effect sizes would need to be refined further after taking into consideration the limitations outlined above, the chapter is important for providing a first approach to study extortion from the repeat victimisation perspective, and for presenting the statistical framework that was used in subsequent chapters.

9.2.2   Chapter 6 – Determinants of extortion compliance

While the study in Chapter 5 focused on extortion patterns at the business level, the second study in the thesis, presented in Chapter 6, examined the ENVE data at the incident level—its most disaggregated form.

The study in Chapter 6 sought to identify the determinants of extortion compliance. Despite being perceived as a country overrun by extortion rackets (Perez, 2018), extortion incidents in Mexico are rarely complied with. Thus, the chapter examined the incident-level responses of extortion victims to identify the determinants of extortion compliance. There were two motivating factors behind this study. First, event dependence is thought to play a particularly important role in crimes where the outcome of a first event clarifies the risk and reward structure of a subsequent event (Farrell et al., 1995). In the case of extortion, this would suggest that compliance with extortion demands could entice further victimisation. Thus, this study sought to understand what situational-, victim- and state-level factors were associated with extortion compliance

Second, one of the main hypotheses explored in the study focused on whether the likelihood of compliance varied for different types of extortion incident. Extortion compliance is thought to be determined by the credibility of the threats made. As the different extortion types involve different communication media, it was hypothesised that threats made over the telephone (i.e. remote extortion) were less likely to be

judged as credible than threats made face-to-face (i.e. in-person extortion). Thus, in-person extortions would be associated with higher probabilities of compliance than remote extortions.

Chapter 6 is the only empirical study in the thesis that does not use the multi-level hurdle framework as the analytical approach. As compliance is a binary variable, logistic regression was used. Though the data were structured in three levels (some businesses experienced more than one incident, and businesses were grouped in states), the multilevel approach could not be used as there were too few businesses that experienced more than one incident. Thus, robust standard errors with business and state clusters were used instead.

The main findings of the compliance models suggested that situational (i.e. incident-level) variables were more relevant in predicting compliance than victim- or state-level variables. In particular, extortion type was the main determinant, with in-person extortions exhibiting substantially higher likelihoods of compliance than remote extortions. The findings are important for two reasons. First, they provide a more nuanced understanding of compliance with extortion demands. As far as I am aware, this is the first study to empirically examine extortion compliance behaviours such as this at the incident-level. Second, and particularly important in the context of the thesis, the findings provide an empirical justification for analysing extortion types as different offence classes.

However, the findings in Chapter 6 have important limitations. The main limitation of this study is the cross-sectional nature of the data. The study found a significant (though negative) relationship between extortion concentration and the likelihood of compliance, which would suggest that businesses that suffered more extortions were less likely to comply with extortion demands. However, the cross-sectional nature of the data did not permit identifying the direction of the causal effect.

9.2.3 Chapter 7 – Extortion victimisation: A crime specific approach

The study in Chapter 7 builds upon the findings of the previous two studies. Given that the findings of Chapter 6 suggested that extortion types may vary significantly according to the type of extortion suffered, this chapter attempted to replicate the study in Chapter 5 for each of the main extortion types captured by the ENVE survey.

Aggregating incidents of different types of extortion into one measurement implies that the different crime types share the same causal mechanism (Copes, 1999). However, given that the different extortion types have different modus operandi and were associated with different likelihoods of compliance, it was expected that they would also be associated with different opportunity structures.

The chapter provided a detailed discussion of the modus operandi of the three extortion types as operationalised in the study (remote, in-person and *cobro de piso* extortion), and discussed how these differences were likely to affect their opportunities structures.

Before proceeding with the modelling analyses, the study first examined the univariate distribution of each extortion type to determine if the level of concentration observed was higher than that expected by chance (as predicted by a Poisson distribution). While both remote and in-person extortion exhibited repeat victimisation patterns that exceeded chance expectation, there were no repeat *cobro de piso* extortions. This finding was surprising, given that one of the defining features of *cobro de piso* extortions is its high rate of repeats. The study was not able to determine if the lack of repeat *cobro de piso* extortions was attributable to chance, to an informal recording practice for series incidents (see Planty, 2006; Rennison & Rand, 2006), or to another unknown reason.

The study tested two hypotheses. First, it assessed whether the risks of extortion victimisation were explained by the same predictors across the three crime types. Second, in an effort to examine the (implicit) presence of event dependence, the study examined whether the predictors for prevalence were the same as the predictors for concentration in the case of remote and in-person extortion (as there were no repeat *cobro de piso* incidents, the second hypothesis could not be tested for this crime type).

The findings supported both hypotheses. Regarding the first hypothesis, very few predictors were significant for two or more of the different extortion types, and most significant predictors exhibited inconsistent associations (in terms of direction and magnitude). The only predictor that was significantly associated with extortion prevalence for all crime types was corruption victimisation (measured at the business-level). However, the relationship was captured by different functional forms, which suggested that the effect of corruption victimisation on extortion risk differs by crime type. Furthermore, the study suggested that between-businesses differences were particularly important for remote extortion concentration, and that differences between states were more important for in-person extortion concentration than for

remote extortions. Thus, the differences in the associations suggested that the three crime types were likely to be associated with different opportunity structures.

Regarding the second hypothesis, the hurdle models for remote and in-person extortions similarly suggested that the factors that affected the risk of becoming a victim of extortion (of either type) were not the same as those that explained the amount of (repeat) incidents suffered by victimised businesses. As in Chapter 5, these inconsistencies were taken as indicators of event dependence, though the lack of longitudinal data did not permit this to be determined explicitly.

Of course, the study in Chapter 7 also had important limitations. Chief amongst them were issues of construct and measurement validity in the case of *cobro de piso* extortion. The lack of clear definitions and recording protocols for *cobro de piso* incidents in the ENVE survey was found to be an issue requiring urgent revision by INEGI. In addition, the analyses reported in Chapter 5 differed from those presented in Chapter 7 in one crucial respect. The former used uncapped figures, whereas the measurements used in the latter were subject to capping practices. The measurements in Chapter 7 have the advantage of being disaggregated by extortion type, and thus can be deemed qualitatively more valid measurements of extortion experiences. On the other hand, the artificial caps imposed by the survey mean that the measurements are quantitatively flawed—meaning that they will tend to underrepresent the true extent of extortion concentration. Thus, while the significance and direction of the associations described in the study are likely to be unaffected by the capping practices, the absolute effect sizes are likely to be underestimates of the true effects.

9.2.4   Chapter 8 – Event dependence in repeat extortion victimisation

The study reported in Chapter 8, the last empirical study in the thesis, aimed to address one of the main limitations identified in all previous studies: the effect of event dependence. The chapter sought to provide a more detailed answer the last research question presented in Chapter 2—do victimisation patterns and mechanisms vary according to the type of extortion suffered?—by examining the role of event dependence for each type of extortion incident.

The findings presented in Chapters 5 and 7 attempted to examine the presence of event dependence implicitly by using the hurdle modelling framework. In contrast, the study reported in Chapter 8 used pseudo-longitudinal data to explore event dependence in repeat extortion victimisation.

Though the ENVE data are cross-sectional, a pseudo-longitudinal measure of extortion victimisation was constructed using the month of occurrence reported in the victim forms. With this information, two analyses were carried out. First, the study examined the time-course (e.g. Johnson et al., 1997) of repeat extortion victimisation to determine if the time elapsed between repeat incidents against the same target was different from that expected by chance (assuming a Poisson process). Second, by dividing the observation period in two sub-periods, a measure of previous victimisation was constructed, which allowed for the modelling of victimisation risks as a function of previous experiences. The study used the same hurdle modelling framework employed in Chapters 5 and 7.

The analysis of waiting times between repeat events suggested that the time course patterns of remote and in-person repeat extortion differ significantly from chance expectation; though this was more evident in the case of remote extortions than for in-person extortions. The findings were robust to the time window effect, which relied on a moving six month time window. An important distinction with the patterns observed in other studies of repeat victimisation (e.g. Johnson et al., 1997; Kleemans, 2001) was that the boost effect following an initial incident was not seen in the same time interval (in the case, month) of occurrence, but one interval later.

The models presented in Chapter 8 tested two hypotheses. The first predicted that the risks of extortion victimisation in the second period would be associated with the risk of extortion victimisation in the first period, after controlling for risk heterogeneity. The findings broadly supported this hypothesis. Logit models suggested that the amount of extortion incidents suffered in the previous semester was associated with the prevalence of remote and in-person extortion in the second semester. Similarly, truncated count models suggested that the amount of previous victimisation incidents was associated with the concentration of extortion in semester two, though the estimates were more robust for remote extortion than for in-person extortion.

In contrast, the other hypothesis predicted that the risk of extortion victimisation in the second semester was not only a function of the amount of incidents suffered in previous periods, but would also be affected by whether businesses had complied with previous extortion attempts, after controlling for risk heterogeneity. The findings provided mixed evidence in support of this hypothesis. Logit models suggested that being a previous victim of extortion was associated with higher risks of victimisation in the subsequent period; however, relative to non-victims, non-compliant victims faced higher risks of subsequent victimisation than compliant victims (for

both crime types). On the other hand, truncated count models suggested that compliance was associated with more remote extortion concentration in semester two (when compared with non-victims and non-compliant victims), though it was not associated with more in-person extortion concentration.

Overall, the study in Chapter 8 provides tentative support for the event dependence mechanism in the case of extortion against businesses, with some variations in magnitude, precision and significance between extortion types. Nonetheless, these findings have important limitations. First, the time course analyses is limited by the arbitrary size of the temporal units used and by the rather short observation period. Second, the pseudo-longitudinal data used to model the effect of prior victimisation provided only an imperfect measure of event dependence, as it is not possible to rule out confounding with unmeasured risk heterogeneity covariates.

9.3 Contributions to the literature

The research presented in this thesis contributes to four academic literatures: environmental criminology and repeat victimisation, organised crime and extortion, quantitative criminology, and the study of crime in Mexico.

9.3.1 Environmental criminology and repeat victimisation

The field of environmental criminology in general, and that of repeat victimisation in particular, has not paid much attention to the phenomenon of crime in non-western settings (see Sidebottom & Wortley, 2015, p. 174). As outlined earlier, expanding the reach of environmental criminology research to non-western settings is important to refine the theories that underpin it, as well as to inform crime prevention practice. Given that globally Latin America suffers a disproportionate amount of crime (e.g. Latin America has 42% of the world's homicides, despite housing only 14% of its population, Muggah & Tobón, 2018), empirical research with clear practical implications in terms of crime prevention policy is urgently needed.

To my knowledge, prior to the research presented in this thesis, there had been no research on the patterns of (repeat) victimisation in Mexico, nor of extortion. Thus, the studies herein contribute to the literature on repeat victimisation and crime concentration by expanding the list of countries and crime types where the phenomenon has been identified.

Furthermore, though in recent times the environmental criminology literature has made inroads into organised crimes—specifically the situational approach to

organised crimes (see Bullock et al., 2010b)—the research thus far had not examined organised crimes from the perspective of repeat victimisation. Thus, the research presented here contributes to this subfield of environmental criminology by expanding the knowledge-base regarding the micro-level patterns of organised crimes.

9.3.2   Organised crime and extortion

The research also contributes to the literature on organised crime and extortion. As noted by Kleemans (2014), organised crime research is often not useful for the development of crime prevention policies. Furthermore, the field tends to focus more on macro-level manifestations of the phenomenon. Lastly, as Sansó-Rubert Pascual (2017) notes, there tends to be too little quantitative research on organised crime patterns.

Thus, this thesis contributes to the field by approaching a quintessential organised crime (extortion) from a micro-level perspective, using advanced quantitative methods, and with clear implications for crime prevention policy (see below).

Specifically regarding the literature on extortion, past research has tended to prioritise macro-level explanations that see extortion as the manifestation of the territorial control exerted by some criminal groups (e.g. Kleemans, 2018; Savona & Zanella, 2010; Varese, 2014). While this approach can explain why extortion flourishes in some contexts but not others, it is less suited to explaining why some businesses within the same context may experience different risks of extortion. The findings presented in this thesis help identify some of the micro-level correlates of extortion risk, and quantify how much risk can be attributed to micro- and area-level measures.

Furthermore, the research also confirmed predictions based on the existing literature on extortion, specifically between organised crime presence and extortion risk. In particular, extortion was found to be consistently associated with measures of organised crime presence (e.g. drug trafficking and weapon-related crimes) which suggested that businesses in areas where criminal groups specialise on certain types of activities face different levels of extortion risk. In addition, the research found that extortion types that are more consistent with mafia-related extortion racketeering (e.g. in-person and *cobro de piso*) experienced more area-level concentration, which supports Kleemans' (2018) observations regarding the concentration of extortion at the level of 'territory'. Thus, the findings provide further evidence on the phenomenon of extra-legal governance, and on the specialisation of criminal groups.

Lastly, the thesis contributes to understanding the patterns of compliance with extortion demands. Before this research, to my knowledge no studies had analysed the incident-level determinants of compliance with extortion demands using real-world data.

9.3.3 Quantitative criminology

The thesis also offers contributions to the broad field of quantitative criminology. In particular, it questioned the long-standing belief that the best framework to model repeat victimisation is the negative binomial model (Pease & Tseloni, 2014).

The studies herein suggest that for some crime types an alternative modelling framework (the multilevel negative binomial-logit hurdle model) may be preferred. In the case of extortion, the hurdle model permitted exploration of whether the factors that explain the prevalence of victimisation also account for its concentration. This approach is likely to be relevant for other crime types where event dependence is thought to play an important role (such as domestic abuse).

Furthermore, the research also makes a contribution in its innovative use of the information captured in victim forms to build a pseudo-longitudinal data set out of a cross-sectional survey. Though the approach does not match the power of a true longitudinal survey, it offers a viable option to study event dependence for crime types where high quality longitudinal data is unlikely to be available.

9.3.4 On crime in Mexico

Extortion is generally perceived to be widely prevalent in Mexico, and has been associated with grave episodes of criminal violence (e.g. Guerrero-Gutiérrez, 2011; Malkin, 2011; Perez, 2018; Wilkinson, 2011). Despite this, there was virtually no empirical research on extortion victimisation patterns before this research was conducted. This was partly due to the paucity of good quality extortion data, though it also reflected the theoretical perspective that tends to dominate organised crime research in Mexico.

Scholars that study Mexican organised crime tend to be primarily concerned with broader manifestations of the phenomenon, rather than with the micro-level patterns of organised criminal activities. Using von Lampe's (2016) typology of the empirical manifestations of organised crime, it could be said that scholars of Mexican organised crime have been primarily concerned with the criminal groups themselves and with

the extra-legal governance they exert. There has been comparatively less attention on specific criminal activities,[1] such as extortion.

Furthermore, before this research was conducted virtually no research had been conducted on (repeat) victimisation patterns in Mexico, despite a growing collection of victimisation data (from household and commercial victimisation surveys). It is hoped that the research presented herein will prompt other scholars to examine Mexican crime data from the repeat victimisation perspective.

In addition to identifying specific risk factors and potential mechanisms fuelling extortion in Mexico, one of the most important contributions of this research concerns the empirical differences discovered between remote extortion, in-person extortion and *cobro de piso*. Current academic and public discussion on extortion in Mexico tends to conflate the different extortion types. However, the thesis provides theoretical arguments and empirical evidence which strongly suggest that in Mexico different extortion types should not be lumped together for most purposes.

9.4   Implications for practice

One of the goals of this thesis was to generate knowledge with practical implications for crime prevention policy. This section discusses the implications of the findings for the measurement of extortion using the ENVE survey, and the implications for crime prevention.

9.4.1   Improvements for the measurement of extortion

An appropriate measurement of crime is a fundamental prerequisite of any crime prevention policy, as data are required to analyse and understand the phenomenon, as well as to evaluate whether preventive measures were successful.

Thus, one of the most important implications of this study concerns the measurement of extortion victimisation. As discussed in Chapter 4, extortion against businesses is a crime that is notoriously difficult to measure. This is because administrative statistics often do not identify whether an extortion incident targeted a business, and because most extortion incidents are not reported to the police or a similar competent authority.

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[1]With some exceptions, such as homicides related to organised criminal activity (e.g. Calderon et al., 2015; Dube et al., 2013; Rios, 2012; Vilalta & Muggah, 2014) and weapons trafficking (Pérez Esparza et al., 2019).

To mitigate these data constraints, the Mexican statistics agency carries out a national large-scale commercial victimisation survey (ENVE) which, among other crime types, measures the prevalence and incidence of extortion.

Nonetheless, the studies revealed that the ENVE survey has important flaws relating to the measurement of extortion. First, when respondents are screened regarding their extortion victimisation experiences, the question used combines remote, in-person and *cobro de piso* extortion into one category. Though respondents then proceed to specify what kind of extortion they suffered in the victim forms, the estimates reported by INEGI (2014a) do not disaggregate the prevalence and incidence of extortion by extortion type.

This contributes to the inaccurate perception that in-person and *cobro de piso* extortion is widespread, when according to the ENVE estimates they are much less common than remote extortion. Furthermore, as the capping procedures in the ENVE are applied per crime type (i.e. it is only possible to report up to seven incidents of extortion of any kind per business), suffering an incident of one type of extortion places artificial limits on the number of incidents of another type of extortion that can be reported.

Second, the survey does not provide a clear definition of *cobro de piso* incidents; thus it is not clear what differentiates them from the other categories of in-person extortion. This is particularly problematic because it undermines the validity of the patterns associated with this crime type: If the crime type is not clearly defined, then it is not clear what is actually being measured. Third, and related to the prior point, it was surprising that there were no repeat *cobro de piso* incidents, given that repetition was assumed to be one of its distinguishing features. While it is possible that this was due to chance, it also raised the suspicion of an informal recording practice whereby only the first incident of a *cobro de piso* series was recorded (see Planty, 2006; Rennison & Rand, 2006).

In addition to the the flaws discussed above, the analyses presented in the thesis were also constrained by the selection of variables captured by the survey. In particular, the analyses could have been improved by responses describing the situational and environmental characteristics of the business premises surveyed. For example, the survey could capture the characteristics of the building (e.g. whether the premises are part of an industrial or commercial complex or stand-alone buildings), their accessibility (e.g. whether the premises are on the ground floor level, if there are access control mechanisms, etc.), and the type of street on which the premises are located (e.g. a high street, a residential street, on a street corner, etc.).

This information could alleviate some of the shortcomings of survey data vis-a-vis administrative records, insofar as the former lack spatial information.

Furthermore, though the ENVE does capture whether businesses have implemented security measures to prevent crime (e.g. locks, security systems, private security, etc.), the manner in which this information is elicited does not permit examination of their effects on victimisation risks.

To explain, in a section of the survey devoted to estimating the perception of security and fear of crime, respondents are asked if they have implemented a battery of security measures during the reference year. The goal of the question is to estimate the cost of security measures adopted by businesses, though the information could also be used to estimate the relationship between security measures and victimisation risk. However, the cross-sectional nature of the survey, and the manner in which this question is asked makes it impossible to determine if such measures had a preventive effect, or if they were adopted in response to crime experiences. Thus, a better approach would be to first ask if the security measures were in place *before* the reference year, and then ask whether any *new* measures were adopted during the reference year.

Thus, one of the practical implications of this thesis is that the ENVE survey should be revised to address the flaws and shortcomings outlined above. Specifically, the modifications proposed are:

- Remote and in-person extortion should be considered as separate offence categories, each with its own screening question and specific victim forms.
- *Cobro de piso* should be clearly defined and the distinction with in-person extortion should be made explicit. If the crime type is indeed distinct, it may make sense for it to have its own screening question and victim forms.
- If *cobro de piso* exhibits a high level of repetition, a series protocol could be implemented (see Planty, 2006; Rennison & Rand, 2006), though this should be clearly indicated.
- The survey could include questions regarding the situational and environmental characteristics of the premises occupied by sampled businesses.
- The questions regarding the implementation of security measures during the reference year should be complemented by a similar question covering the period before the reference year.

Of course, implementing such changes may require further study and a careful process of development and testing to minimise disruption to the series and ensure

that measurements from different sweeps are comparable. The modification of the extortion crime categories would be the most disruptive changes; thus, it may be appropriate to maintain the current questions alongside the proposed changes for some time, in order to estimate how much they affect comparability. Nonetheless, such changes would go a long way towards mitigating the flaws identified herein and would provide more valid measurements to understand (and prevent) extortion victimisation.

9.4.2 Implications for crime prevention

The findings also have implications for the prevention of extortion victimisation. Current policies aimed at curbing extortion against Mexican businesses do not appear to be guided by an understanding of micro-level extortion patterns. Given that the findings suggest that remote and in-person extortion are distinct, the implications for each crime type are discussed in turn.

9.4.2.1 Preventing remote extortions

In the case of remote extortion, government policy has focused on informing potential victims about the differences between 'fake' and legitimate extortions, urging those who experience a remote extortion to 'objectively assess the situation', avoid 'acting without thinking', and to hang up and not comply with whatever demands are being made (Policía Federal, 2018).

While the advice is sensible insofar it mitigates some of the harms associated with remote extortion victimisation, it also places an enormous burden on victims. Remote extortions thrive precisely because victims cannot always be objective when confronted with realistic-sounding threats and scenarios. Furthermore, widely accessible artificial intelligence technologies such as generative adversarial networks (Goodfellow et al., 2014) have facilitated the proliferation of 'deep fakes' (i.e. computer generated audio and video replicating a real person in a fictitious situation, O. Schwartz, 2018). Thus, it is possible that future remote extortionists attempting 'virtual kidnappings' (see Chapter 7) will not have to resort to acting fictitious kidnapping scenarios, as they will be able to generate realistic audio and video of a hostage using artificial intelligence. Such technological developments (as well as unforeseen emerging technologies) will make discriminating between real and fake threats harder still.

Furthermore, the advice does not help prevent the attempts of remote extortion in the first place. This is problematic because even if events do not lead to compliance and monetary losses, they can be traumatic and may negatively affect the perception of security. As the results presented in Chapter 8 suggest, non-compliance with previous remote extortion attempts may be associated with a higher risk of suffering a remote extortion in the following period. Thus, strategies that focus on preventing the attempts from happening in the first place are needed.

The findings presented in the thesis provide some clues as to how such preventive strategies may be implemented. As Chapter 7 showed, remote extortion victimisation is highly concentrated among a small group of businesses. In particular, repeat victims amounted to 1% of businesses (15% of victims), but were burdened with 52% of all remote extortions suffered in the country. Furthermore, the findings also suggested what are some of the risk factors that explain such concentration in extortion risk, and that the risk of repeat is highest one month after an initial event. Thus, focusing preventive resources on those businesses most at risk of victimisation—and those that have been victimised recently—could lead to disproportionate reductions in remote extortion.

Lastly, though a thorough analysis examining the application of situational crime prevention to remote extortion is beyond the scope of this chapter, four broad ideas are outlined. The following draw on three of the 5 principles[2] underpinning situational crime prevention (Clarke & Cornish, 2017), as well as insights from Sidebottom and Tilley (2017).

1. *Increase the effort:* Potential interventions to prevent remote extortion could try to make remote extortion more difficult to execute. Two options to achieve this would be to ensure that contact details and private data of businesses' owners and employees are better protected (thus providing less intelligence to be exploited by extortionists), and to reduce the exposure businesses have to incoming phone calls. The latter could be achieved by using automated answering services and by using customer service contact channels that make it more difficult to speak with an employee that could be extorted. Recent technological innovations allow implementing such interventions at low costs and without impeding business operations. For example, many services (from taxis to restaurant reservations and salon appointments) can be booked online

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[2]As remote extortions are likely to be highly purposive crimes, I did not consider that incidents would be very sensitive to Wortley's situational precipitators (2017), and thus did not explore interventions focused on reducing provocations and removing excuses.

and thus some of these businesses may not need a customer-facing phone line. Similarly, customer service queries can be handled by online messaging apps and automated customer service software ('bots').

2. *Increase the risk:* Another possible intervention strategy could be to make remote extortion riskier for the offender. All else being equal, offenders may desist from carrying out an extortion attempt if they perceive that the risks of attempting to extort a business outweigh its potential rewards. An example of this approach would be to use an automated answering service informing callers that calls are being recorded for security purposes. In principle, such an intervention could discourage remote extortionists who may not want to be recorded committing a criminal act.

3. *Reduce rewards:* Reducing the potential rewards from remote extortions could also help preventing remote extortion victimisation. For example, money laundering regulations could be extended beyond banks to other forms of electronic payment systems (e.g. phone cards). However, given that remote extortions are associated with very small likelihoods of compliance, this type of interventions may have modest impacts.

4. *Focus on leaky systems:* Lastly, crime prevention strategies against remote extortion could benefit from embracing a 'leaky systems' approach (Sidebottom & Tilley, 2017). The opportunity structure for remote extortion is dependent on at least two systems: telecommunication networks and payment infrastructures. Thus, it may be fruitful to understand how the design and implementation of such systems may inadvertently facilitate remote extortion. For example, telecommunication systems could automatically block calls suspected to be remote extortion using algorithmic detection systems, and payment systems could automatically block transfers to suspicious recipients.

The ideas outlined above are not exhaustive and would need to be refined further after conducting more research. Furthermore, it would also be important to balance the interventions proposed with the costs they may impose on businesses (both directly and by discouraging legitimate customers). Lastly, remote extortionists are 'conscious opponents' (Sparrow, 2008), thus interventions should be closely monitored to detect displacement and offender adaptation.

9.4.2.2   Preventing in-person extortion and *cobro de piso*

Thus far there is no specific policy aimed at preventing in-person and *cobro de piso* extortion in Mexico. Instead, the extortion phenomenon is somewhat addressed by either the weakening of organised crime groups through a militaristic 'war on organised crime' (see Chapter 3), or through standard law enforcement actions aimed at arresting and prosecuting offenders.

Policies specifically focused on preventing and addressing in-person extortion and *cobro de piso* would certainly be welcome. The findings presented in the thesis offer some guidance regarding how such policies could be implemented. Though Chapter 7 suggests that repeat in-person and *cobro de piso* extortion is not as common as remote extortion, the crimes are indeed concentrated only a small minority of businesses. In 2013, all incidents of in-person and *cobro de piso* extortion were concentrated among less than 2% of the sample. Unfortunately, the findings were not able to identify many factors that could be used to target preventive interventions towards these vulnerable businesses.

The findings did identify associations with area level variables measuring organised crime presence; thus the current strategy focused on weakening organised crime groups is not entirely misguided. However, more targeted policies specifically addressing businesses in such vulnerable areas could be an appropriate response. Though more research is needed to better understand the dynamics of in-person and *cobro de piso* extortion at the micro- and city-level, the time course of in-person extortion could be used to guide interventions. Chapter 8 showed that the risk of in-person repeats one month after an initial event was significantly higher than expected, thus preventive resources could be deployed to victimised businesses within that time frame in an attempt to reduce repeats.

9.5   Limitations and future research

In addition to limitations discussed throughout the thesis, the findings presented should also consider the following limitations. These limitations, of course, also identify avenues for future research.

This thesis sought to apply a repeat victimisation approach to organised crime. To this end, I decided to analyse extortion against businesses, as it is considered to be an archetypal organised crime (Tilley & Hopkins, 2008). However, the findings presented herein suggest that not all extortion in Mexico fits with the mafia-model of extortion racketeering. Remote extortion—which accounts for the vast majority

of extortion incidents in the country—is probably more similar to fraud or nuisance phone calls (see Tseloni & Pease, 1998) than to traditional extortion racketeering. This finding is important as it helps to better define the extent of organised crime extortion in Mexico.

On the other hand, the findings also suggested that remote extortion was associated with state-level markers of organised crime presence. Furthermore, the studies also found that some victims experienced several kinds of extortion incidents. It was not possible to determine whether experiencing one kind of extortion affects the likelihood of suffering another type of extortion, as the capping procedures would confound any relationship detected. However, it may be a relevant avenue for future research, as anecdotal accounts suggest that organised crime groups may also operate remote extortion rings.

Another limitation refers to the size of the units of analysis. The research identified factors associated with extortion victimisation at the state and micro level. As states in Mexico are quite large, the patterns observed at the 'micro'—especially unobserved heterogeneity—could reflect patterns not only at the business level, but also at the municipal, city, or neighbourhood level that are not detected with the current data. Thus, further studies that examine the patterns of extortion at these levels are needed to properly understand the effects of victim and small-area characteristics on extortion risk.

This study was based on victimisation data. Thus, it offers only a partial view of extortion from the victim's perspective. To further understand the extortion phenomenon, research based on offender interviews and judicial investigations (for example) is needed. Such data sources could be used to construct a detailed crime script (Cornish, 1994) of the different types of extortion, and thus provide a more comprehensive picture of the phenomenon. With this knowledge base, it may be easier to identify pinch-points suitable for crime prevention interventions.

The only variable consistently associated with the prevalence of all extortion types (see Chapter 7) was corruption victimisation. The study was not able to determine the precise mechanism for the association, though some ideas were outlined. Further research that examines the issue in detail would appear to be an important avenue for further work.

From a methodological perspective, the research presented in this thesis modelled (repeat) extortion victimisation patterns using a novel statistical framework: the multilevel negative binomial-logit hurdle model. The findings consistently suggested that the hurdle framework was superior than the standard count model. How-

ever, recent research has also suggested that an alternative modelling framework, the zero-inflated model, might be preferred to study victimisation in overdispersed data sets (Park, 2015; Park & Fisher, 2015). As stated above, in this thesis the hurdle model was preferred as it was better suited to answer the research questions posed. Nonetheless, no study thus far has compared estimates from hurdle and zero-inflated models to examine which might be a better fit for victimisation data. As the modelling frameworks are underpinned by a distinct set of assumptions regarding the data generating process, such a comparison would be relevant to better understand the processes that drive crime concentration.

Another methodological limitation is that the analyses presented were not able to incorporate the survey weights that account for the ENVE's complex sampling procedure. This was because there were no statistical packages available in the research settings that could fit multilevel hurdle models using survey weights. As Lohr and Liu (1994) note, the use of survey weights in models of victimisation can lead to bias in the size and precision of regression estimates, though this is unlikely to affect the inferences derived from the estimates (see also Carle, 2009). Thus, while I believe that the associations detected are reasonably robust, future analyses should incorporate survey weights if statistical packages allow it.

Regarding the generalisation of the findings, this thesis focused on one year of the ENVE survey. While it is likely that the associations detected are also present in other years of the survey, there is scope for future research that incorporates more years of the ENVE to the analysis. For example, modelling extortion victimisation using a dataset combining several sweeps of the survey may be able to capture associations that were not detected in this study. This would be particularly relevant to detect the patterns of rare crime categories (such as *cobro de piso*) and associations with categorical independent variables with very few observations.

Lastly, while some of the patterns observed coincided with those seen in other countries, caution should be exercised when generalising the findings in this thesis to other contexts. The patterns observed also reflect the unique and complex nature of the Mexican organised crime landscape. In particular, the findings may not generalise well to countries where organised crime is of a very different nature.

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