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MRes in Security Science

Repeat extortion victimisation of Mexican businesses

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Abstract

Research on repeat victimisation consistently reveals that crimes to concentrate within a small subset of victims. Given a recent increase on the number of extortions against businesses in Mexico, this research aimed to answer whether extortion concentrates within a small subset of businesses and if so, what could explain this concentration. Drawing from a national commercial victimisation survey conducted in 2013, several hypothesis relating to potential sources of risk heterogeneity were tested using single and multilevel modelling based on the negative binomial regression. Results showed that extortion concentrates far beyond what can be explained by chance, and that extortion incidence is positively associated with corruption incidents, years in business, state homicide rates, and being a restaurant, hotel or bar. Alternatively, it was found that the smallest businesses suffer less extortion than larger businesses. State level effects were found to be comparatively small to differences between businesses. Implications for research and crime policy in Mexico are briefly discussed.

Keywords: Repeat victimisation, extortion, organised crime, victimisation surveys, Mexico

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Contents

1 Introduction

Research suggests that crimes against businesses—like crimes against individuals—tend to be highly concentrated in a small subset of the population (Burrows & Hopkins, 2005; Farrell, Phillips & Pease, 1995; Gill, 1998; Hopkins & Tilley, 2001; Mugelini, 2013a; Perrone, 2000; Sparks, 1981). Results from Mexico's commercial victimisation survey (the *Encuesta Nacional de Victimización de Empresas*, ENVE) are consistent with these findings where a third of the business population (1.3 million businesses) experienced 2.5 million crimes in 2013, suggesting an average concentration of 2 crimes per victimised business (INEGI, 2014b).

However, these average measures mask underlying patterns of repeat victimisation, since research has shown that the risk of suffering repeated crime incidents is not evenly distributed and, while many victims suffer only one incident, a small chronically victimised share of the population experiences a disproportionate amount of crime (Farrell et al., 1995; Sidebottom, 2012; Tseloni & Pease, 2005). Understanding these patterns of repeat victimisation is essential to guide crime prevention efforts, since it allows the strategic allocation of resources according to victimisation risk (Farrell, 1992; Farrell et al., 1995; Kleemans, 2001; Laycock, 2001).

The majority of research on repeat victimisation has been carried out in English-speaking and European countries (e.g., Farrell, Tseloni & Pease, 2005; Lynch, Berbaum & Planty, 2002; Perreault, Sauvé & Burns, 2010; Sagovsky & Johnson, 2007; Tseloni, Wittebrood, Farrell & Pease, 2004). Researchers have only recently begun to analyse the phenomenon in radically different countries such as Malawi (Sidebottom, 2012), Taiwan (Kuo, Cuvelier, Sheu & Zhao, 2012) or South Korea (Park, 2015), where findings of repeat victimisation patterns have been largely consistent with those of previous studies.

Studies on repeat victimisation tend to focus on "traditional" crimes such as burglary, assault, robbery and theft (to name a few), mostly against households and individuals—though there have been studies of repeat victimisation of non-residential premises such as businesses (e.g., Bowers, Hirschfield

& Johnson, 1998; Gill, 1998). To my knowledge, repeat victimisation by organised crime has not yet been studied. As research on organised crime has diversified from descriptive and theoretical approaches to one focused on crime prevention (Bullock, Clarke & Tilley, 2010; Felson, 2006; Felson & Clarke, 2012; Kleemans, Soudijn & Weenink, 2012; van de Bunt & van der Schoot, 2003; von Lampe, 2011), analysing the repeat victimisation patterns of organised crimes can contribute substantial knowledge useful for preventive efforts.

Extortion[2], a crime usually associated with organised crime (Chin, Fagan & Kelly, 1992; La Spina, Frazzica, Punzo & Scaglione, 2014; Lisciandra, 2014; Tilley & Hopkins, 2008; Varese, 2014), is the third most common crime against businesses in Mexico (Jaimes Bello & Vielma Orozco, 2013). According to the ENVE 2014 data, extortion represented 16.4% of the 2.5 million crimes experienced by Mexican businesses in 2013, with 802 extortion victims per 10,000 premises (INEGI, 2014b).

There is essentially no research on repeat victimisation for any type of crime in the Mexican context, nor on repeated extortion by organised crime in any country. Thus, this research aims to break new ground on these two fronts. Its findings aim to open a new avenue for crime research in Mexico, as well as contribute to the understanding of repeat victimisation patterns of organised crimes.

Data for this research comes from one sweep of Mexico's commercial victimisation survey (the *Encuesta Nacional de Victimización de Empresas*, ENVE) published in 2014. Thus, it joins a growing body of studies employing secondary analysis of victimisation surveys to explore repeat victimisation (Farrell, 1992; Farrell, Tseloni & Pease, 2005; Lauritsen, Owens, Planty, Rand & Truman, 2012; Lynch et al., 2002; Sidebottom, 2013; Sparks, 1981).

Specifically, this dissertation seeks to answer whether extortion victimisation concentrates across sampled businesses and, if so, what can explain the patterns of repeat extortion victimisation.

[2]Extortion against businesses is "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).

1.1 Background: Extortion in Mexico

While extortion of businesses is one of the quintessential activities of organised criminals (Gambetta, 1988; Konrad & Skaperdas, 1998; La Spina et al., 2014), it has only recently emerged as a widespread problem in Mexico (Corcoran, 2013). Organised crime groups have been active in the country for almost a century—mostly focused on supplying the North American demand for illegal drugs. The diversification of organised crime activities to extortion and other predatory crimes—such as kidnapping, human trafficking and large-scale theft—is part of a series of dramatic changes in the structures and operations of organised crime groups in Mexico (Bunker, 2013; Dulin & Patiño, 2014; Garzón, 2008; Ochoa, 2012; Rios, 2012). These changes are likely due to a combination of shifts in international trends in drug markets, increased interdiction efforts that disrupted international drug supply chains, and socio-political and economic transformations in Mexico.

While there has been much academic and public discussion devoted to determining the specific causes responsible for these changes (e.g., Aguirre & Herrera, 2013; Bailey & Taylor, 2009; Corcoran, 2013; Felbab-Brown, 2009; Guerrero-Gutiérrez, 2011; Montero, 2012; Morris, 2013; Olson, Shirk & Selee, 2010; Rios, 2012), the outcome remains the same: the landscape of Mexican organised crime shifted from relative peacefulness to a state of war-like violence in just a few years (Rios, 2012).

Most of the violence is related to conflicts between criminal groups and to clashes between criminal groups and the authorities (Chindea, 2012; Dulin & Patiño, 2014; Montero, 2012). However, there has been a noteworthy increase in predatory crime targeted at the general population by organised crime groups, particularly in the form of kidnapping (Jones, 2013; Ochoa, 2012) and extortion (Felbab-Brown, 2011).

While reported extortion is low (though increasing)[3], the two sweeps of the ENVE consistently reveal that extortion is very prevalent—it is now the

[3]There were 8196 extortions reported in Mexico in 2013, up from 4594 and 7284 in 2011 and 2012 respectively (SESNSP, 2015).

third most common crime against businesses[4] (INEGI, 2014b). Extortion by organised crime groups is linked to many prominent cases of violence and national instability. For example, widespread extortion of farmers in the state of Michoacán by a ruthless organised crime group led to exorbitant country-wide increases in the price of avocados and limes (Selmo, 2013) and to a destabilising uprising of "self-defence" paramilitary forces in many rural areas of the country in 2012 and 2013. Whereas in another violence-torn state, Nuevo León, a casino was set ablaze for refusing to pay extortion money to an organised crime group (Wilkinson, 2011). The attack killed 52 people, making it one of the deadliest incidents of violence against civil society related to organised crime in Mexico.

Despite it being a highly prevalent crime, and being featured prominently in Mexico's public agenda, there is no knowledge on the patterns of extortion victimisation, nor of the risk factors associated with increased victimisation risk.

2 Literature Review

While there has been an inconsistent use of terminology to refer to the same phenomenon—i.e., multiple victimisation, recidivist victimisation, re-victimisation, repeat victimisation, etc. (Farrell & Pease, 1993)—, criminological research has consistently found that a small proportion of victims experiences a disproportionate amount of crime. Repeat victimisation (used hereafter) refers to repeated criminal offenses against the same person, household, business, or other target however defined (Farrell, Tseloni & Pease, 2005; Grove & Farrell, 2010).

This phenomenon was first identified by J. H. Johnson, Kerper, Hayes and Killenger (1973, cited in Farrell & Pease, 1993) and Ziegenhagen (1976,

[4] According to Mexico's national household victimisation survey (the *Encuesta Nacional de Victimización y Percepción sobre Seguridad Pública*, ENVIPE) extortion is the second most common crime against households (INEGI, 2014a). However, it is noted that extortion against individuals is generally a very different crime from extortion against businesses, as it is overwhelmingly conducted via telephone and is similar to an aggravated type of fraud or scam where intimidation is involved.

cited in Farrell & Pease, 1993), and was subsequently analysed by Sparks, Genn and Dodd (1977, cited in Farrell & Pease, 1993), Sparks (1981), and Hindelang, Gottfredson and Garofalo (1978, cited in Farrell & Pease, 1993). One of the most relevant results that emerged from these initial studies was that the patterns of repeat victimisation were not the product of chance, as observed distributions did not fit a Poisson distribution. A Poisson distribution would indicate that victimisation experiences were independent from each other and that their likelihood was evenly distributed among the population (Sparks, 1981).

However, research on repeat victimisation remained rare until the 1990s. Farrell (1992), and Farrell and Pease (1993) rekindled interest in the phenomenon as they recognised it had important implications for crime prevention. Since crime prevention resources are scarce, allocating them according to victimisation risk represents a better use of public resources (Farrell & Pease, 1993). Furthermore, as Farrell and Pease (2001) explain, "the extent of repeat victimization necessarily means that a substantial reduction in rates of crime is potentially achievable by reductions in the extent of repetition" (p. 1).

2.1 Victimisation surveys and repeat victimisation

Research on repeat victimisation is very closely linked to the development of victimisation surveys, in particular the British Crime Survey (Hough, Maxfield, Morris & Simmons, 2007). Victimization surveys emerged in the United States in the 1970s (Mayhew & van Dijk, 2012) primarily to produce more accurate counts of crime than police statistics, which are hampered by underreporting (Farrell & Pease, 2007; Hopkins & Tilley, 2001; Sidebottom, 2013). Victimisation surveys ask a representative sample of the population being studied to provide answers to a standardised questionnaire regarding past victimisation experiences within a given reference period, typically one year (Mayhew & van Dijk, 2012; Sidebottom, 2013). Most stand-alone victimisation surveys are comprised of at least two parts: a main questionnaire that asks screening questions that identify those respondents that experi-

enced victimisation incidents, and modules for victims that capture in-depth information regarding each reported victimisation experience (INEGI, 2014d; UNODC/UNECE, 2010).

Surveys provide two types of measurements of crime: prevalence and incidence. As Farrell and Pease (1993) explain, crime prevalence is the proportion of the population that experienced crime during the reference period, i.e., victims per person, whereas crime incidence is the number of criminal events per respondent, i.e., crimes per person (Farrell & Pease, 1993). Derived from these measurements, the concentration of crime is the average number of crimes per victim (Farrell & Pease, 1993). Crime concentration summarises the extent of repeat victimisation, however, its distribution must be analysed to fully assess the phenomenon.

Most victimisation surveys focus on crimes experienced by individuals and households; however, surveys designed to measure crimes against businesses have become more common as it is recognised that police statistics tend to offer poor measurements of crimes against such targets (Burrows & Hopkins, 2005; Frate, 2004; Gill, 1998; Hollinger, 1997; Hopkins, 2002; Hopkins & Tilley, 2001; Mayhew & van Dijk, 2012; Mugelini, 2013a). These type of surveys have shown that crimes against businesses are exceedingly prevalent—in many cases more so than for households or individuals (Gill, 1998; Hopkins, 2002). Furthermore, business victimisation surveys reveal that repeat victimisation is a significant problem for businesses and may suffer an overall higher level of repeats per premises than residences (Burrows & Hopkins, 2005; Hopkins & Tilley, 2001).

Organised crimes are particularly difficult to measure through victimisation surveys, mostly because many organised crimes—such as drug trafficking and money laundering—generate collective harms that do not directly victimise individual subjects of surveys (van Dijk, 2007a). Extortion, by definition a predatory crime against a target and a notable marker for organised crime activity (van Dijk, 2007b), is an exception that is routinely captured by victimisation surveys, in particular those focused on businesses (Mugelini, 2013b).

Nonetheless, victimisation surveys have limitations that likely lead to an

underrepresentation of the true magnitude of crime (see Lynch & Addington, 2010). Two limitations are of particular relevance for repeat victimisation. First, the reference period artificially bounds measurement by imposing a time-window on repeat victimisation, i.e., some crimes early in the period may be repeats of crimes that took place before the period began and some crimes at the end of the period may have repeats that take place after the period ends (Farrell & Pease, 1993; UNODC/UNECE, 2010). Second, victimisation surveys (and in particular the British Crime Survey) have been criticised by imposing arbitrary caps on the number of victimisations that each respondent can report per crime type (Farrell & Pease, 2007). The reasons for capping offered by practitioners are reducing costs, unburdening respondents, and avoiding a supposed risk of inflating crime rates (UNODC/UNECE, 2010). Capping can occur in two ways: by limiting the number of victim modules, or by modifying the number of incidents reported. The ENVE limits the number of victimisation modules that can be filled by each respondent to seven per crime type, however the screening section captures uncapped victimisation incidents for each crime type (INEGI, 2014d).

Victimisation surveys capture a wealth of data on population characteristics in addition to victimisation experiences. Such characteristics include demographic and socio-economic data, ecological factors, lifestyles and routines, protective measures, attitudes, perceptions and fear of crime (Rand, 2006; UN, 2005; UNODC/UNECE, 2010). These measurements can be used as independent variables in analyses that attempt to understand the dynamics of victimisation (Rand, 2006). Research on repeat victimisation readily makes use of such data to seek explanations for the highly skewed distributions of crime incidence, in general, through statistical modelling based on the negative binomial distribution (Farrell, Clark, Ellingworth & Pease, 2005; Kuo et al., 2012; Park, 2015; Tseloni, Osborn, Trickett & Pease, 2002; Tseloni & Pease, 2003; Tseloni et al., 2004).

2.2 Repeat victimisation theories

There are two main theoretical explanations to account for repeat victimisation patterns: risk heterogeneity and event dependence (Farrell, Clark et al., 2005; Farrell et al., 1995). Risk heterogeneity (*flags*) assumes that differences in target characteristics makes one target more vulnerable or attractive than another to different offenders (Farrell, Clark et al., 2005); whereas event dependence (*boosts*) implies that an initial offense against one target increases the probability of subsequent events against the same target, usually by the same offender (Bernasco, 2008; S. D. Johnson, 2008; S. D. Johnson, Summers & Pease, 2008; Tseloni & Pease, 2003). The balance between boost and flag accounts remains a source of ongoing academic discussion (e.g., Farrell et al., 1995; S. D. Johnson, 2008; Kleemans, 2001; Tseloni & Pease, 2003); however, it is likely that both explanations contribute to the phenomenon of repeat victimisation (S. D. Johnson, 2008; Pease, 1998). Moreover, the actual contribution from each mechanism will likely vary considerably regarding different crime types (S. D. Johnson, 2008).

Of particular relevance to extortion, Farrell et al. (1995) note that boost mechanisms will likely play a considerable part when the effort of a subsequent offense is clarified by victim response to a first offense, and when the crime implies a high level of co-offending (as in organised crimes). This would suggest that businesses that comply with extortion demands by organised crime groups could be increasing their risk of successive victimisations by becoming known to organised criminals as easy victims. Unfortunately, detailed assessment of boost mechanisms is not possible using cross-sectional surveys as they are insensitive to time differences, meaning that it is not possible to analyse the the impact of relevant events (S. D. Johnson, 2008; Osborn, Ellingworth, Hope & Trickett, 1996; Tseloni et al., 2002, 2004).

Both boost and flag mechanisms are theoretically underpinned by environmental criminology, specifically the rational choice perspective (Clarke, 2013), the routine activity approach (Felson, 2013), and crime pattern theory (Brantingham & Brantingham, 2013). The rational choice perspective suggests that offenders weigh the benefits of committing a crime against its

risks, choosing those opportunities that offer higher rewards and lower risks, and that criminal events unfold in a sequence of stages and decisions (Clarke & Cornish, 2013; Cornish & Clarke, 1986). As boost and flag mechanisms both refer to offender perceptions regarding target selection (Sidebottom, 2012), the rational choice perspective provides a sound explanation for repeat victimisation (Farrell et al., 1995) by clarifying how offenders choose targets based on perceived (flags) or known (boosts) differences in risks and rewards between potential targets.

The routine activity approach states that crime takes place when a suitable target, a motivated offender and a lack of capable guardians converge in time and space (Cohen & Felson, 1979; Felson, 2013). Crime pattern theory explains how urban ecology generates opportunities for crime by encouraging the convergence of offenders and targets at specific nodes of activity, resulting in clusters of criminal activity (Brantingham & Brantingham, 2013). As Grove and Farrell (2010) suggest:

> Routine activity and crime pattern theory provide the best explanation of aggregate patterns of repeats. The same targets go to the same places where they interact with the same offenders, whether on the streets, in the home, or online. (Grove & Farrell, 2010, p. 767)

These theoretical approaches provide explanations particularly suitable to account for risk heterogeneity among targets. For example, attributes related to target suitability and lack of guardianship—such as the presence of valuable objects, target exposure, prevention and security equipment, daily activities, etc.—have been found to be related to patterns of repeat victimisation (Bowers, Johnson & Pease, 2005; Kuo et al., 2012; Park, 2015; Tseloni & Pease, 2003; Tseloni et al., 2004). On the other hand, attributes related to proximity to offenders, as measured by area crime levels or affluence for example, have also proven significant factors in repeat victimisation (Bowers et al., 2005; Farrell, Clark et al., 2005; Park, 2015; Sidebottom, 2012; Trickett, Osborn, Seymour & Pease, 1992).

Furthermore, by branching into to the processes that generate opportunities for co-offending and to the ecosystem for organised crime (Felson, 2006), these theories explain why businesses that deal in questionable affairs may me more vulnerable to extortion (Schelling, 1971), as they may be more exposed to motivated offenders.

2.3 Repeat extortion victimisation in Mexico

Patterns of repeat victimisation have been identified in practically all countries where it has been studied. While most research has focused on English-speaking or western countries (e.g., Farrell, Tseloni & Pease, 2005; Lynch et al., 2002; Perreault et al., 2010; Sagovsky & Johnson, 2007; Tseloni et al., 2004), research on non-western countries (e.g., Kuo et al., 2012; Park, 2015; Sidebottom, 2012) has revealed that repeat victimisation is consistent across national boundaries.

To date, while there have not been any detailed analyses of repeat victimisation in Mexico, there are reasons to believe that the phenomenon is common in the country. Some of the earliest evidence of repeat victimisation in Mexico was provided by ICESI (2010) who reported that based on a national survey, 32% of victimised individuals in 2008 were repeat victims and overall crime concentration was 1.6 crimes per victims[5]. Figures on repeat victimisation have been consistently collected and reported by the national statistics agency (*Instituto Nacional de Estadística y Geografía*, INEGI) ever since it began conducting national victimisation surveys focused on households (INEGI, 2014a, 2014f) and on businesses (INEGI, 2014b, 2014d). In their study of property crime against households across Mexico, Martinez and Cortez-Yactayo (2015) note that prior victimisation is positively correlated with the probability of being victimised in the future, however the authors did not analyse the distribution of victimisation experiences.

ONC (2014) produced an assessment of extortion in Mexico. While it

[5]ICESI reports a prevalence of 11% and an incidence of 11,973 crimes per 100,000 inhabitants (ICESI, 2010). The precise prevalence figures used calculate to crime concentration as reported by ICESI were not available. Note that ICESI reports figures expanded to the population using survey weights.

contains a good summary on public discussion surrounding the issue, and provided an interesting exercise analysing extortion reports, it briefly reports on past ENVE data, summarising aggregated results provided by INEGI.

There is little research that analyses patterns of repeat extortion victimisation. However, there is ample evidence to suggest that extortion is likely to exhibit such patterns. Perrone (2000) reports that from a sample of surveyed businesses in Australia, 45% of victims of extortion suffered repeats. La Spina et al. (2014) note that "the stable and recognized practice of extortion in a given territory is the hallmark of MTOs" (MTOs: mafia-type organisations; La Spina et al., 2014, p. 4), and that businesses are periodically extorted in territories controlled by organised crime groups in Italy. Chin et al. (1992) note that Chinese gang extortion of businesses involve periodic payments, and Kelly, Chin and Fagan (2000) mention that "extortion and victimization of Chinese businesses appear to be lengthy processes with continuous interaction between victim and offender and repeated incidents of victimization" (Kelly et al., 2000, p. 64). Finally, Best (1982) enlists numerous examples of systematic extortion where organised crime groups repeatedly extort targets.

The assumption that extortion generally involves repeated events is so common that INEGI exemplifies the concept of repeat victimisation for the ENVE with a victim that is extorted weekly, leading to 52 incidents in a year (INEGI, 2014d, p. 29). However, to empirically assess if this assumption is true, it must be determined that the distribution of extortion victimisations is not due to chance. Thus, the first hypothesis explored in this dissertation is:

H_1 *There are significantly more repeat extortion incidents than would be expected on the basis of random victimization.*

Once it is established that extortion concentrates in a subset of victims, we need to explain why this pattern occurs. While there is no previous research on factors associated with repeat extortion victimisation, the literature on extortion and crimes against businesses provides some clues to motivate testable hypotheses.

It has been noted that organised crimes are intrinsically related to State legitimacy, and that extortion tends to flourish in countries where institutions are weak and corruption is rampant (Skaperdas, 2001; Sung, 2004; Tulyakov, 2001). The are several mechanisms that could explain why high levels of corruption increases the risk of extortion victimisation, (i) persistent corruption signals the absence of state enforcement, which creates a power vacuum that is filled by organised crime (La Spina et al., 2014; Skaperdas, 2001); (ii) links between organised criminals and government authorities may be fuelling a state similar to state-dependence, where offenders and officials may be exchanging information regarding "profitable" victims; and (iii) the practice of paying bribes may have already "conditioned" business owners into paying illicit demands as a cost of doing business, thus they may be "easier" to extort. Thus it is reasonable to assume that businesses that experience high levels of corruption will also face higher incidents of extortion:

H_2 *Repeat extortion incidents are positively correlated with incidents of corruption experienced by surveyed businesses.*

Research on the dynamics and patterns of extortion by the Mafia in Italy (e.g., Frazzica, La Spina & Scaglione, 2013; La Spina et al., 2014) and Chinese gangs (e.g., Chin, 2000; Chin et al., 1992; Kelly et al., 2000) provides details on the factors that could influence victim selection for extortion victimisation. New businesses are expected to be more vulnerable to extortion. According to Chin (2000), Chinese gangs specifically target newly opened businesses, as it is believed that they are more willing to comply with extortion demands. There are several reasons that could explain this relationship, (i) it is presumed that connections with local organised criminals may provide some level of protection against extortion (Varese, 2011, 2014), thus new businesses may lack such contacts; (ii) new businesses may inadvertently draw attention to themselves through opening ceremonies or advertising, which could attract organised criminals (Chin et al., 1992); (iii) new businesses, burdened with costs of opening a business, may be less willing to incur new costs caused by failing to comply with extortionists; and (iv) new businesses may lack experience in dealing with extortion attempts in previous years. Thus it is

reasonable to assume that new businesses will experience more incidents of extortion:

H_3 *Repeat extortion incidents are negatively correlated with the number of years that surveyed businesses have been in operation.*

Business size is also expected to influence the probability of experiencing repeated extortion victimisation. Nonetheless, the nature of the influence is not clear. ONC (2014) cite ENVE data to report that the smallest Mexican businesses suffer more extortion; however their analysis fails to consider that these businesses constitute more than 50% of the survey sample, thus they naturally appear as a bigger proportion of victims. Gill (1998) notes that small businesses in the UK suffer disproportionally more crime, while Broadhurst, Bouhours, Bacon-Shone and Bouhours (2011) find that large businesses in China suffer more crime in general, and more extortion in particular. Similarly, Kelly et al. (2000) find that large businesses are more vulnerable to extortion among New York's Chinese business owners, though Chinese gang members mention that size is not relevant when selecting a victim (Chin, 2000, p. 72). However, since these studies measured business size differently—Gill (1998) used turnover, Broadhurst et al. (2011) used the number of employees, and Kelly et al. (2000) used the estimated size of the surveyed premises—, there is no established knowledge to predict how business size would impact extortion victimisation in Mexico. It could be speculated that size could imply a trade-off between vulnerability and profitability: while smaller business may be more vulnerable, their smaller cash flows might prove unattractive. Nonetheless, the size hypothesis will be limited to explore whether or not size is a factor:

H_4 *Repeat extortion victimisation varies according to the size of surveyed businesses.*

Additionally, business sector is considered a relevant factor, with increased risk for the service—specially restaurants, hotels and bars—and retail sectors, and lower risk for the manufacturing sector and professional offices. The

influence of sector type is assumed to be related to the inherent vulnerability to intimidation of certain types of businesses; as Schelling (1971) points out:

> Restaurants may be comparatively easy targets for racketeers. They are so easily harassed, because their business is really rather fragile. Noises and bad odors and startling events can spoil the clientele, and even physical damage cannot be guarded against. (Schelling, 1971, p. 648–649)

Therefore, I would expect repeat extortion victimisation to be more common in the service and retail sectors:

H_5 *Surveyed businesses in the service and retail sectors experience higher incidents of repeat extortion victimisation.*

Public discussion on extortion in Mexico concentrates on aggregated state figures. Differences in extortion incidence between states are usually associated to the fact that presence of organised crime groups varies across Mexican states (Guerrero-Gutiérrez, 2011; Rios, 2012). Repeat victimisation studies note the importance of area-level effects, however these are usually of a much smaller scale than "state". As the ENVE data set does not contain any information on a smaller scale, analysis will be limited to test if state is relevant in extortion incidence:

H_6 *Repeat extortion incidents vary according to the state in which surveyed businesses operate.*

The influence of local organised crime activity could be further analysed using a measurement of such presence. While, reliable measurements and assessments of organised crime activity remain elusive (van Duyne & van Dijck, 2007; von Lampe, 2005), researchers have used proxy measures (van Dijk, 2007a, 2007b) to estimate a measurement of organised crime presence. In Mexico, one of the most common proxies is the number of homicides, which in recent times are largely attributed to organised crime violence (Rios, 2012). Thus, it would be expected for repeat extortion victimisation to increase in states with high homicide rates:

H_7 *Repeat extortion incidents are positively correlated with state homicide rates.*

The variables identified in the literature as predictors of repeat extortion victimisation coincide with the theoretical underpinnings of repeat victimisation—the rational choice perspective, the routine activity approach, and crime pattern theory—since they have clear implications for the decision-making process extortionists follow when selecting a target, and because they capture some measure of target vulnerability and the presence of motivated offenders. Unfortunately, however, the identified variables do not capture all sources of risk heterogeneity that may influence repeat extortion victimisation. Of particular relevance are environmental characteristics, such as the neighbourhoods and the buildings where businesses operate, which have been found to be related to extortion victimisation risk (Chin, 2000), but about which data are not captured by the ENVE. Furthermore, the literature on repeat victimisation of businesses has shown that protective measures and interventions based on situational crime prevention (Clarke, 2013) can be successful in reducing repeat crimes against businesses (Hopkins & Tilley, 2001; Taylor, 1999). However, analysing the influence of such measures is not possible using the ENVE data. In addition, these research is limited to analysing variables related to risk heterogeneity, as cross-sectional data is unsuitable to make inferences regarding event-dependence.

3 Methodology

The research design explores the micro-level relationship between extortion incidents—our dependent variable—and a set of independent variables identified in the literature review as potentially associated with this crime. In the subsections that follow, I describe the data sources used, provide an exploratory bivariate analysis of the dependent and independent variables, and detail the multivariate statistical method that was used to test for evidence of the relationships predicted by the hypotheses.

3.1 Data

All unit-level data come from the 2014 sweep of Mexico's commercial victimisation survey, ENVE[6]. The survey measures incidence and prevalence of crimes against economic units in Mexico. The units are business premises[7], the survey is conducted every two years, and the reference period is the calendar year of the preceding year[8]. Survey responses are collected through in-person interviews with the highest-ranking person in micro and small businesses, and with security or finance managers for medium and large businesses. Computer assisted telephone interviewing (CATI) was used to follow-up incomplete questionnaires. The survey had a response rate of 85% (Jaimes Bello & Vielma Orozco, 2013).

A random and stratified[9] sample (33,479 units in 2014) was selected out of INEGI's National Statistical Directory of Economic Units[10] (*Directorio Estadístico Nacional de Unidades Económicas*, DENUE). After excluding non-response interviews, the data set contains $n = 28179$ distinct observations.

The survey is structured into two sections: the main questionnaire gathers respondents' characteristics, perception of safety, trust in the authorities, impact of crime on business performance, experiences with corruption, and a screening section that captures whether or not the respondent was victimised during the reference period and if so, how many crimes were experienced. The second section, a module on victimisation, collects data on each victimisation incident suffered by victimised respondents, capturing details of the crime context, use of violence, subsequent crime reporting, and the economic cost of the event (Jaimes Bello & Vielma Orozco, 2013). This research will focus on responses captured by the main questionnaire, as the

[6]Sources for area-level variables are described in the appropriate subsection.

[7]All sectors are covered, except agriculture-related businesses and the public sector.

[8]In the ENVE 2014, the survey captured crimes that took place between January 1 to December 31, 2013.

[9]Stratification was based on business size as defined by the number of employees. The classification used by INEGI, which follows Mexican legislation set by the Economy Ministry, can be seen in Table 9

[10]The final sampling frame included 3.7 million economic units operating in the country (INEGI, 2014c).

screening section contains a readily available summary of victimisation experiences (Trickett et al., 1992) which—unlike the victim module—is not affected by capping[11] (Farrell & Pease, 1993).

3.1.1 Dependent variable

The dependent variable is the number of extortion victimisations suffered by businesses during the reference period. Respondents are first asked if they were victims of extortion[12] during 2013, and if they were, how many incidents they suffered.

Table 1 presents the distribution of extortion based on survey responses. Repeat victims—i.e., businesses that suffered two or more extortion incidents in 2013—constitute 2.18% of all respondents and accounted for a disproportionate 55.75% of all extortion incidents. Businesses that experienced three or more incidents amount to 0.99% of the sample, yet they suffered 37.67% of total extortions. While the overall observed probability of becoming a victim of extortion in 2013 was 8.04%[13], the probability of a victimised business suffering a repeat extortion was 26.9%[14]. This suggests that after being extorted once, businesses are 3.3 times more likely to experience another victimisation in that year[15].

However, a high concentration of events does not automatically show that repeat extortion victimisation is not due to chance, as we would still expect some businesses to be extorted more than once if extortion occurred randomly. Thus, to rule out this possibility, we must assess whether our observed distribution corresponds to a Poisson distribution (Sidebottom, 2012;

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

[12] As previously stated, extortion is defined by the ENVE 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).

[13] Calculated by dividing the number of victims (2267) by the total sample (28179).

[14] Calculated by dividing the number of repeat victims (612) by the number of victims (2267).

[15] In fact, as businesses experience more extortions, the likelihood of suffering another event increases: 44.7% for three or more, 49.%2 for four or more, 59.2% for five or more, 72.5% for six or more, 79.3% for seven or more, and 93.4% for eight or more.

Events	Businesses	Crimes	% Bus.	% Victims	% Crimes
0	25912	–	91.955	–	–
1	1655	1655	5.873	73.004	44.251
2	338	676	1.199	14.910	18.075
3	139	417	0.493	6.131	11.150
4	55	220	0.195	2.426	5.882
5	22	110	0.078	0.970	2.941
6	12	72	0.043	0.529	1.925
7	3	21	0.011	0.132	0.561
8	8	64	0.028	0.353	1.711
10	20	200	0.071	0.882	5.348
12	3	36	0.011	0.132	0.963
15	4	60	0.014	0.176	1.604
20	3	60	0.011	0.132	1.604
24	1	24	0.004	0.044	0.642
25	1	25	0.004	0.044	0.668
30	2	60	0.007	0.088	1.604
40	1	40	0.004	0.044	1.070
Totals	28179	3740	100%	100%	100%

Table 1: The distribution of extortion victimisation.

Sparks, 1981). A Poisson distribution is a statistical distribution of event counts[16] that assumes events are *random* (i.e., they occur at a constant rate for each observation) and *independent* (i.e., events in the past do not affect the probability of future events) (see: Cameron & Trivedi, 1998; King, 1988; Sparks, 1981). Poisson distributions are defined solely by one parameter, μ, which corresponds to the mean of event counts and—as a particular property of Poisson distributions—is equal to the variance of the distribution[17] (Crawley, 2012; DeMaris, 2004).

First, we test for Poisson dispersion (Boddy & Smith, 2009; Upton &

[16]Event counts are variables that measure the number of times an event—in our case a victimisation incident—occurs within a fixed domain, be it temporal, spatial or otherwise defined (King, 1988).

[17]Formally, the Poisson distribution probability function is $Pr(y|\mu) = \frac{e^{-\mu}\mu^y}{y!}$ for $y = 0, 1, 2, 3 \ldots$, where y represents an event count, and the parameter μ is the sample mean (Cameron & Trivedi, 1998; Crawley, 2012; DeMaris, 2004; MacDonald & Lattimore, 2010).

Cook, 2008b) and evaluate whether the mean is equal to the variance. As Table 2 shows, the variance is more than 4.1 times larger than the mean and the index of dispersion[18] ($I = 116148.8$, $df = 28178$, $p < 0.001$) is significantly different from what would be expected if the data were Poisson-distributed[19]. Thus, the distribution of extortion clearly exhibits overdispersion (MacDonald & Lattimore, 2010; Upton & Cook, 2008b), which suggests that the variation in event counts cannot be explained by random variation alone.

Mean	Variance	Ratio (σ^2/μ)	Index of dispersion
0.1327	0.5471	4.1220	116148.8

Table 2: Evidence of overdispersion in the distribution of extortion victimisation.

To further test this claim, we can compare the observed counts with the expected counts under a Poisson distribution. Figure 1 presents the frequency of expected counts under a Poisson distribution [20] ($\mu = 0.1327$) plotted on a log(10) scale. As shown, the Poisson expected counts are very different from the observed distribution. A Chi-squared test[21] ($\chi^2 = 7942.71$, $df = 2$, $p < 0.001$) and a Kolmogorov-Smirnov test[22] (KS test, D = 0.042372, $p < 0.001$) both confirm that the observed distribution is significantly different from a Poisson distribution. Thus, based on these three tests, it is reasonable to as-

[18]The index of dispersion, I, is given by $I = \frac{(n-1)\sigma^2}{\mu}$, where μ and σ^2 are the mean and variance of a sample of n observations. Under the null hypothesis of a Poisson distribution, the index of dispersion should have an approximate Chi-squared distribution with $n-1$ degrees of freedom (Upton & Cook, 2008b).

[19]The index of dispersion is clearly above the 28569.61 Chi-Squared value for 28178 $(n-1)$ degrees of freedom at $p = 0.05$, right-tail.

[20]To obtain the expected Poisson counts, we first obtained the Poisson probabilities for the observed counts and multiplied them by the total number of observations in the sample.

[21]To conform with the assumptions of the Chi-squared test, the distribution was collapsed to obtain frequencies of more than five per event count.

[22]The Kolmogorov-Smirnov test evaluates whether a sample of observations has been drawn from a specified distribution (be it discrete or continuous) (Upton & Cook, 2008c). We used the implementation of the KS test for discrete distributions proposed by Arnold and Emerson (2011).

sume that the distribution of extortion victimisation of surveyed businesses is unlikely to be the product of chance, and therefore warrants further analysis.

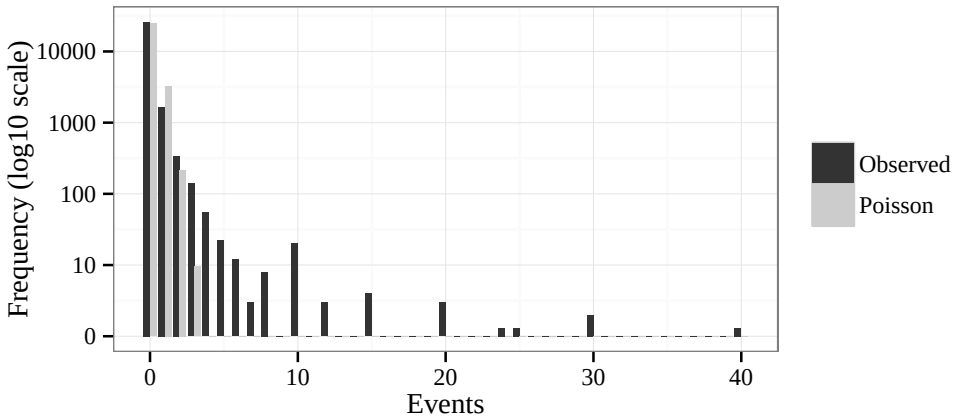

Figure 1: The observed and expected (Poisson) count frequencies.

3.1.2 Independent variables

Four of the independent variables are unit-level measurements, while homicide rates are measured at the state level[23]. Table 3 presents a summary of the different independent variables: the number of corruption incidents suffered by a business, the number of years a business has been in operation, a variable of three sector categories, a variable of eighteen subsector categories, a variable of four business size categories, and state homicide rates for 2013.

Unit-level variables Corruption incidents are captured as counts by the question: "In total, how many separate acts of corruption did you suffer during 2013?" (INEGI, 2014e). Table 4 presents the joint distribution of extortion victimisations and corruption incidents[24]. According to a Chi-squared

[23]The ENVE data only specifies the state in which businesses are located, thus it is not possible to explore the distribution at a lower scale, such as municipalities or cities.

[24]For the remainder of this subsection, counts of five or more events were collapsed into one category to facilitate visualisation and testing.

Variable	Obs.	(%)	Mean	σ	Min.	Max.
Unit-level variables						
Corruption inc.	28179		0.1	1.3	0	98
Years	28179		14.9	14.0	0	212
Sector						
Commerce (*base*)	12041	(42.7%)				
Industry	4629	(16.4%)				
Services	11509	(40.8%)				
Subsector						
Mining (*base*)	89	(0.3%)				
Utilities	13	(0%)				
Construction	820	(2.9%)				
Manufacturing	3707	(13.2%)				
Wholesale	1952	(6.9%)				
Retail	10088	(35.8%)				
Transport	720	(2.6%)				
Media	259	(0.9%)				
Finance	318	(1.1%)				
Real estate	417	(1.5%)				
Prof. services	753	(2.7%)				
Corporate	5	(0%)				
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*)	3067	(10.9%)				
Medium	3640	(12.9%)				
Small	5842	(20.7%)				
Micro	15630	(55.5%)				
Area-level variables (32 states)						
Homicide rate*	32		16.1	12.6	1.9	59.2

*Homicides per 100,000 inhabitants.

Table 3: Descriptive statistics of independent variables.

test ($\chi^2 = 2569.9,\ p < 0.001$, Cramér's[25] $V = 0.14$, simulated p-value based on 9999 replicates[26]), the distribution is unlikely to be the product of chance. Furthermore, a Pearson's correlation test ($r = 0.072$, $p < 0.001$, $n = 28179$) suggests that the relationship between the variables is positive and statistically significant.

	Extortions					
Corruption incidents	0	1	2	3	4	5+
0	24934	146	281	109	39	66
1	666	133	28	14	8	2
2	151	27	17	7	2	2
3	70	14	4	4	3	3
4	21	5	4	1	1	3
5+	70	10	4	4	2	4

Table 4: Joint distribution of extortion and corruption incidents.

The number of years a business has been in operation was calculated by subtracting the reference year (2013) from the year respondents said to have started operations (INEGI, 2014e). Table 5 presents the distribution of 0 to 5+ extortion victimisations in four categories of years in operation. According to a Chi-squared test ($\chi^2 = 89.6,\ p < 0.001$, Cramér's $V = 0.03$, simulated p-value based on 9999 replicates), this distribution is unlikely to be the product of chance. Furthermore, a Pearson's correlation test ($r = 0.025$, $p < 0.001$, $n = 28179$) suggests that, though the relationship between years and extortion is positive and statistically significant, it appears to be weak.

Business sector is classified according to the North American Industrial Classification System (*Sistema de Clasificación Industrial de Norte América*, SCIAN). Respondents are assigned to a sector in the DENUE sampling frame,

[25]Cramér's V is a measure of association between nominal variables based on the value of the chi-square statistic. The value of V is standardised between 0 and 1, where one indicates a perfect association, and zero a lack of association (Weisburd & Britt, 2014).

[26]When the expected counts were smaller than 5, and no suitable alternatives were found, the statistical significance of the χ^2 test statistic was estimatd using Monte Carlo methods (Hope, 1968).

	Extortions					
Years	0	1	2	3	4	5+
0-1	1138	41	10	1	0	0
2-10	11341	628	153	45	19	21
11-30	10823	814	136	73	29	44
31-50	1963	132	30	16	5	9
51+	647	40	9	4	2	6

Table 5: Extortion incidents by 4 categories of years in business.

which is corroborated[27] during the survey interview. The data specifies which sector and subsector respondents belongs to. Table 6 presents how sectors and subsectors are classified, whereas Tables 7 and 8 present the distribution of 0 to 5+ extortion victimisations according to sector and subsector respectively. According to Chi-squared tests, the distribution of extortion incidents by sector is not quite significant at the 95% threshold ($\chi^2 = 17.078$, $df = 10$, $p = 0.072$, Cramer's $V = 0.01$). However, the distribution by subsector is significant ($\chi^2 = 177.1$, $p = 0.007$, Cramer's $V = 0.03$, simulated p-value based on 9999 replicates), though the association is weak.

The size variable classifies respondents into four categories (Micro, Small, Medium and Large) according to the number of employees (see: Table 9). Table 10 presents the distribution of uncapped extortion incidents according to respondents' size. The results of a Chi-squared test ($\chi^2 = 276.858$, $df = 15$, $p < 0.001$, Cramér's $V = 0.06$) suggest that it is unlikely that this distribution is the product of chance.

Area-level variables Businesses can be grouped into states to see if geographical location and state homicide rates influence repeat extortion. Figure 2 presents a map of Mexico with state divisions, while Table 11 and Figure[28] 3 present how extortion and homicide vary by state.

Regarding extortion, state prevalence and incidence are significantly cor-

[27]If at the time of the interview the respondent has substantively changed their business activities, the sector is modified accordingly.

[28]Thematic classes for maps were defined by up to three standard deviations away from the mean.

Sector	Subsector
Industry	
	Mining
	Gas, water and electric utilities
	Construction
	Manufacturing
Commerce	
	Retail
	Wholesale
Services	
	Transport, mail and storage
	Media
	Finance and insurance
	Real estate
	Professional, scientific and technical services
	Corporate offices
	Office support, waste and maintenance
	Education
	Health
	Leisure, arts and sports
	Hotels, restaurants and bars
	Other, except government

Table 6: Sectors and subsectors in ENVE 2014 (INEGI, 2014d)

	Extortions					
Sector	0	1	2	3	4	5+
Commerce	11129	675	139	45	19	34
Industry	4264	261	56	22	14	12
Services	10519	719	143	72	22	34

Table 7: Exortion incidents by sector

related ($r = 0.921$, $p < 0.001$, $n = 32$) as expected; however, prevalence and concentration ($r = -0.086$, $p = 0.638$, $n = 32$), and incidence and concentration ($r = 0.281$, $p = 0.117$, $n = 32$) are not significantly correlated, which suggests that repeat extortion is not more common in states with more victimised businesses nor in states with more extortion incidents.

	Extortions					
Subsector	0	1	2	3	4	5+
Mining	82	5	1	0	1	0
Utilities	13	0	0	0	0	0
Construction	731	64	14	4	5	2
Manufacturing	3438	192	41	18	8	10
Wholesale	1758	139	30	11	6	8
Retail	9370	536	109	34	13	26
Transport	629	67	13	6	4	1
Media	251	6	1	1	0	0
Finance	290	21	4	1	2	0
Real estate	378	25	10	4	0	0
Prof. services	682	52	10	6	1	2
Corporate	4	1	0	0	0	0
Maintenance	839	54	10	3	1	1
Education	867	65	14	5	2	2
Health	1055	77	11	10	0	4
Leisure	294	17	3	1	0	1
Hotels, Rest., & Bars	2486	202	48	24	9	18
Other	2745	132	19	11	3	5

Table 8: Exortion incidents by subsector

The number of homicides in each state was obtained from the Executive Secretariat of the National System for Public Security (*Secretariado Ejecutivo del Sistema Nacional de Seguridad Pública*, SESNSP), which collects homicide reports from state prosecutors offices (SESNSP, 2015). The figures correspond to homicides reported in 2013. To facilitate comparison between states, rates per 100,000 inhabitants[29] were used. Results from Pearson's correlation tests (see: Table 12) suggest that state homicide rates are significantly and positively correlated with extortion prevalence and incidence rates, though not with extortion concentration—however, the effect sizes are quite small.

[29]The population in each state for year 2013 comes from the population estimates of the National Population Council (*Consejo Nacional de Población*, CONAPO) generated from the 2010 Population Census (CONAPO, 2012).

	Sector		
Size	Industry	Commerce	Services
Micro	0 - 10	0 - 10	0 - 10
Small	11 - 50	11 - 30	11 - 50
Medium	51 - 250	31 - 100	51 - 100
Large	251+	101+	101+

Table 9: Business size by sector, classified by number of employees. Adapted from INEGI (2014c, p. 3).

	Extortions					
Size	0	1	2	3	4	5+
Large	2807	174	39	20	7	20
Medium	3253	254	71	33	10	19
Small	5159	486	111	46	19	21
Micro	14693	741	117	40	19	20

Table 10: Exortion incidents by size

3.2 Statistical modelling

Statistical modelling of victimisation survey data has mostly focused on the individual risk of becoming a victim given a set of independent variables (Osborn & Tseloni, 1998; Tseloni et al., 2002; UNODC/UNECE, 2010). This approach can severely misrepresent the level—and heterogeneous nature—of victimisation risk, since as Section 3.1.1 and previous research has shown, victims and repeat victims face heightened risks when compared to non-victims (e.g., Osborn & Tseloni, 1998; Sidebottom, 2012). Thus, to account for the concentration of crimes—and thus repeat victimisation—a preferred approach is to model the entire distribution of crime incidents as event counts (Osborn & Tseloni, 1998; Tseloni, 2006).

This can be accomplished using modelling techniques suitable for count data, such as Poisson regression (Cameron & Trivedi, 1998; DeMaris, 2004; MacDonald & Lattimore, 2010). Nonetheless, when there is overdispersion in the data—as is the case here—Poisson regression may lead to invalid statistical inference, as t-statistics will be incorrect and standard errors overly

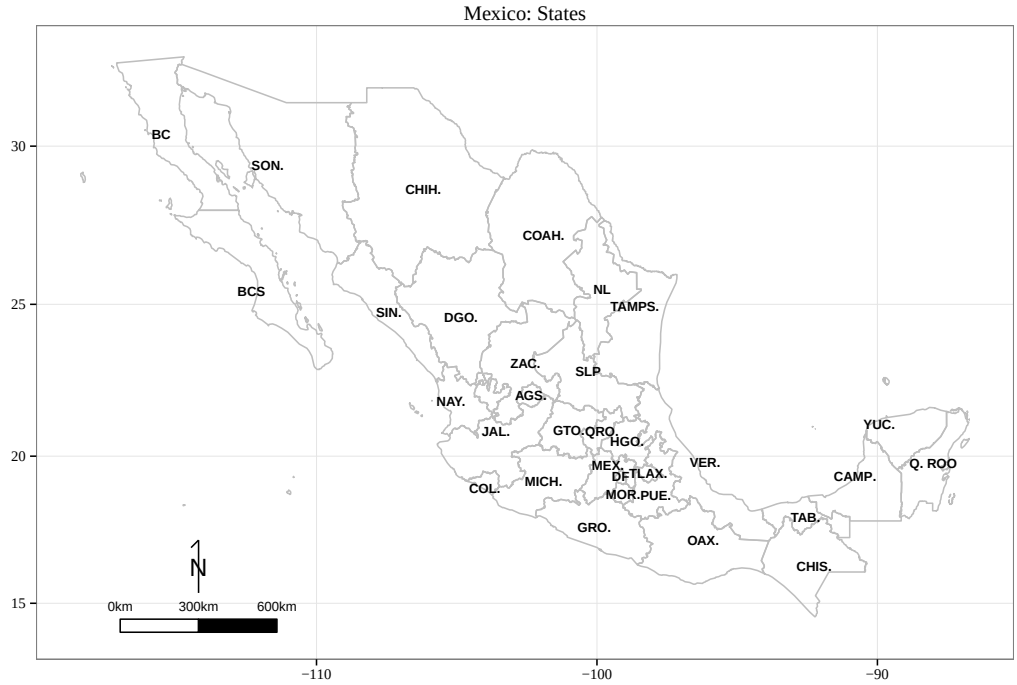

Figure 2: Map of Mexico. Source: INEGI.

optimistic (Cameron & Trivedi, 1998), increasing the chance of committing a type I statistical error[30]. In such cases, a common solution is to use a variation of the Poisson regression based on the Negative Binomial distribution (Cameron & Trivedi, 1998; MacDonald & Lattimore, 2010; Osgood, 2000).

3.2.1 Negative Binomial regression

The Poisson regression model provides the starting point to describe regression models for event counts (Cameron & Trivedi, 1998; Osborn & Tseloni, 1998). Considering a number of independent observations n, for which the

[30]A type I error occurs when we accept the alternative hypothesis of a relationship between the independent and dependent variable when there is no significant relationship (Upton & Cook, 2008a).

		Extortion			
State	Obs.	Preval.[a]	Incid.[a]	Concen.	Hom. rate[b]
Aguascalientes	781	57.62	67.86	1.18	3.11
Baja California	597	82.08	95.48	1.16	22.92
Baja California Sur	782	40.92	51.15	1.25	7.80
Campeche	961	123.83	190.43	1.54	7.61
Coahuila	770	37.66	58.44	1.55	22.32
Colima	827	93.11	159.61	1.71	25.49
Chiapas	1245	60.24	92.37	1.53	9.83
Chihuahua	967	61.01	105.48	1.73	39.69
Distrito Federal	880	56.82	78.41	1.38	8.42
Durango	704	53.98	102.27	1.89	27.54
Guanajuato	534	99.25	117.98	1.19	11.21
Guerrero	881	190.69	287.17	1.51	59.22
Hidalgo	796	69.10	187.19	2.71	4.38
Jalisco	745	65.77	85.91	1.31	14.19
México	628	164.01	219.75	1.34	11.81
Michoacán	977	123.85	246.67	1.99	19.91
Morelos	648	169.75	290.12	1.71	31.85
Nayarit	664	61.75	106.93	1.73	12.81
Nuevo León	838	75.18	133.65	1.78	14.55
Oaxaca	870	114.94	209.20	1.82	13.54
Puebla	955	77.49	150.79	1.95	6.74
Querétaro	923	67.17	83.42	1.24	5.71
Quintana Roo	813	49.20	72.57	1.48	14.41
San Luis Potosí	976	66.60	116.80	1.75	9.66
Sinaloa	721	51.32	128.99	2.51	41.20
Sonora	635	29.92	45.67	1.53	20.17
Tabasco	954	51.36	107.97	2.10	6.00
Tamaulipas	1657	108.63	172.60	1.59	16.03
Tlaxcala	883	87.20	141.56	1.62	5.63
Veracruz	1050	114.29	211.43	1.85	10.89
Yucatán	1048	23.85	48.66	2.04	1.94
Zacatecas	1469	56.50	73.52	1.30	10.77
National	28179	80.78	132.50	1.65	16.16

[a]Prevalence and incidence per 1,000 respondents; [b]Homicide rate per 100,000 inhabitants.

Table 11: A summary of relevant indicators by state.

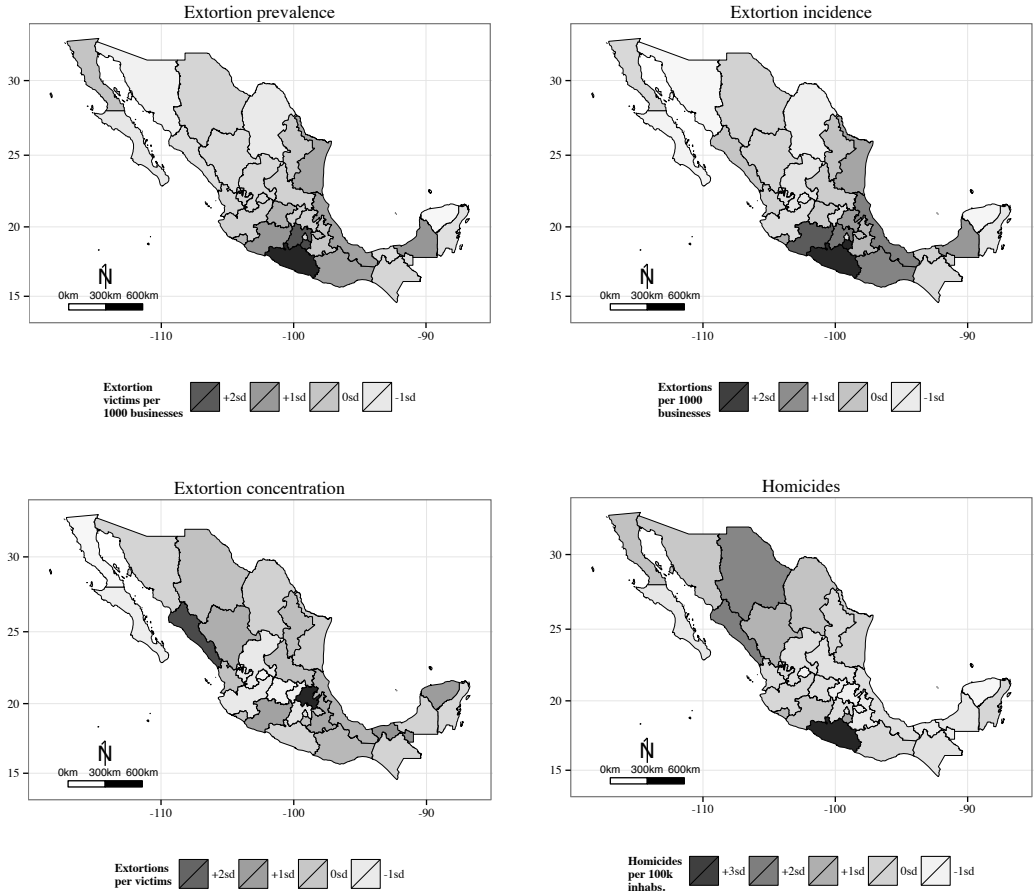

Figure 3: Thematic maps of extortion incidence, prevalence and concentration, and homicides by state. Source: INEGI and SESNSP.

	Prevalence	Incidence	Concentration
Homicide rate	$r = 0.381$	$r = 0.345$	$r = 0.103$
$n = 32$	$(p = 0.031)$	$(p = 0.029)$	$(p = 0.573)$

Table 12: Correlation tests between state homicide rates and extortion rates.

i^{th} observation is (y_i, x_i), where y_i is a dependent variable of event counts and x_i is a vector of regressors thought to determine y_i, the Poisson regression model assumes that the mean of events, $\mu_i = \mathsf{E}[y_i|x_i]$, is related to x_i by

$$\ln(\mu_i) = \beta x_i' \tag{1}$$

where ln indicates the natural logarithm, x_i' is a k-dimensional vector of regressors $x_i' = [x_{1i}, \ldots, x_{ki}]$, and parameters β correspond to the regression coefficients. Furthermore, the probability of y_i given x_i is Poisson-distributed with density function

$$f(y_i|x_i) = \frac{e^{-\mu_i}\mu_i^{y_i}}{y_i!}, \; y_i = 0, 1, 2, \ldots \tag{2}$$

and the conditional variance follows the Poisson condition $\mu_i = \mathsf{V}[y_i|x_i]$.

The Negative Binomial model introduces overdispersion as unexplained variation in the mean parameter by adding an error term, ε_i, in

$$\ln(\mu_i) = \beta x_i' + \varepsilon_i \tag{3}$$

where $exp(\varepsilon_i)$ follows a gamma distribution with mean 1 and variance α (Osborn & Tseloni, 1998). Thus, while the mean remains the same as in the Poisson model, $\mu_i = \mathsf{E}[y_i|x_i] = exp(\beta x_i')$, the variance[31] is given by

$$\mathsf{V}[y_i|x_i] = \mu_i + \alpha\mu_i^2 \tag{4}$$

and the density, given that $\alpha \geq 1$, is

$$f(y_i|\mu_i, \alpha) = \frac{\Gamma(y_i + \alpha^{-1})}{\Gamma(y_i + 1)\Gamma(\alpha^{-1})} \left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu_i}\right)^{\alpha^{-1}} \left(\frac{\mu_i}{\alpha^{-1} + \mu_i}\right)^{y_i}, \; y_i = 0, 1, 2, \ldots \tag{5}$$

where Γ is the gamma function, and the inverse of alpha, α^{-1}, is also known as the precision parameter (Cameron & Trivedi, 1998; Osborn & Tseloni, 1998).

In practice, parameter values for both Poisson and Negative Binomial regression are estimated using maximum-likelihood and other iterative methods (Cameron & Trivedi, 1998; Osborn & Tseloni, 1998), thus the estimated probability distribution of $\mathsf{E}[y_i|x_i]$ is generated from estimated values $\hat{\alpha}$ and $\hat{\mu}_i = exp(\hat{\beta}x_i)$ (Osborn & Tseloni, 1998).

[31] We are using the standard NB2 formulation of the Negative Binomial variance function (Cameron & Trivedi, 1998).

Interpretation of coefficients is relatively straightforward. An increase of one unit in an independent variable, say x_{ik}, has a multiplicative effect on the estimated mean of $exp(\hat{\beta}_k) \times \mathsf{E}[y_i|x_i]$, which is usually reported as a percentage change on the incidence[32]. If the dependent variable is categorical, the effect given by the coefficient is relative to a base category (Cameron & Trivedi, 1998; Osborn & Tseloni, 1998). In the case of the Negative Binomial model, the value of $\hat{\alpha}$ represents the amount of heterogeneity that cannot be explained by the regressors. For extortion incidents, this unobserved heterogeneity would arise when two identical businesses—as defined by our dependent variables—face unexplained differences in extortion risks (Tseloni et al., 2002). This analysis, though, cannot distinguish how much unobserved heterogeneity is due to differences in the businesses, event-dependence, or non-systematic errors.

3.2.2 Multilevel modelling

Multilevel modelling with random intercepts was used to estimate the influence of the state in which businesses operate. Essentially, multilevel models with random intercepts account for the hierarchical nature of the data—e.g., individual businesses grouped within states—by estimating the influence of the regressors as constant β coefficients across groups, but allowing the intercept to vary from group to group. The extension of multilevel models to count data regression adds a layer of complexity to the equations presented in Subsection 3.2.1. The equations that follow were adapted from Goldstein (2011) and Tseloni and Pease (2003). First we substitute the subscript i with ij, where i denotes units grouped in j areas for dependent variable y_{ij} and regressors x_{ij}. The multilevel Poisson regression model assumes that the mean of events, $\mu_{ij} = \mathsf{E}[y_{ij}|x_{ij}]$, is related to x_{ij} by

$$\ln(\mu_{ij}) = \beta_0 + \beta_1 x'_{ij} + u_{0j} \tag{6}$$

[32]The exponentiated coefficient is also referred to as an *Incidence Rate Ratio* (IRR, Hilbe, 2011). By subtracting 1 from the IRR and multiplying by 100, we obtain the percentage difference. For example, a coefficient of 0.40 would represent a 49% increase on incidence, as given by: $(exp(0.40) - 1) \times 100 = 49.18$. If the IRR is smaller that one, the resulting percentage difference will be negative, which indicates a decrease in incidence.

where parameter β_0 is the intercept, u_{0j} is the random variation in β_0 associated with each group j, and β_1 is a vector of fixed regression coefficients—these regression coefficients are also referred to as *fixed effects*, whereas the random intercepts are the *random effects*. As in the single-level model, $f(y_{ij}|x_{ij})$ is Poisson-distributed with the same density function as equation 2, substituting the subscript i for ij to denote the structure of the data. Similarly, the conditional variance follows the Poisson condition $\mu_{ij} = \mathsf{V}[y_{ij}|x_{ij}]$, but an additional parameter $\mathsf{V}[u_{0j}] = \sigma^2_{u0}$ measures the random intercepts variance, i.e., the variance of between-groups differences.

The multilevel Negative Binomial model with random intercept (Tseloni & Pease, 2003) introduces overdispersion in a similar way as in equation 3, adding ε_{ij} to equation 6,

$$\ln(\mu_{ij}) = \beta_0 + \beta_1 x'_{ij} + u_{0j} + \varepsilon_{ij} \tag{7}$$

where $exp(\varepsilon_{0ij})$ follows a gamma distribution with mean 1 and variance α (Osborn & Tseloni, 1998). The variance and density are given by equations 4 and 5, substituting i for ij. As in single-level models, parameter estimation is computed using iterative methods such as maximum-likelihood (Goldstein, 2011; Tseloni & Pease, 2003).

Interpretation of model results is essentially the same as for single-level models: an increase of one unit in a dependent variable, say x_{ijk}, has a multiplicative effect on the estimated mean of $exp(\hat{\beta}_{1k}) \times \mathsf{E}[y_{ij}|x_{ij}]$, and $\hat{\alpha}$ captures the between-businesses unobserved heterogeneity that cannot be explained by level-one regressors. As the value of $\hat{\sigma}^2_{u0}$ captures the unobserved heterogeneity of the random intercepts, the intra-group correlation given by

$$\hat{\rho} = \frac{\hat{\sigma}^2_{u0}}{(\hat{\sigma}^2_{u0} + \hat{\alpha})} \tag{8}$$

represents the correlation of the mean of extortion incidents between two businesses in the same state (Goldstein, 2011; Tseloni & Pease, 2003), and indicates persistent unexplained state heterogeneity (Tseloni & Pease, 2003), i.e, between-group differences that are unaccounted for in the model.

3.2.3 Modelling implementation

As recommended by Cameron and Trivedi (1998), analysis followed a specification, estimation, testing and evaluation cycle. Three specifications containing the variables detailed in Subsection 3.1.2 were made: one with the aggregated sector variable, another with subsector instead, and a final null specification containing only the intercept. Single-level and multilevel models were estimated for each (See: Table 13). As the distribution of extortion exhibits overdispersion, we opted for models based on the negative binomial distribution (MacDonald & Lattimore, 2010; Osgood, 2000). Nonetheless, we also fitted Poisson variants to the full models to compare the estimations.

Model	Specification	2nd level	Distribution
PO_a	A*	-	Poisson
NB_a	A	-	Negative Binomial
MPO_a	A	*States*	Poisson
MNB_a	A	*States*	Negative Binomial
PO_b	B**	-	Poisson
NB_b	B	-	Negative Binomial
MPO_b	B	*States*	Poisson
MNB_b	B	*States*	Negative Binomial
NB_{null}	(Intercept)	-	Negative Binomial
MNB_{null}	(Intercept)	*States*	Negative Binomial

*Corruption incidents + Years + Sector + Size + Homicide rate

**Corruption incidents + Years + Subsector + Size + Homicide rate

Table 13: Models fitted for the analysis.

Models were evaluated using likelihood ratio (LR) tests (Cameron & Trivedi, 1998; Goldstein, 2011). First, each model was compared to its null version (e.g., NB_a vs. NB_{null}) to assess the significance of the model. Then, we evaluated the fit of the two distributions (e.g., PO_a vs. NB_a and MPO_a vs. MNB_a), and the single-level and multilevel versions (e.g., NB_a vs. MNB_a). Finally, we compared the different models by examining the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Smaller AIC and BIC values indicate a better fit, though it is worth noting that

there is no probabilistic method to establish whether the difference in these information criteria is statistically significant (Goldstein, 2011).

Access to the micro-level dataset required for this project is restricted by INEGI. While the dataset is anonymised, access is controlled because the combined characteristics of each respondent could potentially be used to infer their identity. Researchers may request access from INEGI, which can be granted either in INEGI's facilites in Mexico City or through remote processing of programming scripts. This project opted for the latter[33].

Models were fitted using R version 3.2.1 (R Core Development Team, 2015) running under Windows 8 (64-bit). Single-level models were fitted by maximum likelihood using iteratively reweighted least squares (IWLS) using core R functionality (R Core Development Team, 2015) and the "MASS" package (Venables & Ripley, 2002). Multilevel models were fitted by maximum likelihood using Laplace approximation as implemented in the "lme4" (Bates, Maechler, Bolker & Walker, 2015b, 2015a), and the "glmmADMB" packages (Bolker, Skaug, Magnusson & Nielsen, 2012; Fournier et al., 2012).

4 Results

4.1 Model evaluation and testing

First, considering estimations for models including the sector variable. Tables 14 and 15 present estimations for these and null models respectively, while Table 16 presents results of likelihood ratio (LR) tests. Overall, single-level and multilevel models for this specification are significant when compared with null models. Furthermore, LR tests suggest that models based on the Negative Binomial distribution are significantly different from Poisson-based models, confirming our prior assumptions regarding overdispersion and choice of distribution. A final LR test between single-level and multilevel Negative Binomial models suggests that the amount of variation between groups is statistically significant.

[33]The programming scripts developed for this project can be found in the author's code repository: `https://goo.gl/q3jKAR`.

It should be noted that p-values for LR tests between Negative Binomial and Poisson models, and between single-level and multilevel models, are half the value expected under a χ^2 distribution with 1 degree of freedom, as the null hypotheses—that $\hat{\alpha} = 0$, and that $\hat{\sigma}_{u0} = 0$—are on the boundary of the feasible parameter space (Goldstein, 2011), i.e., we do not expect negative values for $\hat{\alpha}$ or $\hat{\sigma}_{u0}$.

	PO_a	NB_a	MPO_a	MNB_a
(Intercept)	-2.01^{***}	-2.17^{***}	-2.06^{***}	-2.23^{***}
Corruption inc.	0.04^{***}	0.31^{***}	0.03^{***}	0.29^{***}
Homicide rate	0.01^{***}	0.02^{***}	0.01	0.01^{*}
Years	0.003^{**}	0.004^{**}	0.002^{**}	0.004^{*}
Industry	-0.19^{***}	-0.19^{*}	-0.18^{***}	-0.18^{*}
Services	0.02	0.04	0.02	0.04
Medium	0.16^{**}	0.19^{*}	0.10	0.18
Small	0.04	0.09	0.02	0.09
Micro	-0.70^{***}	-0.65^{***}	-0.78^{***}	-0.70^{***}
$\hat{\alpha}$	-	8.80	-	7.78
$\hat{\sigma}^2_{u0}$	-	-	0.22	0.21
AIC	25632.32	20071.70	24985.3	19839.68
BIC	25706.54	20154.16	25067.8	19930.39
Log Likelihood	-12807.16	-10025.85	-12482.6	-9908.84
Deviance	20507.01	7310.03	24965.3	-[†]
Num. obs.	28179	28179	28179	28179
Num. groups:	-	-	32	32

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

[†]The deviance was not available for models fitted using package "glmmADMB".

Table 14: Results of estimations for models including "Sector".

A multilevel Negative Binomial model that included the subsector variable could not be estimated, as the statistical packages reported failures in the maximizer functions. I suspect that since some of the 18 categories of subsector are very uncommon (See: Table 3 in Subection 3.1.2), their distribution among the 32 groups of the multilevel model proved too complex for

	NB_{null}	MNB_{null}
(Intercept)	-2.17^{***}	-2.14^{***}
$\hat{\alpha}$	10.49	9.09
$\hat{\sigma}^2_{u0}$		0.23
AIC	20504.18	20236.80
BIC	20520.67	20261.54
Log Likelihood	-10250.09	-10115.40
Deviance	7148.54	-†
Num. obs.	28179	28179
Num. groups:		32

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

†Deviance was not available for models fitted using package "glmmADMB".

Table 15: Results of estimations for null models.

	LR test	*df*	*p*-value
NB_a vs NB_{null}	448.48	8	< 0.001
MNB_a vs MNB_{null}	413.12	8	< 0.001
NB_a vs PO_a	5562.62	1	$< 0.001^{\dagger}$
MNB_a vs MPO_a	5147.52	1	$< 0.001^{\dagger}$
MNB_a vs NB_a	234.02	1	$< 0.001^{\dagger}$

†Half the *p*-value of a χ^2 distribution with 1 *df* (Goldstein, 2011).

Table 16: Likelihood ratio tests for models including "Sector"

the modelling algorithms[34]. Thus, Tables 17 and 18 present the estimations and LR tests for single-level Negative Binomial and Poisson models for this specification.

Goodness-of-fit for the single-level Negative Binomial model is statistically significant when compared with a null model containing only the intercept. Additionally, the LR tests again suggest that the Negative Binomial model is significantly different from a Poisson-based model.

AIC and BIC values are lowest for the multilevel Negative Binomial model

[34]Unfortunately, I could not obtain precise information regarding the distribution of susbsectors by states within the time-frame for this project.

	PO_b	NB_b
(Intercept)	-2.37^{***}	-2.68^{***}
Corruption inc.	0.04^{***}	0.32^{***}
Homicide rate	0.01^{***}	0.02^{***}
Years	0.004^{***}	0.004^{**}
Medium	0.10	0.13
Small	-0.04	0.02
Micro	-0.76^{***}	-0.68^{***}
Utilities	-11.14	-34.68
Construction	0.36	0.53
Manufacturing	0.18	0.33
Retail	0.40	0.53
Wholesale	0.43	0.59
Transport	0.37	0.52
Media	-1.04^{*}	-0.96
Finance	0.38	0.62
Real estate	0.48	0.65
Prof. services	0.44	0.67
Corporate	0.49	0.78
Maintenance	-0.04	0.17
Education	0.19	0.41
Health	0.46	0.73
Leisure	0.10	0.33
Hotels, rest. & bars	0.87^{**}	0.92^{*}
Other	0.21	0.36
$\hat{\alpha}$	-	8.79
AIC	25467.69	20034.18
BIC	25665.61	20240.34
Log Likelihood	-12709.85	-9992.09
Deviance	20312.38	7334.91
Num. obs.	28179	28179

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table 17: Results of estimations for models including "Subsector".

(MNB_a), which would suggest that it is the best fitting model. However, evaluating the model by sequentially adding each regressor suggests that the

	LR test	*df*	*p*-value
NB_b vs NB_{null}	448.48	8	< 0.001
NB_b vs PO_b	5562.62	1	$< 0.001^{\dagger}$

†Half the *p*-value of a χ^2 distribution with 1 *df* (Goldstein, 2011).

Table 18: Likelihood ratio tests for models including "Subsector"

sector variable does not improve the fit significantly[35] (See: Table 19). On the other hand, the same analysis of NB_b found that all regressors significantly improve goodness-of-fit (See: Table 20), which suggests that using subsector might be a better alternative to sector[36].

In the absence of a multilevel Negative Binomial model that included subsector, effects for unit-level variables based on estimations from NB_b are reported, while area-level effects will be drawn from MNB_a.

	Term	Log-lik	Test	LR test	*df*	*p*-value
1	(Intercept)	-10115.40				
2	Corruption inc.	-10044.90	1 vs. 2	141.00	1	< 0.001
3	Homicide rate	-10042.80	2 vs. 3	4.20	1	0.040
4	Years	-10026.60	3 vs. 4	32.40	1	< 0.001
5	Sector	-10025.00	4 vs. 5	3.20	2	0.201
6	Size	-9908.84	5 vs. 6	232.32	3	< 0.001

Table 19: Likelihood ratio tests for sequentially including terms of MNB_a

4.2 Unit-level effects

The intercept summarizes the effects of base categories for nominal variables on the expected mean of extortions assuming zero values for continuous variables. Thus, considering estimations for NB_b in Table 17, the reference business is large, in the mining subsector, experienced zero corruption incidents, started operations in 2013 (as the value for years is zero), and is in a

[35]We also tested each regressor for the single-level model (NB_a) and found similar results.

[36]AIC and BIC values are not much help to discriminate between NB_a and NB_b, since AIC is lower for the latter and BIC for the former.

	Term	Log-lik	Test	LR test	*df*	*p*-value
1	(Intercept)	-10250.09				
2	Corruption inc.	-10177.27	1 vs. 2	145.63	1	< 0.001
3	Homicide rate	-10146.82	2 vs. 3	60.91	1	< 0.001
4	Years	-10131.78	3 vs. 4	30.08	1	< 0.001
5	Subsector	-10078.37	4 vs. 5	106.82	17	< 0.001
6	Size	-9992.09	5 vs. 6	172.56	3	< 0.001

Table 20: Likelihood ratio tests for sequentially including terms of NB_b

hypothetical state with zero homicides per 100,000 inhabitants. The mean number of extortion incidents for such reference business is 0.07, given by exponentiating the intercept of model NB_b ($exp(-2.68) = 0.07$).

The coefficient for corruption incidents is significant and positive—which is consistent with preliminary findings in Subsection 3.1.2. However, the effect appears to be much larger than what the bivariate test suggested: every corruption incident experienced by a business in 2013 increases extortion incidence by 38% ($(exp(0.32) - 1) \times 100 = 37.7$).

The number of years in operation is significant and positive as well; yet the effect is quite negligible, as an additional year in business represents an increase of 0.4% in extortions ($(exp(0.004) - 1) \times 100 = 0.4$). This finding is not surprising, given the weak association between years and extortion incidents reported by bivariate testing in Subsection 3.1.2.

Medium and small businesses experience the same mean number of extortions as large businesses, as their coefficients are not significant. However, the coefficient for micro-sized businesses—i.e., those with less than 10 employees—is significant and negative, meaning that a micro-sized business will experience 49% less extortions than larger businesses ($(exp(-0.68) - 1) \times 100 = -49.3$).

Finally, coefficients for most subsector categories—other than "Hotels, restaurants and bars"—are not significant, thus there is no difference in extortion incidence between most subsectors. On the other hand, "Hotels, restaurants and bars" experience a significant one and half times (151%) greater

incidence of extortion than the reference business ($(exp(0.92) - 1) \times 100 = 150.92$).

Coefficients estimated via Poisson regression were generally consistent with those estimated by the Negative Binomial model, except for the coefficient for corruption incidents, which varies greatly between both models. The corruption IRR in NB_b is 9.5 times higher than in PO_b, where suffering one corruption incident increases extortion incidence by only 4% ($(exp(0.04) - 1) \times 100 = 4.0$). This discrepancy will be addressed in the Discussion Section (5).

4.3 Area-level effects

As multilevel models control for unobserved differences between states, the effect of state homicide rates will be more precisely estimated using such a design. Thus, estimates for this variable are from Table 14. The homicide rate is significant for both Negative Binomial models. However, note how the size of the effect is halved between the multilevel and single-level models. In MNB_a an increase of one homicide per 100,000 inhabitants represents an increase of 1% ($(exp(0.01) - 1) \times 100 = 1.00$) in extortion incidence, whereas NB_a predicts a 2% increase ($(exp(0.02) - 1) \times 100 = 2.02$). Furthermore, the significance of homicides in MNB_a is much closer to the 0.05 rejection threshold. This suggests that, once unobserved differences between states are accounted for by the random intercepts variance, the effect of the state homicide rate diminishes both in size and in statistical significance.

Nonetheless, as the homicide rate varies largely between states (See: Table 11) it is informative to explore its effect on the mean incidence of extortion within a state. For example, businesses in Yucatán—the state with the lowest rate in the country with 1.94 homicides per 100,000 inhabitants—can expect an increase of nearly 2% on extortion incidence due to the state homicide rate ($(exp(0.01 \times 1.94) - 1) \times 100 = 1.96$). On the other hand, businesses in Guerrero—the state with the highest homicide rate with 59.22 homicides per 100,000 inhabitants—can expect an increase of 81% in the incidence of extortion attributable to the homicide rate alone ($(exp(0.01 \times 59.22) -$

1) $\times$ 100 = 80.79). Once unobserved state differences are accounted for, the national average rate of 16.16 homicides per 100,000 inhabitants raises the expected incidence of extortion by 17% ($(exp(0.01\times16.16)-1)\times100 = 17.53$).

4.4 Unobserved heterogeneity

As discussed in Subection 3.2, unobserved heterogeneity is captured by the $\hat{\alpha}$ parameter and accounts for differences in extortion risk that cannot be explained by regressors. This measure of unobserved heterogeneity becomes more meaningful when comparing different values of $\hat{\alpha}$ from models fit to the same dataset. Thus, consider how the value of $\hat{\alpha}$ from null model NB_{null} decreases from $\hat{\alpha} = 10.49$ to $\hat{\alpha} = 8.79$ in model NB_b in Tables 15 and 17, respectively; meaning that the regressors in NB_b reduce unobserved heterogeneity by 16%. Furthermore, introducing random intercepts further decreases unobserved heterogeneity by 11%, from $\hat{\alpha} = 8.80$ in the single-level model (NB_a) to $\hat{\alpha} = 7.08$ in multilevel model MNB_a in Table 14.

The between-states variance, $\hat{\sigma}_{u0}$, can be similarly analysed. Introducing regressors diminishes between-state differences by 8%, from 0.23 in MNB_{null} to 0.21 in MNB_a. However, once unobserved heterogeneity from regressors captured by $\hat{\alpha}$ is taken into account, the persistent unexplained state heterogeneity actually increases by 6% from $\hat{\rho} = 0.024$ in MNB_{null} to $\hat{\rho} = 0.026$ in MNB_a[37], which suggests that state homicide rates capture a small amount of between-states differences.

On the other hand, recall from Subsection 3.2.2 that persistent unexplained state heterogeneity reported in the preceding paragraph is given by the intra-state correlation, $\hat{\rho}$. Thus, another way of interpreting the value of $\hat{\rho}$ is to see it as the likelihood of two identical businesses experiencing the same extortion incidence simply due to being in the same state. The considerably small value of $\hat{\rho}$ suggests that, after controlling for business characteristics and unobserved heterogeneity, businesses in different states experience little variation in extortion incidence.

[37] Calculated by $\frac{0.23}{(0.23+9.09)} = 0.024$, and $\frac{0.21}{(0.21+7.78)} = 0.026$, respectively

5 Discussion

This research addressed two questions: whether extortion victimisation concentrates within a small subset of businesses, and, if so, what could explain these patterns.

The analysis in Subsections 3.1.1 and 4.1 provides strong evidence in favour of our first hypothesis: the concentration of extortion cannot be explained by chance alone. These results bridge findings from the literature on repeat victimisation with research on extortion, which has long assumed that extortion involves periodic payments and serial victimisation (Best, 1982; Kelly et al., 2000; La Spina et al., 2014), though, this assumption must be nuanced. Common characterisations of extortion assume that organised crime groups request payments from businesses weekly or monthly. However, the observed distribution in Table 1 (See: Subsection 3.1.1) suggests that very few businesses experience such high frequencies: only 0.12% of businesses (1.5% of victims) were extorted more than ten times 2013—yet this small subset of repeatedly extorted businesses was burdened with 13.5% of all incidents. Thus, it appears that while the overall prevalence of such systematic extortion may be low, its incidence is disproportionally high.

Regarding the second hypothesis, corruption incidents were found to be positively associated with a higher extortion incidence, as predicted. It is not possible to assert a direct causal relationship between corruption incidents and extortion using cross-sectional data, however we proposed three possible mechanisms in Subsection 2.3 that may explain the link between the two variables. Nonetheless, regression results suggested the presence of endogeneity, meaning that both corruption and extortion may be determined by unobserved heterogeneity affecting target attractiveness for both crimes[38].

On the other hand, there was no evidence to support the third hypothesis, which expected new businesses to experience higher extortion incidence. In fact, the opposite appears to be true: businesses with more years in operation are likely to suffer more extortion. Three explanations for the divergence seem plausible, (i) if a business that started operations in 2013 opened late

[38]This issue is discussed in further length in Subsection 5.1.3.

in the year, they are likely to report fewer extortion incidents than other businesses, as they were vulnerable to victimisation for a shorter period of time; (ii) the association may be the product of data anomalies, such as outliers; and (iii) it may be that businesses that have been in operation for longer are indeed more vulnerable to extortion. To counter the first point, a subsequent study could include the effect of being a new business by incorporating an indicator variable. The second issue could be addressed by scrutinising outlying data points and reclassifying the years variable from continuous to categorical. Subsequent studies could explore the third issue in more detail, as at the moment it is not clear what is the mechanism fueling this association.

There was evidence to support the fourth hypothesis, which tested whether extortion incidence varied according to business size. However, as the literature provided contradictory accounts as to how size would influence extortion, no specific predictions were made. Results indicated that extortion incidence is not different for large, medium and small businesses, and that the smallest micro-businesses suffer significantly less extortions. These results contradict specific conclusions regarding extortion in Mexico (ONC, 2014)[39], and more general findings regarding crimes against businesses in the UK (Gill, 1998). On the other hand, they are somewhat consistent with those reported by Broadhurst et al. (2011), as they found that large businesses (i.e., those with more than 250 employees) suffer more extortion than smaller businesses. While the specific way through which business size influences extortion in Mexico is not clear, a mechanism based on the rational choice perspective is proposed: micro-businesses make less money than larger businesses, thus they may prove an unattractive target not worth the risk nor the effort involved with committing extortion. When confronted with the option of extorting one large business or twenty small ones to obtain the same amount of money, a rational criminal would opt for the former, as it may involve less effort and exposure.

The fifth hypothesis predicted that business sector was a relevant factor, and specified that hotels, restaurants and bars, and businesses in retail ex-

[39]Though it should be noted that analysis by ONC (2014) was technically flawed.

perienced more extortion. Results revealed that aggregated categories of business sector do not experience significantly different levels of extortion; however a more detailed classification by subsector suggested that hotels, restaurants and bars indeed suffer significantly more extortion, though no differences were found between any other subsectors. These results support findings by Hopkins (2002), who points out that aggregating sectors assumes that businesses within these categories share the same attributes and—as a result—the same crime risks, while research has shown that "the experience of victimization is more adequately measured by individual business type rather than sector" (Hopkins, 2002, p. 785).

The subsector categories used in this research could still be disaggregated to more meaningful business types; for example, retail lumps very different businesses in one category, from petrol stations and convenience stores to large general supermarkets, as well as e-commerce and telemarketing. However, it is uncertain if the ENVE data could be modelled using such specific categories; perhaps using specific indicator variables for certain business types considered relevant would be a suitable compromise.

The last two hypotheses tested for area-level effects. Results suggested that there is a statistically significant variation in extortion incidence between different states, and that states with higher homicide rates have higher extortion incidence. However, both area-level effects have a modest impact on extortion incidence. These findings contrast with public debates that tend to analyse extortion—and other crime phenomena in Mexico—at aggregated state-levels (e.g., ONC, 2014). Results indicated that differences between individual businesses, rather than between states, account for most sources of extortion risks.

Overall, between-businesses and between-states differences contributed to explaining a third of the individual variation in extortion incidence. However, results show that unobserved heterogeneity—i.e., the amount of differences that are still unaccounted for—remains quite large. Results reported in this research cannot distinguish how much unobserved heterogeneity is due to risk heterogeneity or to event-dependence, and while a comprehensive analysis of the latter is not possible using cross-sectional data, subsequent ENVE sweeps

could measure additional variables relevant to risk heterogeneity, such as type of building and location, operating hours, and type of ownership, to name a few. This information would be relevant for victimisation studies of a wide range of crimes.

5.1 Limitations

Beyond specific limitations mentioned throughout the document, this section deals with the main sources of threats to validity to assess the overall limitations of the project.

5.1.1 Construct validity

Other than limitations inherent to victimisation surveys mentioned in Subsection 2.1, it is pertinent to discuss whether differences in how extortion incidents were executed—e.g., in person or via telephone—constitute different types of extortion. Mexican debate on extortion distinguishes between telephone-extortion—which involves convincing victims via telephone that they will be harmed if they do not comply with demands, though there is usually little actual risk—and extortion rackets[40]—which are usually directed at businesses and have led to grave episodes of violence (ONC, 2014). The former is believed to be a form of scam, while the latter is considered a more "genuine" form of extortion by organised crime.

While telephone-extortion is defined by the method by which victims are approached, there is no indication that victims of extortion rackets are *not* approached by telephone. Felbab-Brown (2011) reports that organised criminals in Mexico contact businesses by phone when approaching the premises in-person becomes too risky, and Broadhurst et al. (2011) finds that extortion against businesses in China is equally likely to involve visits to premises and telephone threats. Thus, there is little support from the literature to categorically differentiate extortion incidents against businesses based on the method of approach.

[40]The Spanish term is *cobro de piso*, and can be roughly translated as a fee to operate.

Additionally, this research cannot differentiate whether extortion incidents were committed by "true" organised crime groups one usually associates with the *Organised Crime* phenomenon[41], or by more informal bands of "organised criminals". Analysis of victimisation survey data can provide insights into offender's choice of target (Hough, 1987), yet other than the assumption of rational decision-making (Clarke & Cornish, 2013; Cornish & Clarke, 2002; Natarajan, 2012) and acknowledging that extortion is a crime usually committed by organised crime (La Spina et al., 2014; Tilley & Hopkins, 2008; van Dijk, 2007b), this research makes no assumption regarding offenders and their degree of organisation. Ultimately, if offenders engaged in different types of organisations and co-offending structures select extortion victims based on the same features of businesses, offender organisation becomes less important, as addressing the sources of risk heterogeneity may have impact on a wide range of offenders.

5.1.2 Internal validity

Cross-sectional data limits the ability to draw inferences of causality between variables when associations are detected (Sidebottom, 2013). While this is not a problem for the majority of the variables in this study, it is a threat for the association between extortions and corruptions incidents. While it cannot be established that suffering a corruption incident *directly* increases the likelihood of extortion victimisation, the association might suggest that the variables share underlying patterns of risk (See: Subsection 5.1.3).

This limitation guided variable choices in other ways. For example, ENVE data collects information regarding the implementation of security measures, perceptions of security and whether victims complied with extortion demands. It would been very valuable to test whether such variables were related to extortion risk; however, the cross-sectional nature of the data makes it impossible to draw meaningful associations between these type of variables, as causality could flow both to and from extortion incidence.

A potential way to deal with this limitation in future ENVE sweeps is

[41]By which we mean the sophisticated groups and networks also referred to as drug "cartels" and Mafia-type organisations (Bunker, 2013; Frazzica et al., 2013; Garzón, 2008).

to modify sampling procedures and include an embedded panel (Hopkins & Tilley, 2001), thus allowing comparisons between different time periods. This approach would also facilitate testing whether previous victimisation incidents are related to future victimisation, something that is limited in cross-sectional surveys as well (Osborn & Tseloni, 1998; Tseloni et al., 2002).

5.1.3 Statistical conclusion validity

There are two main sources of threats to statistical conclusion validity in this research.

First, as mentioned in Section 5, results suggested that there was a problem of endogeneity regarding corruption incidents. This variable measures event counts as well, and its distribution appears to be greatly overdispersed[42]. This suggests that, rather than being caused by random variation, corruption victimisation may be related to differences between businesses. Thus, it is possible that extortion and corruption are jointly determined by omitted variables. This suggests that corruption incidents may be correlated with unobserved heterogeneity (Cameron & Trivedi, 1998), and when controlling for such in the Negative Binomial model, the estimated coefficient for corruption incidents may be affected.

It was not possible to address this issue within the time frame for this research, though subsequent studies may attempt to control endogeneity using instrumental variables or alternative modelling approaches (Cameron & Trivedi, 1998).

Second, multilevel modelling increases complexity significantly, thus alternative methods of estimation and evaluation should be implemented to improve robustness of estimates and standard errors. While such exercises were beyond the scope of this project, subsequent studies would benefit from implementing models and testing methods based on simulations, such as bootstrapping and Markov Chain Monte Carlo (Cameron & Trivedi, 1998; Goldstein, 2011).

[42]The distribution's mean-variance relationship ($\mu = 0.1080$, $\sigma^2 = 1.82$, $\frac{\mu}{\sigma^2} = 16.85$) and its associated index of dispersion ($I = 474907.3$, $df = 28178$, $p < 0.001$) confirm this assumption.

Nonetheless, as most results proved to be consistent across the different models implemented, findings are judged as reasonably robust.

5.1.4 External validity

The generalisability of results in this research is somewhat limited. First, survey weights were not used. The ENVE survey employs complex sampling procedures that deliberately oversample medium and large businesses and accounts for differences between states. Such complex designs mean that statistical analysis should use survey weights to control for violating the assumption of random sampling. However, weighted multilevel modelling is still not implemented in R (see Lumley, 2011). Nonetheless, in an evaluation of different software tools that implement weighted multilevel models, Carle (2009) found that differences between estimates and standard errors from weighted and unweighted models were small and did not lead to different inferences. Thus, it can be assumed that results from this project are reasonably representative of the sampled population.

An altogether different issue regarding generalisability is that the sampling frame includes only formal businesses. Business informality is an extended feature of the Mexican economy, thus a sample taken from formal businesses may not be representative of the entire population of formal and informal businesses. Additionally, informal businesses may be more vulnerable to extortion, as their irregular status may prevent them from seeking recourse from law enforcement and they are more likely to operate in exposed conditions, such as on streets and public markets. Therefore estimates presented here are limited to the population of formal businesses in Mexico, while the true incidence of extortion may well be higher.

Lastly, as findings were somewhat consistent with predictions drawn from international experiences with crimes against businesses in general, and extortion in particular, results contribute to general trends identified regarding this crime in other countries. Nonetheless, specific predictions and estimates are constrained to the Mexican context.

6 Conclusions

To my knowledge, this project represents the first rigorous analysis of repeat victimisation in Mexico, as well as the first analysis of repeat extortion victimisation. Thus it contributes to the literature in several ways. First it corroborates the importance of repeat victimisation to explain overall crime patterns by applying this paradigm to a new context. In this way it joins a very small number of efforts that have been conducted outside English-speaking and European countries. Second, it expands the application of repeat victimisation to non-traditional crimes, branching towards organised crimes and providing more bridges between environmental criminology and the study of organised crimes. Third, it contributes to studies on crimes against businesses, both by focusing on a new context and by analysing a prevalent—though understudied—crime.

However, the project has implications that go far beyond academia. While a detailed discussion of these is beyond the scope of this document, the main policy implications are as follows:

- Crime Prevention: Results provide guidance as to risk factors associated with extortion, thus by developing interventions targeted at a small subset of chronically victimised businesses, the overall incidence of extortion may be greatly reduced.

- Crime research and policy: The project provides initial evidence to support a shift towards research-based crime policy in Mexico.

- Victimisation surveys: Several suggestions to improve the measurement of victimisation in the country can be drawn from the results, in particular the need to expand measurement of business and environmental characteristics that may be related to risk factors for extortion.

Lastly, the project represents a first step towards understanding—and eventually preventing—a largely understudied crime. Findings highlight many areas that need to be researched further, for example: scrutinising the relationship between business age and extortion, analysing extortion incidence in more specific business types for some subsectors, exploring the

relationship between building type and location with extortion, and the procedural analysis of extortion victimisation, to name but a few areas. Hopefully, subsequent studies will find in this project a useful starting point to build upon and develop finer insights.

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