Dynamic relationships between criminal offending and victimization[1]

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ABSTRACT

In the economics of crime, it is a stylized fact that those who commit crimes are more likely to be victims of crime. Similarly, victims of crime are more likely to be criminals. We explore the simultaneous nature of this relationship using a census of all police investigations in New Zealand between 2014 and 2020. We first revisit this hypothesis by following previous literature and pooling data over time and using recursive bivariate probit methods. This provides evidence of a weak, but fully simultaneous, relationship between criminality and victimhood. We next explore the overlap hypothesis by examining the intertemporal relationships between criminality and victimhood using a monthly panel of individuals chosen randomly from the New Zealand population. Panel fixed effects models reveal that previous victimization (offending) is only positively linked to current offending (victimization) in the months occurring immediately before offending (victimization). This suggests that the overlap between victimhood and criminality is driven primarily by 1) criminal incidents occurring close together in time or 2) incidents where individuals are at once considered both the victim of a crime and an offender (e.g., mutually combative assaults). The detailed nature of New Zealand Police records allows us to further explore intertemporal relationships by incident type, including violent crimes, property crimes, intimate partner violence, and offenses involving weapons.

JEL Classification: C35, J12, K42, I19, Z13
Keywords: victim-offender overlap, simultaneity, crime, victimization

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[1]Disclaimer: The results in this article are not official statistics, they have been created for research purposes from the Integrated Data Infrastructure (IDI), managed by Statistics NZ. The opinions, findings, recommendations, and conclusions expressed in this article are those of the authors, not Statistics NZ. Access to the anonymized data used in this study was provided by Statistics NZ in accordance with security and confidentiality provisions of the Statistics Act 1975. Only people authorized by the Statistics Act 1975 are allowed to see data about a particular person, household, business, or organization, and the results in this report have been confidentialised to protect these groups from identification. Careful consideration has been given to the privacy, security, and confidentiality issues associated with using administrative and survey data in the IDI. Further detail can be found in the Privacy impact assessment for the Integrated Data Infrastructure available from http://www.stats.govt.nz.

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1. INTRODUCTION

Von Hentig (1940) noted that the reciprocal relationship between offenders and victims of crime, the so-called victim-offender overlap, *``is one of the most curious phenomena of criminal life…''*. But over 80 years after Von Hentig's seminal work, our knowledge of the nature of this overlap is still very limited. While the criminology literature on the link between offending and victimization is huge (see e.g. Lauritsen and Laub 2007; Berg et al. 2012; Jennings, Piquero, and Reingle 2012; Berg and Mulford 2020 for comprehensive literature overviews)[6], for a long time, the focus of the literature was on the identification of the descriptive relationship and on the role of time-invariant population heterogeneity in simultaneously determining victimization and offending without any specific focus on dynamic causal effects.

With the rise of the literature on the economics of crime, it was especially economists who first attempted to identify causal relationships between offenders and victims with their focus being on the economic rationale behind criminal behavior (Entorf 2013; Balkin and McDonald 1981; Deadman and MacDonald 2004). In this literature, an empirically identified dynamic link of previous offending and current victimization is often discussed in the light of earlier offenders being less risky targets for current offenders as they are often more exposed. On the other hand, the rational decision of an earlier victim to commit a crime is mostly attributed to retaliatory behavior spurred by anger and negative reciprocity. Although the empirical literature has made progress in isolating population heterogeneity from dynamic causal effects in the past years, it still lacks a clear and generalizable conclusion. The major reason for this is the lack of good administrative data with detailed information on the timing of offending and victimization. Previous studies attempted to identify the overlap using, in parts, very selective, survey data that lacked information on the exact timing of offending and victimization. This meant that the results may lack external validity and could not fully examine the dynamic nature of the relationship.

This is where we make a major contribution to the literature. Based on administrative data on all recorded criminal occurrences, including the identification of offenders and victims, in New Zealand (NZ) between 2014 and 2020, we are able to identify a victim-offender overlap in the universe of reported crimes.

[6] Section 2 also gives a detailed overview over the most relevant literature of the past years.

Due to its moderate crime rates[7] as well as the close similarity of its criminal justice system with the systems in e.g., the United States and the United Kingdom[8], the international relevance of a study which concentrates on data from New Zealand is distinct.
Specifically, we use monthly panel data available from the Integrated Data Infrastructure (IDI) of Statistics NZ. The IDI connects data from various sources, including crime data from NZ Police, which records information on both offenders and victims (if not victimless crimes) for all criminal incidents from 2014 to 2020. Thus, we have a unique high-frequency panel dataset of offenders and victims of all, allowing us to estimate the dynamic causal effects between offending and victimization for the resident population of New Zealand.

We first follow previous literature by pooling data over time and using recursive bivariate probit methods. Based on this analysis, we find similar results to previous literature of a weak, but fully simultaneous relationship between criminality and victimhood. We next explore the overlap hypothesis by examining the intertemporal relationships between criminality and victimhood. Panel fixed effects models reveal that there is little relationship between previous victimization (offending) and current offending (victimization). Indeed, previous victimization (offending) is only positively linked to current offending (victimization) in the months occurring immediately before offending (victimization). These results are further corroborated by Arellano-Bond dynamic panel models.

Our findings shed an interesting new light on the causal nature of the victim-offender overlap. As opposed to the earlier literature, we can show that the dynamic link can only be observed in the very short run and becomes very weak as soon as we exclude simultaneous events (where an individual is both an offender and victim) from the consideration. Very large parts of the observed dynamic links are thus driven by these simultaneous events. The remaining consecutive overlap between victimization and offending can in very large parts be explained by time-invariant individual characteristics and are thus driven by population heterogeneity.

Population heterogeneity explanations of the VOO hold up empirically. This includes explanations from criminology literature and rational choice theory …. In terms of rational choice theory, expected costs and benefits of crime depends on individual characteristics and

[7] Data from the United Nations Gallup World Poll reveals that New Zealand has comparable crime rates for certain offenses compared to the U.S. and U.K. Specifically, over the years 2006-2019 the estimated percent of the New Zealand population that was affected by theft and violence (i.e., assault/mugging) was 16 percent and 2 percent, respectively. For the U.S. these percentages were estimated to be 14 percent and 2 percent, respectively. Over the same period, the percentage of the population that was estimated to be victimized by theft and violence in northern Europe was 11 and 3 percent, respectively (van Dijk, Niewbeerta, and Larsen, 2021).

[8] For example, the US, the UK and New Zealand criminal justice system follows case law, based on a common law system (as opposed to civil law system which is common e.g., in continental Europe).

these are largely time invariant, at least over the short- to medium-term. Experiencing victimization or undertaking offending doesn't seem to change these expected costs and benefits (e.g., due to revealing new information in presence of imperfect info). Small exception for some types of crime in the very short run, but this also fits with rational choice theory. E.g., some short-term dynamic relationships for violent crimes, where expect that retaliation may come into place…. But no short-term dynamic relationship for property crimes, where rational choice theory predicts that offenders will choose high-value victims where the expected payoff is higher, but there's little reason to expect these victims to retaliate given the relatively low expected payoff vs. high expected costs to them doing so.

The outline of the paper is as follows. Section 2 gives a brief overview over the existing literature and the theoretical background behind the victim-offender overlap. Section 3 describes the data and Section 4 summarized the estimation strategy. Section 5 presents an overview of the estimation results and Section 6 gives an overview over various heterogeneity analyses. The paper concludes in Section 7.

2. EXISTING LITERATURE AND THEORETICAL BACKGROUND

The positive association between observed offending and observed victimization is a relatively undisputable stylized fact in the criminology literature. The works of Hans von Hentig (1940; 1948) and Marvin E. Wolfgang (1958) were among the earliest and most influential contributions to the criminology literature, introducing the idea of a mutual and reciprocal relationship between perpetrators and victims. Since then, a significant body of literature has evolved on the link between victimization and offending, drawing a surprisingly clear picture: *"…we are unaware of any research that has examined the link between offending and victimization and failed to find a strong relationship. The relationship has been found across time, place, and for various subgroups."* (Lauritsen and Laub 2007, p.60) [9] Recognizing this stylized fact had a tremendous effect on the criminological literature and was a milestone for the research on the drivers and causes of crime in general (Reiss 1981; Berg and Mulford 2020).

The criminology literature which attempts to explain the association between victimization and offending can be roughly divided into two types. First, attempts based on assumptions about population heterogeneity. These explanations highlight that a victim-offender overlap exists due to (largely) time-invariant individual characteristics, but do not suggest a dynamic

[9] See Lauritsen and Laub (2007), Berg et al. (2012), Jennings et al. (2012) and Berg and Mulford (2020) for comprehensive literature overviews.

relationship whereby offending will lead to subsequent victimization or victimization will lead to subsequent offending. Second, attempts to identify dynamic causal effects caused by state-dependent processes, whereby offending does lead to an increased risk of subsequent victimization and/or vice versa. (Lauritsen and Laub 2007).

Population Heterogeneity in Criminology

The analysis of population heterogeneity dominated the criminology literature for many years. This concept describes a relationship between victimization and offending driven by unobserved socio-demographic, economic or psychological characteristics. The most prominent explanation is the so-called "lifestyle perspective'' initiated by the work of Hindelang *et al.* (1978), which assumes an important role of differential exposure to crime. Based on this theory, the lifestyle and everyday activities of many offenders and victims are dominated by relatively risky behavior patterns which directly increase their risk of being exposed to crime (Osgood et al. 1996; Cohen and Felson 1979; Foreman-Peck and Moore 2010). These theoretical considerations were supported in multiple empirical studies finding a strong link in the socio-demographic profiles of victims and offenders (Singer 1981; Sampson and Lauritsen 1990; Wittebrood and Nieuwbeerta 1999; Broidy et al. 2006; Silver et al. 2011; Turanovic, Reisig, and Pratt 2015). Very closely linked to this is the idea of "crime concentration'' which was introduced by Weisburd and co-authors (2012; 2014). This suggests a very high importance of neighborhoods for the explanation of the overlap between victimization and offending. In addition to these lifestyle and exposure explanations, a personality perspective has also been put forward. This suggests that individuals with certain personality traits, such as low self-control, are more likely to be offenders and victims, leading to a victim/offender overlap (Gottfredson and Hirschi 1990; Piquero et al. 2005; Flexon, Meldrum, and Piquero 2016; Turanovic, Reisig, and Pratt 2015; van Gelder et al. 2015).

Population Heterogeneity in Economics of Crime

While the victimization and offending overlap first emerged in the criminology literature, and the economics of crime literature does not say much explicitly about it, it is also consistent with the rational choice and behavioral economics literature in this area. Since the application of rational choice theory to the economics of crime considers that individuals weigh up the expected costs and benefits of crime, and these will vary depending on the characteristics of the individual in terms of outside opportunities (e.g., younger, lower income, less educated individuals have less to lose and more to gain from committing crimes), their degree of risk aversion and how heavily they discount the future.

In terms of the overlap with victimization, this literature offers two conflicting possibilities. First, a rational offender will target victims who offer a high payoff, for example, higher wealth individuals. However, higher wealth individuals have more to lose and less to gain from committing crimes, leading to a clear difference in characteristics between those who theory would predict would be offenders and victims. On the other hand, those who are less risk averse and/or have higher discount rates are more likely to partake in a risky lifestyle and pay less mind to their personal safety, leaving them more exposed to being a potential victim. This seems to suggest that the victim/offender overlap would differ depending on crime type, and in particular, would be stronger for violent crimes where the population heterogeneity explanations would be more relevant, and weaker for property crimes where the rational choice to target victims with higher expected payoffs would be more relevant.

While some insights into population heterogeneity explanations can be drawn from rational choice theory, there are only a handful of economic models which explicitly address the victim/offender overlap. These mostly fall under this first umbrella of population heterogeneity and emerged relatively early on. Balkin and McDonald (1981) suggested an economic model of crime which is based on the amount of time spent in public spaces which expose potential victims to the risk of crime. Closely related is the idea of a "subculture of violence'' in which victims and offenders are exposed to very similar crime-endorsing values and behaviors which again reinforce the same behavior among them as detection rates as well as especially informal punishment are low (Jensen and Brownfield 1986; Agnew 1992; Akers 2011; Berg et al. 2012). An extreme example for this idea is the analysis of gang memberships and its role in explaining the victim-offender overlap (Pyrooz, Moule, and Decker 2014).

Dynamic causal relationship

While the descriptive empirical literature on these different aspects of population heterogeneity is rich, very few empirical studies attempt to identity the dynamic relationship between offending and victimization. As summarized by Lauritsen and Laub (2007), these dynamic relationships are caused by state-dependency whereby current experiences affect future risks. In line with the discussion of the lifestyle hypothesis above, a dynamic effect of offending on victimization and vice versa exists if the event causes the victim or offender to change aspects of her lifestyle, her risk-preferences, or her social environment. In addition to this indirect effect, a direct effect can be hypothesized especially from earlier offending on victimization risk in line with the arguments in Jensen and Brownfield (1986) as well as Deadman and McDonald (2004), if we assume that offending increases a person's vulnerability and exposure to future crime.

Behavioral economics also offers insights into the victim/offender overlap, particularly the possibility of a dynamic relationship in the direction of victimization leading to subsequent offending, as summarized in (Entorf 2013). Humans seem to have an innate desire for fairness and willingness to retaliate even if this is costly to themselves in the short run (Fehr and Gächter 2002). This is confirmed by the findings of experimental economics (Fehr and Schmidt 2006). This suggests that retaliation by victims, leading to a dynamic relationship whereby victimization leads to offending. This idea is also found in the criminological literature, where anger in response to being victimized triggers retaliation (for example, Agnew 1992; Kubrin and Weitzer 2003; Jacobs and Wright 2010; Simons and Burt 2011). However, the criminology literature suggests that this could be directed towards the perpetrator or undirected 'lashing out' towards those who were not involved in the original perpetrating, the latter of which does not fit as well with the economics literature. Directed retaliation may also be considered rational in the context of a repeated game where punishment reinforces cooperative behaviour. This is consistent with results from experimental economics which highlights that altruistic punishment to maintain cooperation is only used when conditions are relatively favorable – that is, where costs to the punisher are relatively low and the impact on the punished is relatively high (Egas and Riedl 2008). It should also be noted that these retaliatory motives explanation implies a dynamic relationship in one direction only: from victimization to offending, but not vice versa. Even more closely connecting victimization and offending than retaliation are simultaneous victim-offender events. For example, in mutually combative events such as bar fights, a direct causal link between victimization and offending can be observed (Daday et al. 2005).

Empirical Evidence

To date, there has been limited empirical testing of these theories. One major reason for the gap in the empirical literature which attempts to identify a dynamic causal relationship between offending and victimization was the lack of good longitudinal data which allows for such a perspective. Lauritsen et al. (1991) were among the first studies to use longitudinal survey data in order to identify the sequencing of victimization and offending in more detail. They found a strong dynamic relationship between both even when sociodemographic and environmental characteristics are controlled for. These findings have later been supported by a number of empirical studies (see e.g. Jennings et al. 2010; Schreck, Stewart, and Osgood 2008). As opposed to the above discussed literature, more recent studies concentrate on more sophisticated econometric models in combination with longitudinal data to identify the dynamic causal relationship between victimization and offending. For example, Deadman and MacDonald (2004) analyze data from the 1998 Youth Lifestyles Survey of about 4,000 people aged 12-30 in England and Wales. Using recursive bivariate probit analysis, they find that offenders are more likely to be victims, but not vice-versa. Ousey *et al.* (2011) base their analysis on data from the rural Substance Abuse and Violence Project (RSVP) which follows 4,102 students in Kentucky from 7th to 10th grade (13 – 16). Using fully simultaneous latent variable structural equation modelling they find that offenders are more likely to be victims but they, too, do not find any dynamic effect of victimization on offending. Finally, Entorf (2013) uses data from the German Crime Survey involving a highly selective sample of 960 adults above the age of 18[10]. Based on a recursive bivariate estimation model, he comes to a very similar conclusion as the other two studies.

Nevertheless, these studies also lack external validity as they are based on selective samples of e.g., teenagers, young adults or prisoners, or they lack accuracy because they only rely on self-reported information about victimization and offending from survey data (see Jennings, Piquero, and Reingle 2012). This limits the generalizability of the results – it is unclear if they really apply to the average citizen. The timing of any offending and victimization also lacks precision, with the survey data only recording whether the respondent said they were a victim or offender within a certain time period (e.g., the last 12 months), and not whether the offending occurred before the victimization or vice versa. This limits the ability to use dynamic panel models that take account of whether the observed offending occurred before or after any victimization.

As will be described in the next section, this study uses monthly recorded offending and victimization from national police administrative data. This allows us to apply dynamic panel econometric techniques that take account of the timing of any victimization and offending to an extremely rich dataset that covers the entire population. This allows us to

[10] The sample is highly selective as it was designed as a nationwide control group (of the non-incarcerated population) for the German Inmate Survey and thus resemble the prison population. It is, thus on average, younger and less educated than the general German population as well as predominantly male.

explore the nature of the relationship between offending and victimization in a way that previous studies have not yet been able to. In particular, the richness of the data allows us to test various explanations for the observed stylized fact that offending and victimization overlap. Whether it is explained by population heterogeneity or dynamic state-dependency. We are also able to explore the role of simultaneous victim/offending incidents and retaliation. Moreover, the ability to differentiate between different crime types to an extent previous survey-based research has not been able to allows us to provide additional insights into the hypotheses behind the victim/offender overlap.

3. DATA

Integrated Data Infrastructure

For our empirical analysis, we are using administrative data from New Zealand available within the Integrated Data Infrastructure (IDI) of Statistics NZ.[11] The IDI links individual-level administrative and survey data from a range of sources, including population-level justice, tax, welfare, health and education data, via a unique person identifier. Relying on administrative, rather than survey, data for an entire population is novel in the literature regarding victim-offender overlap.

The main IDI sources used in this study are the recorded crime offenders and recorded victims databases collected by the New Zealand Police according to their National Recording Standard (see Statistics New Zealand 2016a; 2016b for a detailed description). The most current version of the offender database collects information on every alleged offender reported between July 2009 to June 2020. Detailed information is available on each criminal incidence. This includes the type of alleged offence committed[12], a standardized measure of its seriousness[13] and the police action taken (e.g., whether the police proceeded with the offence and how, such as informal/formal warning, arrest, and prosecution etc.). Similarly, the recorded victims database includes information on all allege victims of non-victim-less crime recorded by the police on an incident basis between July 2014 and June 2020. Like all IDI data tables, the offenders and victims data are linked via the unique person identifier, allowing us to observe if a person is both an offender and victim. Moreover, each police incident has a unique

[11] We are using data from the October 2020 refreshment of the IDI.
[12] Crime types are categorized based on the Australian and New Zealand Standard Offence Classification (ANZSOC).
[13] The New Zealand justice sector user seriousness scores based on the average sentences that such an offence would carry. For details, see McRae, Sullivan and Ong (2017).

identifier, allowing us to see who was involved in each as either an offender or victim (or both). Since the police records are comprehensive, they include very minor infractions. We, therefore, exclude incidents involving very minor offenses that are not punishable by imprisonment, such as minor traffic offenses.[14]

These data, therefore, gives us the universe of all reported crimes in New Zealand over the period of the data coverage, which is a major advantage as opposed to the survey data. However, some limitations remain. It does not include unreported offences as well as offences that did not involve police proceedings (on the offender-side). Survey data suggests that only about a quarter of crimes are reported to the police (Ministry of Justice 2021). However, surveys which ask respondents about both their offending and victimization are also likely to involve significant reporting, recall and perception errors. A further limitation is that the offenders' data is potentially more complete than the victims' data as police are unlikely to collect personal information from victims who are reluctant to supply it if it is unnecessary, as well as in cases in which victims cannot be clearly identified (such as in the case of burglaries[15]). Lastly, because we are only using 7 years of data, we cannot rule out the possibility of much earlier victimization leading to future offending, for example, in the case of being a victim in childhood. However, having an indicator of parent criminal history may partially deal with this (particularly if the perpetrator of a childhood victimization was the parent).

Sample Definition and Variables of interest

Based on this, we use the dataset of the estimated residential population (ERP) in New Zealand between 2014 and 2020 to define the whole resident NZ population in each month. The ERP estimates who is a member of the resident population based on activity in administrative systems (i.e., the tax, health and accident compensation or education systems, combined with information on border movements) that indicates an individual is present in New Zealand during that year. It, therefore, removes individuals who left the population due to death or outmigration. (See Gibb, Bycroft, and Matheson-Dunning 2016 for details.)
For reasons of computational power, we draw a random subsample of 10% of the population as our spine. We expand the annual ERP observation to a monthly dataset based on the assumption that an individual is part of the NZ population in every month of the year in which

[14] Formally, we exclude Category 1 offenses, as defined by the Criminal Procedure Act 2011. Online at https://www.legislation.govt.nz/act/public/2011/0081/latest/dlm3359962.html (accessed 15 October 2021).
[15] The Police data does not contain information on the victims of burglaries.

she is observed in the ERP. We then merge the observed victimization and offending in a given month to the spine. That is, we exclude offenders and victims who are, for example, visiting New Zealand for only a short time to get a cleaner view of the victim-offender overlap. A single month can involve multiple incidents and an incident can involve multiple alleged offences. For example, an armed robbery may involve both theft and firearm offences. To merge the victim and offender information to a monthly database of the NZ population, we thus collapse the information on the monthly level only keeping the most severe offence per incident and the most severe incident per month. Based on this approach of aggregating the information on the monthly level, our explanatory and dependent variables of interest are indicators for at least one victimization or offence in each month.

Descriptive Statistics

Our 10% random sample includes 393,000 [16] unique individuals with a total of 13,381,700 observation-months (on average about 34 observation months per individual). Between 2014 and 2020, these individuals were involved in 19,000 reported offending/ and 24,300 recorded victimization incidents. As is shown in Table 1, the majority of these individuals (90.53%) were not involved in any incident as either an offender or victim. About 5.14% were involved in at least one incident as an offender, and 3.82% as a victim. About 1% (4,000) were both offenders and victims.

[16] Based on the confidentiality requirements from Stats NZ, all counts, and observation numbers presented are randomly rounded on base 3, percentages are based on rounded counts and counts below 50 are suppressed.

Table 1. Bivariate frequencies and unadjusted conditional probabilities of any victimization or offending, 2014-2020

		victim			
		no	yes	total	
offender	*no*	*353,800*	20,200	374,000	Pr(V_i=1|O_i = 0)
	(cell %)	*(90.53%)*	*(5.14%)*	*(95.17%)*	0.0540
	yes	15,000	4,000	19,000	Pr(V_i=1|O_i = 1)
	(cell %)	*(3.82%)*	*(1.02%)*	*(4.83%)*	0.2105
	total	368,800	24,300	393,000	
	(cell %)	*(93.84%)*	*(6.18%)*		
		Pr(O_i =1|V_i =0)	Pr(O_i =1|V_i =1)		
		0.0407	.1646		

Source: New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS). Counts are from a random sample of ten percent of the New Zealand estimated resident population from June 2014 to May 2020. Counts reflect all victims and offenders investigated for criminal incidents deemed low seriousness, moderate seriousness, or high seriousness. Counts have been randomly rounded to the nearest hundred in accordance with the Stats NZ confidentiality protocol.

While the share of individuals who are both victims and offenders is small, conditional probabilities better highlight the degree of overlap between offending and victimization. For those who were not offenders over the 2014 to 2020 period, there is a 5.1% probability that they are victims. If the individual was an offender, this probability of being a victim increases almost four-fold to 19.8%. Similarly, for those who were not victims, the probability of offending was 4.1%, compared to a probability of offending of 16.2% for those who had been a victim.

Table 2 gives an overview over the characteristics of those who fall into the four groups 1. neither a victim nor offender; 2. an offender but not a victim; 3. a victim but not an offender; and 4. both a victim and offender is as expected. Females are most underrepresented in the Group 2 (an offender but not a victim), and are also underrepresented in Group 4 (both an offender and a victim). Group 4 (both an offender and victim) has a lower average age, followed by Group 2 (offender only), while those who are neither offenders nor victims are older on average. Those in the overlap Group 4 are less likely to be European or Asian and more likely to be Māori or Pacifica. They also have lower average earnings and are much more likely to have had a parent who has been charged with a crime since court records began in 1992.

Table 2 - Descriptive Statistics

	$V_i = 0, O_i = 0$	$V_i = 0, O_i = 1$	$V_i = 1, O_i = 0$	$V_i = 1, O_i = 1$
	mean (s.d.)	*mean (s.d.)*	*mean (s.d.)*	*mean (s.d.)*
Female	.521	.167	.494	.398
Age	46.89 (19.18)	37.62 (13.64)	38.30 (15.42)	34.07 (11.68)
Ethnicity				
European	.644	.404	.541	.366
Māori	.125	.430	.222	.507
Pacific	.059	.110	.065	.074
Asian	.151	.045	.155	.040
MELAA	.015	.011	.016	.012
Other	.006	< .001	.001	< .001
Parent charged	.034	.091	.062	.110
Annual earnings	31,399 (40,736)	20,402 (24,392)	32,590 (38,697)	12,872 (19,015)
Observations	353,800	15,000	20,200	4,000

Source: New Zealand Police Recorded Crime – Victims Statistics (RCVS), Recorded Crime – Offenders Statistics (RCOS), Immigration New Zealand, Inland Revenue, and Ministry of Justice. "Parent charged" equals one if any parent was charged with a crime, and zero otherwise.

Table 3 describes the observed criminal incidents. Two special cases of criminal incidents warrant attention when examining V/O overlap. First, incidents of simultaneous V/O where a person is an alleged offender and victim within the same event. For example, a fight where each person may accuse the other of offending. But, the victimization and offending does not necessarily have to involve the same people. For example, if Fred hits Jim in a bar fight, and then Fred is hit by Mike, then Fred would be recorded as both an offender and victim, although he offended against Jim and was victimized by Mike. About 4.4% of offenders, and 2.6% victims have been involved in at least such incident. The second special case is retaliatory incidents. There is some overlap between these two special cases, but retaliatory incidents must involve the same victim/offender pairing. Retaliatory incidents occur when Fred offends against Jim, and Jim also offends against Fred, either simultaneously or at a later date. Note that this is direct retaliation where the victim retaliates against the specific person who offended against them rather than retaliation involving the victim lashing out at any available victim, as described by Jacobs and Wright (2010). About 5.6% of offenders and 4.1% of victims have been involved in at least one retaliatory incident.

The share who are repeat offenders and repeat victims is higher among those who are both offenders and victims than among those who are only offenders or only victims. Those who are both offenders and victims are more likely to be involved in violent and intimate partner crimes and crimes involving weapons than those who are only victims or only offenders. Also unsurprisingly, those who are offenders only or both victims and offenders are more likely to be involved in intimate partner violence (IPV).

In terms of types of incidents, the share of those who are both offenders and victims who are involved in violent crimes, crimes involving weapons, intimate partner violence is higher than among those who are both offenders and victims. Also, unsurprisingly, violent crimes are the most prevalent type of incident among those who are offenders only or both victims and offenders, property crimes are the most prevalent among those who are only victims.

Table 3. Proportions of crime and victimization types

	$V_i = 0, O_i = 1$ mean (s.d.)	$V_i = 1, O_i = 0$ mean (s.d.)	$V_i = 1, O_i = 1$ mean (s.d.)
Offender:			
Retaliatory	< .001	-	.056
Simultaneous V/O	.006	-	.044
Repeat offending	.393	-	.522
Violent	.538	-	.571
Property	.263	-	.362
Family	.271	-	.306
IPV	.211	-	.237
Sexual	.061	-	.042
Weapon	.172	-	.225
Victim:			
Retaliatory	-	-	.041
Simultaneous V/O	-	-	.026
Repeat victimization	-	.142	.309
Violent	-	.321	.610
Property	-	.714	.502
Family	-	.089	.204
IPV	-	.090	.211
Sexual	-	.045	.050
Weapon	-	.063	.183
Observations	15,000	20,200	4,000

Source: New Zealand Police Recorded Crime – Victims Statistics (RCVS), Recorded Crime – Offenders Statistics (RCOS).

4. EMPIRICAL MODELS

We employ three approaches to examine the overlap between criminality and victimhood: 1) recursive bivariate probit (RBP) models, 2) event study models with individual and time fixed effects, and 3) dynamic panel models. Each approach has its respective *pros* and *cons* which will be discussed in detail in the following.

Recursive bivariate probit

Firstly, recursive bivariate probit models (RBP) allow us to make primary comments on the simultaneity of criminality and victimhood. Results examine overall effects, pooling data over several years. Although this misses the primary focus of our analysis—the dynamics between criminality and victimhood—it is instrumental in analyzing whether outcomes are jointly determined.

RBP models are a natural extension of single-equation probit models, except the outcome in each equation is assumed to be jointly determined. The system allows for correlated disturbances, similar to seemingly unrelated regression models. These models take the form:

(1) $V_i^* = \boldsymbol{X_i \alpha_i} + \theta_1 O_i + \varepsilon_{1,i}, \quad V_i = 1(V_i^* > 0),$

(2) $O_i^* = \boldsymbol{X_i \beta_i} + \varepsilon_{2,i}, \quad O_i = 1(O_i^* > 0),$

(3) $\begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \end{pmatrix} |\boldsymbol{X_i}\Big) \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_1 \\ \rho_1 & 1 \end{pmatrix}\right]$

and

(4) $V_i^* = \boldsymbol{X_i \gamma_i} + \varepsilon_{3,i}, \quad V_i = 1(V_i^* > 0),$

(5) $O_i^* = \boldsymbol{X_i \delta_i} + \theta_2 V_i + \varepsilon_{4,i}, \quad O_i = 1(O_i^* > 0),$

(6) $\begin{pmatrix} \varepsilon_3 \\ \varepsilon_4 \end{pmatrix} |\boldsymbol{X_i}\Big) \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_2 \\ \rho_2 & 1 \end{pmatrix}\right].$

V_i and O_i are equal to one if individual i was the victim of a crime or a criminal offender at any time over the sample period, respectively, and zero otherwise. $\boldsymbol{X_i}$ is a vector of covariates common to each equation, with $\varepsilon_j \; \forall j = 1 \ldots 4 \sim N(0,1)$. Conditional tetrachoric correlations are denoted as ρ_k for $k = 1,2$.[17] ρ_k is a weighted average of the RBP tetrachoric correlation and the parameter of the endogenous variables, here V_{it} or O_{it} (Filippini *et al.* 2018). However, ρ_k may be used to construct Hausman tests of the endogeneity of criminality in the victimhood equation, and *vice versa* (Knapp and Seaks 1998). We appeal to RBP because when $\rho_k \neq 0$, single equation probit produces inconsistent estimates of $\boldsymbol{\alpha}$, $\boldsymbol{\delta}$, and $\boldsymbol{\theta}$.[18]

A major advantage of RBP is that exclusion restrictions are not needed to identify a system with an endogenous regressor due to the nonlinear nature of the maximum likelihood problem (Maddala 1983; Wilde 2000; Wooldridge 2010; Greene 2012). We expect that certain unobserved variables, such as culture and risk preferences, are at once correlated with the likelihood of committing a crime and being the victim of a crime.

Nevertheless, the major drawback in using recursive bivariate probit models is that it necessarily requires one to pool data over time. This prevents the researcher from investigating

[17] Note that because of the recursive nature of models, the conditional tetrachoric correlation may *not* be interpreted as the correlation one would expect if the underlying continuous latent variables, in our case V^* and O^*, could be observed (see Filippini *et al.* (2018)).

[18] Also of note, fully simultaneous probit systems are not identified, which is why we instead opt to estimate two separate recursive bivariate probit models (Maddala 1983).

the dynamic relationship between victimhood and criminalization—our primary interest in this work.

Event study with individual and time fixed effects

Secondly, in order to take full advantage of the panel structure of the data, we turn to event study models accounting for individual and time fixed effects. These models are central because they remove time-invariant individual-level characteristics from the analysis, which may be both correlated with both victimization and offending. Potential confounders at the individual-level include growing up in a high-crime neighborhood, family structure, risk preferences, having at least one parent or guardian that was a victim or offender, and socioeconomic status, to name a few. Monthly time fixed effects help capture unobserved characteristics specific to certain months, such as police enforcement intensity, law enforcement resources, trends in certain crime types, as well as seasonal effects (e.g., more domestic disturbances during the holidays, more general crime during the summer, etc.). These linear probability models can be represented as:

$$(7)\quad O_{it} = \alpha_0 + \sum_{j=1}^{12} \beta_j\, O_{i,t-j} + \sum_{k=0}^{12} \gamma_{k+1}\, V_{i,t-k} + \boldsymbol{X_{it}\delta_{it}} + \theta_i + \theta_t + \varepsilon_{it}.$$

$$(8)\quad V_{it} = \alpha_0 + \sum_{j=1}^{12} \beta_j\, V_{i,t-j} + \sum_{k=0}^{12} \gamma_{k+1}\, O_{i,t-k} + \boldsymbol{X_{it}\delta_{it}} + \theta_i + \theta_t + \varepsilon_{it}$$

Equations (7) and (8) predict victimization (offending) using 12 previous monthly lags and the current and lagged values of offending (victimization). Although insightful in terms of investigating the dynamics between criminality and victimhood, these models are not without their limitations. Specifically, introducing a lagged outcome variable on the right-hand side of the equation produces inconsistent results, even in the context of fixed effects since the compound error term is correlated with the lagged dependent variable. Although this is likely to impose a relatively small amount of bias given the size of our panel, it is worth noting (Anderson and Hsiao, 1981, 1982). Additionally, equations (7) and (8) do not allow for correlated disturbances. Maddala (1983, pp. 122-123) showed that ignoring correlation in disturbances across RBP equations results in inconsistent results. This motivates our next approach.

Dynamic panel estimators

Third, we estimate dynamic panel models. These are perhaps the preferred vehicle in terms of capturing the relationship between victim and offender status as they address both heterogeneity and endogeneity concerns. However, they are subject to strict identification requirements and are not able to take advantage of the long nature of the panel data (Arellano and Bond 1991).

Dynamic panel are a class of estimators designed to provide consistent estimates when the dependent variable is at least partially dependent on its own past values. These models are specifically tailored to situations where the number of panel members, N, is large and the number of time periods, T, is small. The earliest models were developed by Holtz-Eakin, Newey, and Rosen (1988) and were popularized by Arellano and Bond (1991). These models use first differencing to remove heterogeneity, then apply instrumental variables (IV) methods to consistently estimate parameters on lagged dependent variables. The instruments considered are "deeper" lags of the dependent (also independent) variables in the model. The idea is that deep lags of the dependent variable are likely correlated with more recent values of the independent variable itself, but uncorrelated with current values of the dependent variable. These assumptions are testable.

Recognizing that Arellano-Bond estimators often suffer from weak instruments, multiple improvements have been made to original estimators in order to increase precision (Arellano and Bover 1995; Blundell and Bond 1998). We utilize generalized methods of moments (GMM) estimation following Blundell and Bond (1998) to increase the relevancy of IVs used in the analysis.[19] These estimates are preferred in terms of controlling for time-invariant individual characteristics and time trends. However, there remains a risk that certain unobservable individual-level time-variant characteristics remain unaccounted for. In fact, items such as family structure, neighborhood, and SES may very well change over time, although can be argued to be generally slow to change and therefore fairly stable especially over reasonably short time periods.

5. RESULTS

Recursive bivariate probit models

To compare our results with the existing literature, we begin with seemingly unrelated and recursive bivariate probit models. The results are summarized in Table 4 and full estimation

[19] The implementation of these estimators has been operationalized in Stata following Roodman (2009).

results including all control variables are provided in Table A.1 and tetrachoric correlations from unadjusted seemingly unrelated bivariate probit models by crime type in Table A.2.

Table 4. Seemingly unrelated and recursive bivariate probit models

	(1)	(2)	(3)
	$\Pr(O = 1, V = 1 \mid \boldsymbol{X})$	$\Pr(O = 1, V = 1 \mid \boldsymbol{X}, O = 1)$	$\Pr(O = 1, V = 1 \mid \boldsymbol{X}, V = 1)$
Offender		-.1720*** (.0511)	
Victim			.0195*** (.0049)
$\hat{\rho}$	.3311*** (.0057)	.4662*** (.0322)	-.4145*** (.0272)
Observations			393,000

Source: Authors' calculations using New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS). Robust standard errors are reported. The population consists of the estimated resident population from 2014 to 2020. Observations have been randomly rounded to the nearest hundred in accordance with the Stats NZ confidentiality protocol. *, **, and *** denote statistical significance at the 10, 5, and 1 percent-levels, respectively. Full estimation results are included in Table A.1 the appendix.

These results show a simultaneous relationship between offending and victimization—those who are offenders are more likely to be victims and vice versa. This differs from the findings of the two previous studies employing the same recursive bivariate profit method. Both Deadman and MacDonald (2004) and Entorf (2013) found that offenders are more likely to be victims, but victims are not more likely to be offenders. While we cannot say with certainty what is driving the different findings, there are notable differences in the data we are using. In particular, we use a random sample of the entire population, whereas both of these previous studies use a specific subset of the population (youth and a sample designed to mimic the prison population). In addition, our data include all reported crimes whereas these previous studies relied on survey respondents' recall of offending and victimization incidents.

Adding validity to our results, the signs on the control variables are as expected. For example, VOO is more prevalent among males and it tends to increase with age but at a decreasing rate, consistent with the well-known age-crime curve (Loeber and Farrington 2014) (Table A.1). By crime type, the unadjusted seemingly unrelated bivariate probits also show a positive tetrachoric correlation for each crime type (Table A.2). Also unsurprisingly, the VOO relationship is stronger for repeated offending, violent crimes and crimes involving the use of weapons and weaker for property and sexual offending. This is consistent with population heterogeneity concepts as it would be expected that violent crimes, for example, are more likely to fit with arguments like the lifestyle hypothesis. In additional, as discussed, rational choice theory suggests that the VOO would be stronger for violent crimes than property crimes.

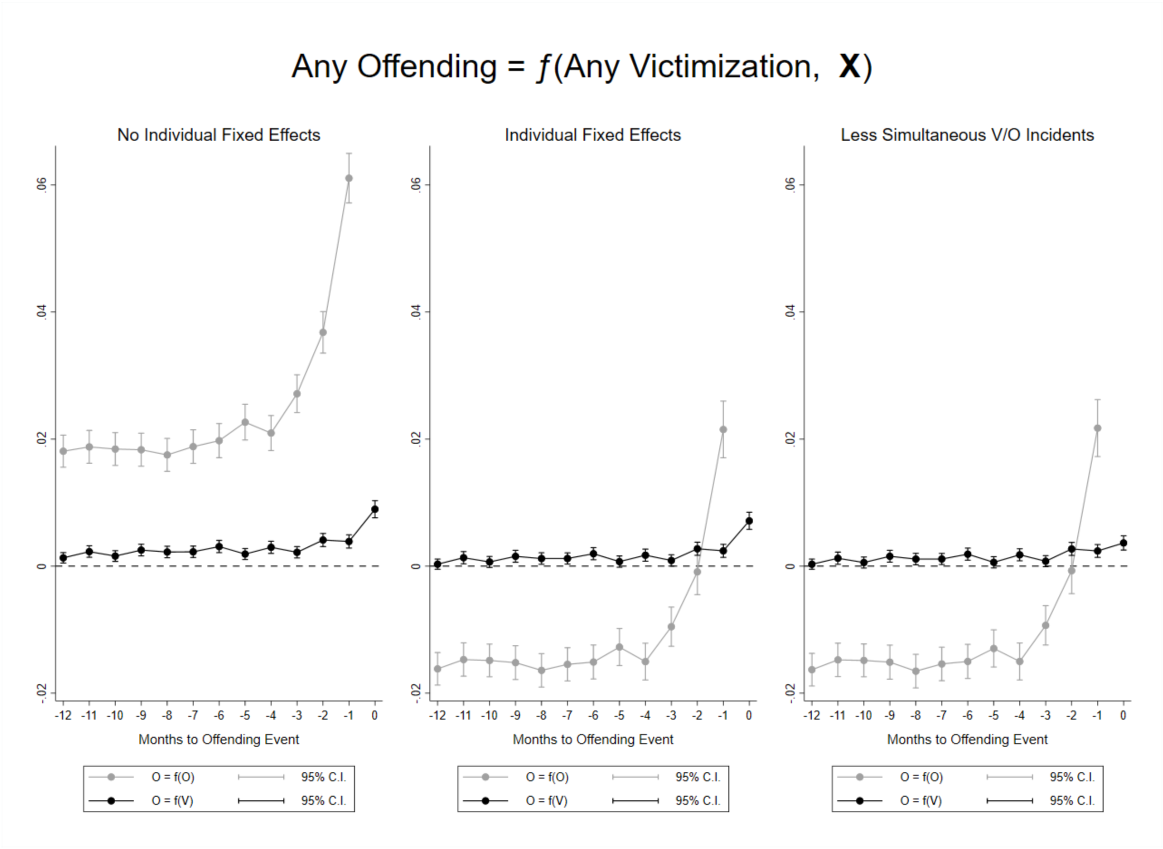
Event Study models with individual and time fixed effects

Recursive bivariate probit models reveal only part of the story and do not allow us to differentiate between VOO theories relating to individual heterogeneity (such as lifestyle and risk preference) and those relating to a dynamic relationship whereby offending (victimization) increases the risk of future victimization (offending). The detailed panel nature of our dataset, which provides monthly, population-wide offending and victimization records allow us to investigate these different hypotheses in a way that has not previously been possible.

As a first step, we use event study methods to account for the timing of offending and victimization to see if victimization follows offending or vice versa. We undertake this analysis with and without fixed effects to examine whether individual heterogeneity is driving the VOO observed in the bivariate probit results.

Figure 1 presents results for equation (7), where offending at time zero is a function of current and lagged victimization, as well as lagged offending and time-varying individual characteristics (namely age and income). Panel A (left) estimates Equation (7) with no fixed effects and Panel B estimates the same equation with individual-level fixed effects. Similarly, Figure 2 presents results for equation (8), where victimization at time zero is a function of current and lagged offending, as well as lagged victimization and time-varying individual characteristics. Full estimation results are shown in Tables A.3 and A.4 in Appendix A.

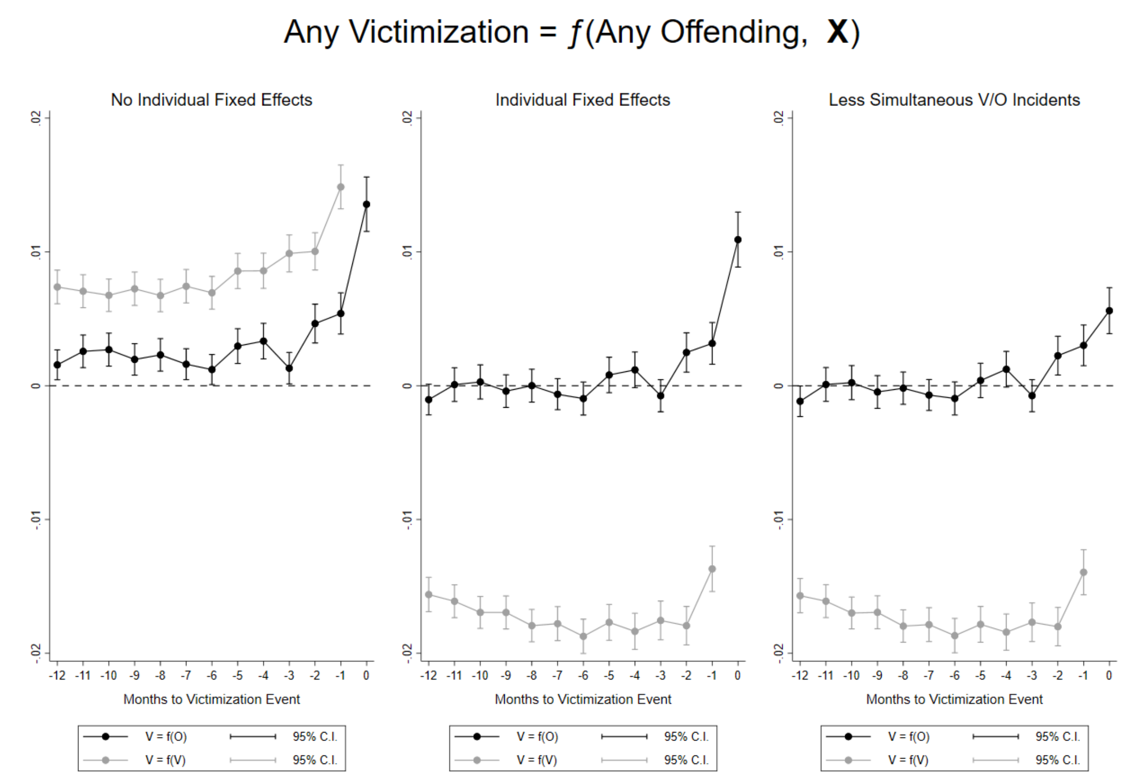
Figure 1.A with no individual fixed effects shows that in the 12 months leading up to an offending event, the likelihood of offending was also higher, with the likelihood increasing closer to the offending event time zero. That is, there is a positive relationship between current and past offending. In terms of victimization, there is also an increased likelihood of victimization in the months leading up to, and in the month of, the offending event, with the likelihood increasing as event time zero draws closer.



Source: Authors' illustration and calculations using New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS). The population consists of the estimated resident population from 2014 to 2020.

Figure 1. Main estimation results (outcome is offending)

However, the magnitude of this greater likelihood is small, particularly compared with the relationship between current and past offending. Figure 1B suggests that population heterogeneity is an important part of the explanation for the dynamic relationship seen in Figure 1A. In terms of the relationship between current and past offending, there is either a negative relationship or no statistically significant relationship up until two months before the time zero offending event. A positive relationship between past and current offending only appears one month out from the offending event. In terms of the relationship between past victimization and offending, when population heterogeneity is controlled for, there is little to no positive relationship between past victimization and current offending up until two months before the offending event. However, there is a positive relationship between victimization and current offending in the immediate past two months. Thus, much of the apparent relationship between current offending and past victimization, and indeed current offending and past offending, is driven by population heterogeneity. Any dynamic relationship appears to be very short run in nature.



Source: Authors' illustration and calculations using New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS). The population consists of the estimated resident population from 2014 to 2020.

Figure 2. Main estimation results (outcome is victimization)

To explore the possibility that the remaining relationship is driven by simultaneous victim/offender incidents, these events are removed from Figure 1C. The same patterns emerge, but are somewhat dampened, particularly in terms of the positive dynamic relationship between past victimization and current offending. Appendix Table A.3 and A.4 presents the results without retaliatory events, and the results are very similar to those without simultaneous events. We now turn to Figure 2 showing the relationship between current victimization and past offending and victimization without individual fixed effects. Figure 2A without fixed effects shows a positive dynamic relationship between past victimization and current victimization, with the magnitude of the relationship increasing as the victimization event at time zero approaches. There is a similar relationship between past offending and current victimization, albeit of smaller magnitude.

However, the relationship between current and past victimization is very different once individual fixed effects are added to the estimation in Figure 2B. The relationship between current and past victimization is negative. This negative relationship suggests that the apparent relationship between past and present victimization at the aggregate level is driven by population heterogeneity. Once an individual has been victimized, they seem to be less likely to be victimized, possibly because they take extra precautionary measures to avoid being a repeat victim.

Similar to the case of the relationship between current offending and current and lagged victimization, once individual fixed effects are added, the positive relationship between past offending and current victimization mostly disappears except in the very short term (two months out from the victimization event). If simultaneous V/O events are removed from the analysis, this magnitude of this short-term positive relationship decreases.

Once population heterogeneity is removed, what is the possible explanation for the remaining small, short-run positive dynamic relationship between offending and victimization? With some crimes, the original offending (or victimization) may lead to further offending or victimization, but this may be confined mostly to the immediate future. For example, this may involve retaliatory events. Our analysis investigated the possibility of retaliatory events that were directed (where the victim retaliates against the specific offender who victimized them) and found the short-run positive relationship persisted even when these events were removed from the analysis. However, undirected retaliation is still a possibility, whereby a victim lashes out more generally at others who were not involved in the original incident. Theory suggests these retaliatory events are motivated by anger, which likely subsides over time and therefore leads to a concentration of these events in the near term. This could also be partly about crime detection. Since we can observe only crimes that come to the attention of police, it may be that those who have had a recent offending or victimization event are more likely to be monitored by police, and therefore, their subsequent offending or victimization is more likely to be detected, at least in the near term. The timing of detection could also play a role – for example, if an offender commits a number of crimes such as burglaries over two months but they are not immediately caught by police, if they are eventually caught, they may be charged with the earlier crimes if evidence gathered by police is able to link them to those earlier crimes.

Dynamic Panel Models

Results of Arellano-Bond dynamic panel models are presented in Table 5. Because dynamic panel models require a short panel (i.e., large number of groups, *N*, and small number of time periods, *T*), the analysis only uses 2019 data. In columns (1) and (2), only the lagged dependent variables are assumed to be exogenous. In columns (3) and (4) all

Table 5. Dynamic panel (Arellano-Bond) estimates, 2019

	(1)	(2)	(3)	(4)
	Only lagged dependent variables considered endogenous		All V/O variables considered endogenous	
variable	*Victim(t)*	*Offender(t)*	*Victim(t)*	*Offender(t)*
Offender(*t*)	.014***		.194***	
	(.004)		(.065)	
Offender (*t-1*)	.010***	.066***	-.005	.039***
	(.005)	(.007)	(.034)	(.011)
Offender (*t-2*)	.013***	.027***	.024	.025***
	(.003)	(.005)	(.025)	(.008)
Offender (*t*-3)	-.004	.012***	.015	.013**
	(.004)	(.004)	(.030)	(.005)
Victim(*t*)		.006**		.194**
		(.002)		(.092)
Victim (*t-1*)	.010***	.009***	.005**	-.019
	(. 003)	(.002)	(.002)	(.0082)
Victim (*t-2*)	.008***	-.003	.004*	-.087
	(.003)	(.002)	(.002)	(.093)
Victim (*t-3*)	.006**	.0004	.002*	-.005
	(.003)	(.002)	(.001)	(.066)

Tests for zero autocorrelation in first-differenced errors:

order	*p*-value	*p*-value	*p*-value	*p*-value
1	.000	.000	.0000	.000
2	.665	.570	.819	.120
year effects	YES	YES	YES	YES
individual effects	YES	YES	YES	YES
obs.				2,926,600

Source: New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS). In order to satisfy the requirement of having a “short” panel, only the latest 12 months of data are considered. Two-step estimators are computed with Windmeijer (2005) WC-robust standard errors reported in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1 percent-levels, respectively. The null hypothesis for autocorrelation tests is no autocorrelation in first-differenced errors.

independent victimization and offending variables are considered endogenous. Note that these models pure time series in that there are no other controls in the model. Individual and month fixed effects are included in each model. In Arellano-Bond models an important identifying assumption is no autocorrelation in the idiosyncratic errors. Results of these tests are shown in Table 5, with all four models rejecting autocorrelation in lags deeper than one.

When assuming that only lagged dependent variables are endogenous, results are similar to what we find in the event study models presented earlier: positive overlap that decays in the first few monthly lags. Perhaps more appropriately, we consider our main results to be columns (3) and (4). In these models, we detect a large positive victim-offender overlap in both victimization and offending equations. Specifically, offending in month t is associated with a 19.4 percent higher likelihood of being the victim of a crime in month t, and *vice versa*. Lagged dependent variables are positively correlated with outcomes in the current month, with effect sizes decreasing in longer lagged values.

6. HETEROGENEITY ANALYSIS

Detailed results of recursive bivariate probit models are given in Table A.1 Table A.2 present tetrachoric correlations from seemingly unrelated bivariate probit models for various crime types. All tetrachoric correlations are signficiantly different from zero, and range from .110 (crimes of a sexual nature) to .446 (repeat offending and repeat victimization). This suggests a positive amount of overlap across crime types, although the relationships is less precisely measured for crime of a sexual nature. Tables A.3 and A.4 present full model results for the event study analysis.

Figures A.1 through A.12 present visual results for event study models by crime type. In terms of violent crimes, there is an increased likelihood of being the victim of a violent crime, given that the individual themselves committed a violent crime. This overlap is largely driven by incidents where individuals are considered both a victim and an offender. After removing these simultaneous events, overlap is only signficant for the current month. There is a small sut statistically significant link between victimization in the previous two months and offending in the current month.

Not surprisingly, there is a strong overlap beween committing intimate partner violence and being the victim of it, although this is almost entirely driven by event where both parties are considered both victims and criminals. As expected, there is no link between being the victim of a sexual crime and being an offender. Offenders of property crimes are more likely to become victims of property crimes when the offending occurred in the previous one month or less. This relationship does not hold in the opposite direction. After removing simultaneous offending/victimization events, there is little evidence of overlap when it comes to crimes involoving weapons.

7. CONCLUSIONS

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APPENDIX A. EVENT STUDY RESULTS BY CRIME TYPE

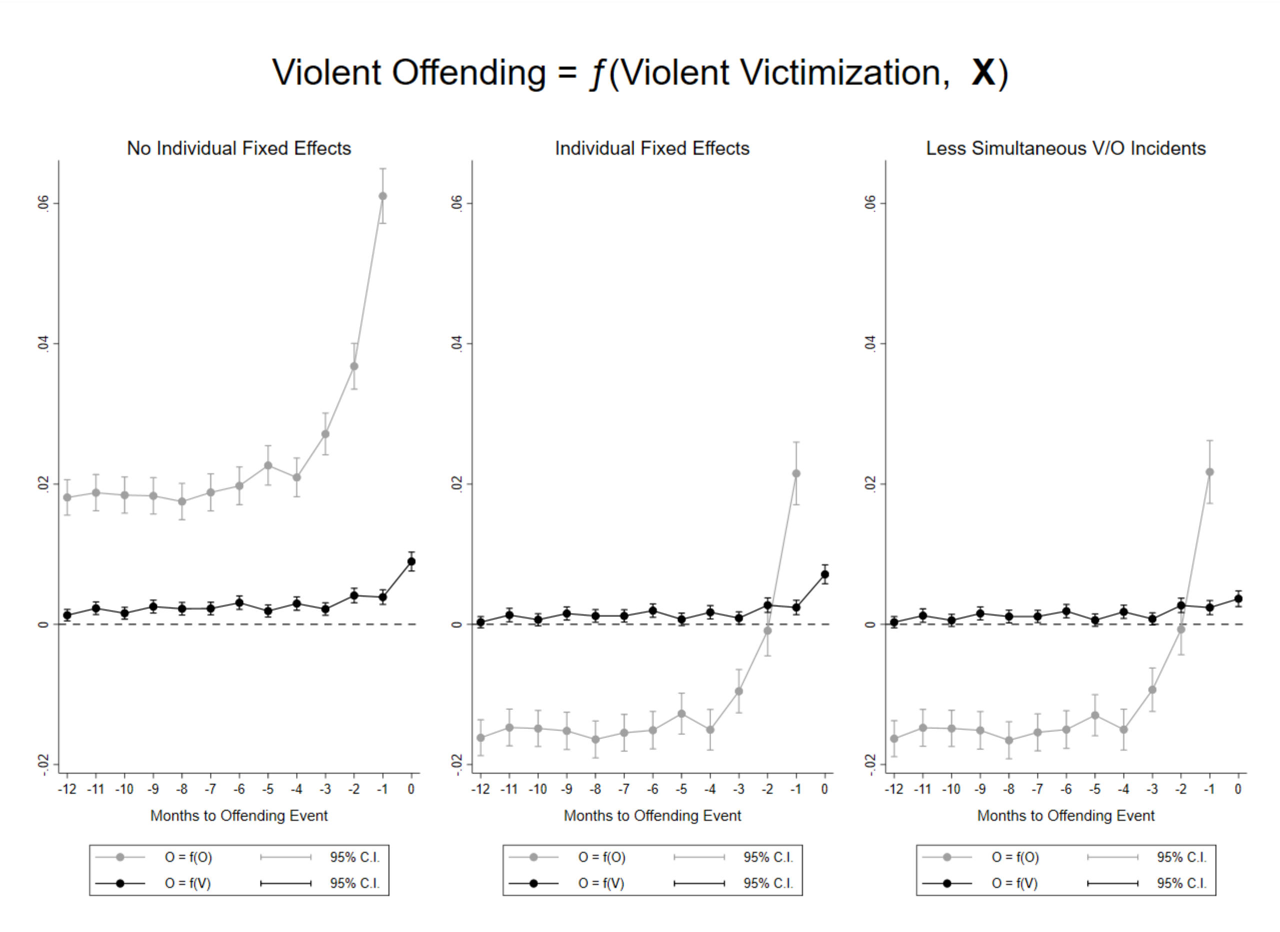

Figure A.1 - Results by offense type, violent offending

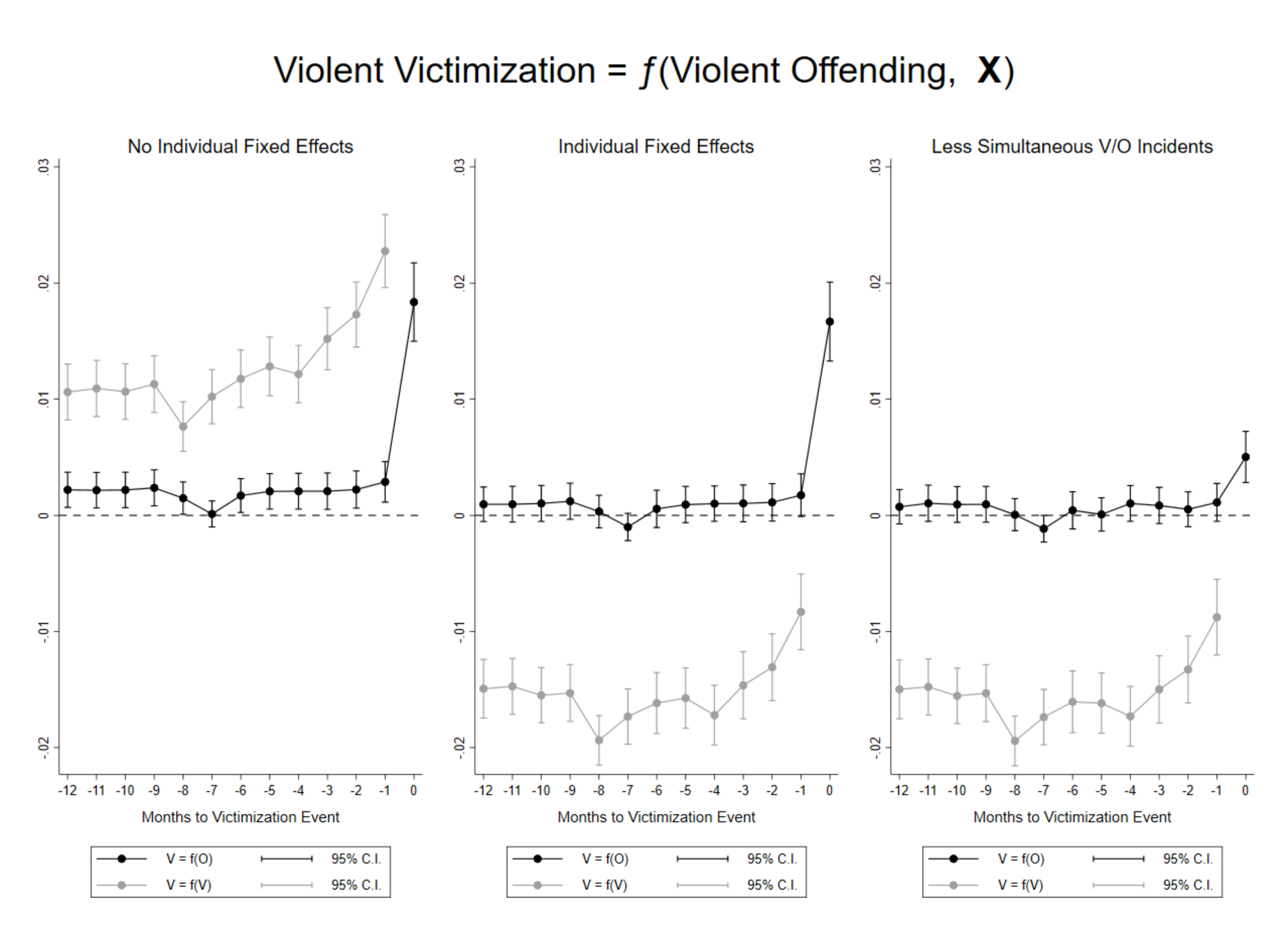

Figure A.2 - Results by offense type, violent victimization

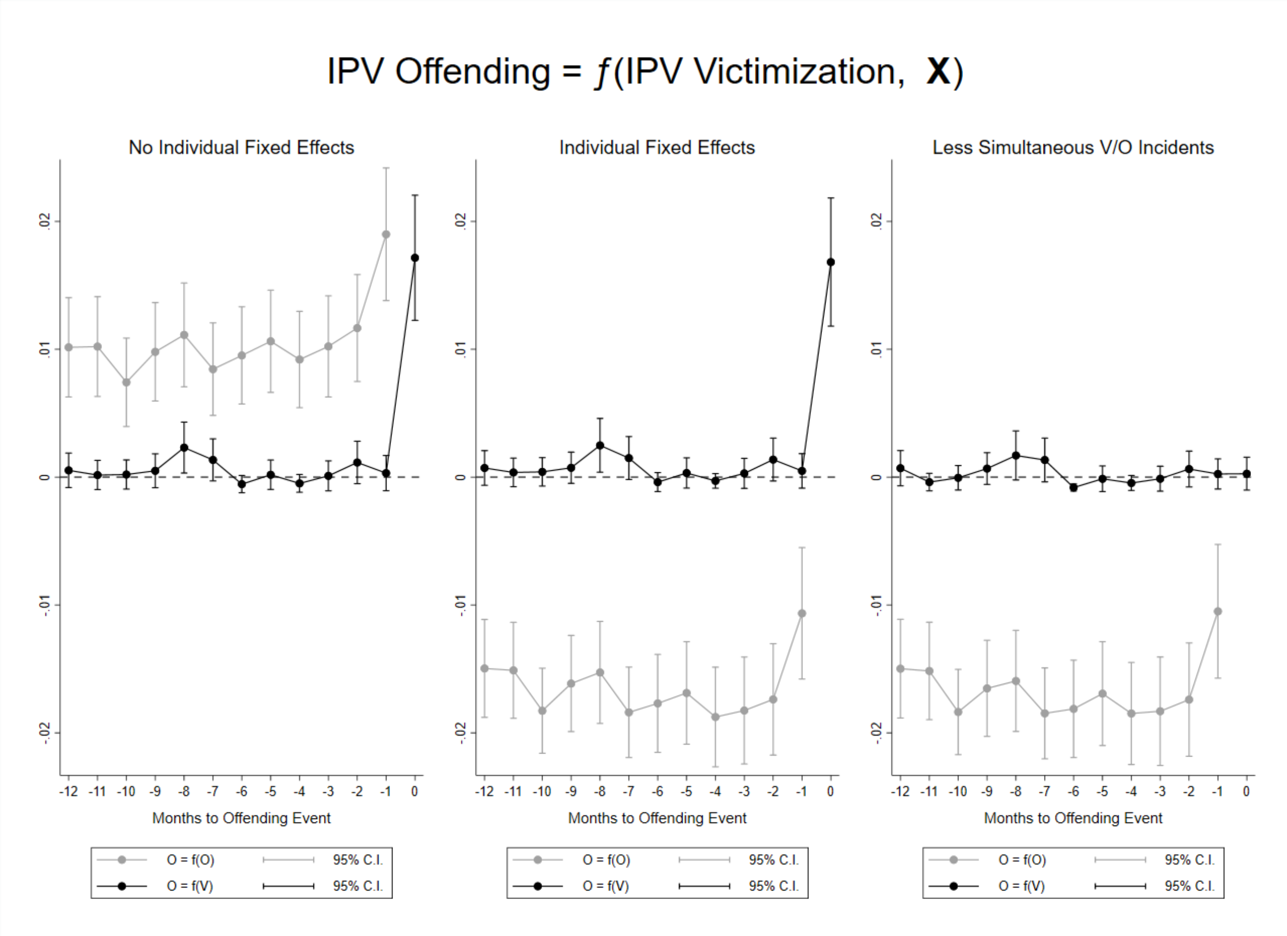

Figure A.3 - Results by offense type, intimate partner violence offending

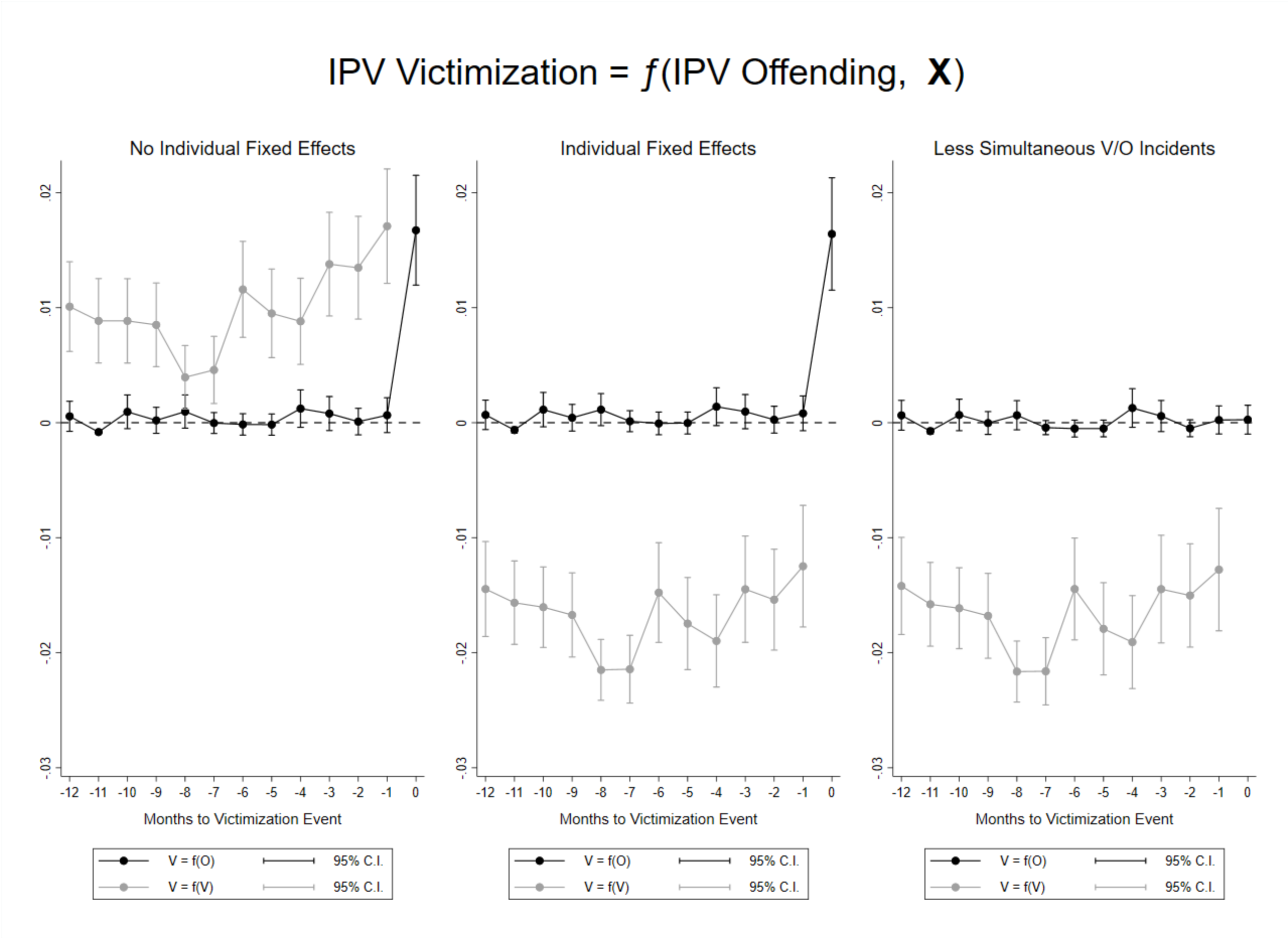

Figure A.4 - Results by offense type, intimate partner violence offending

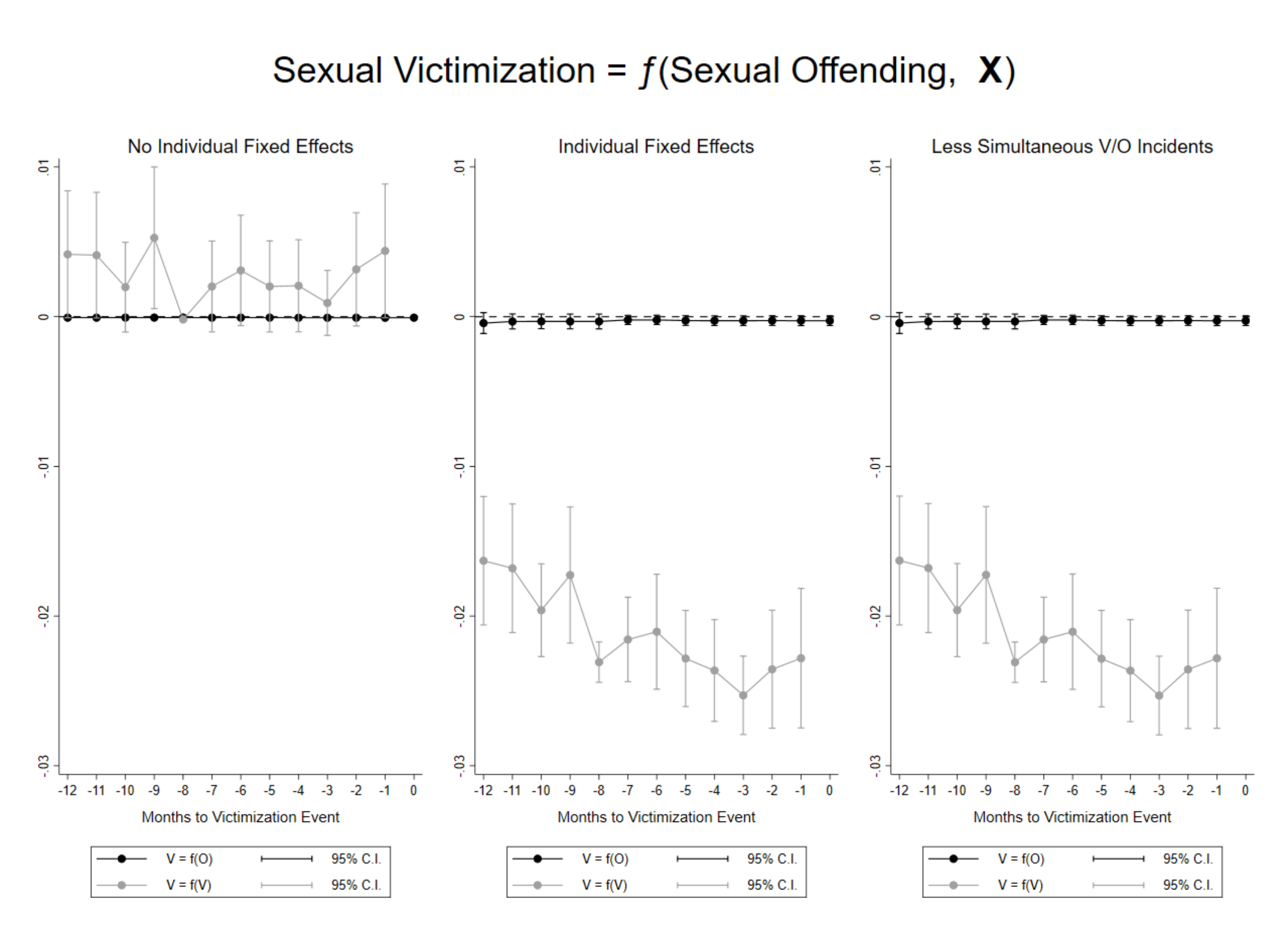

Figure A.5 - Results by offense type, sexual crime victimization

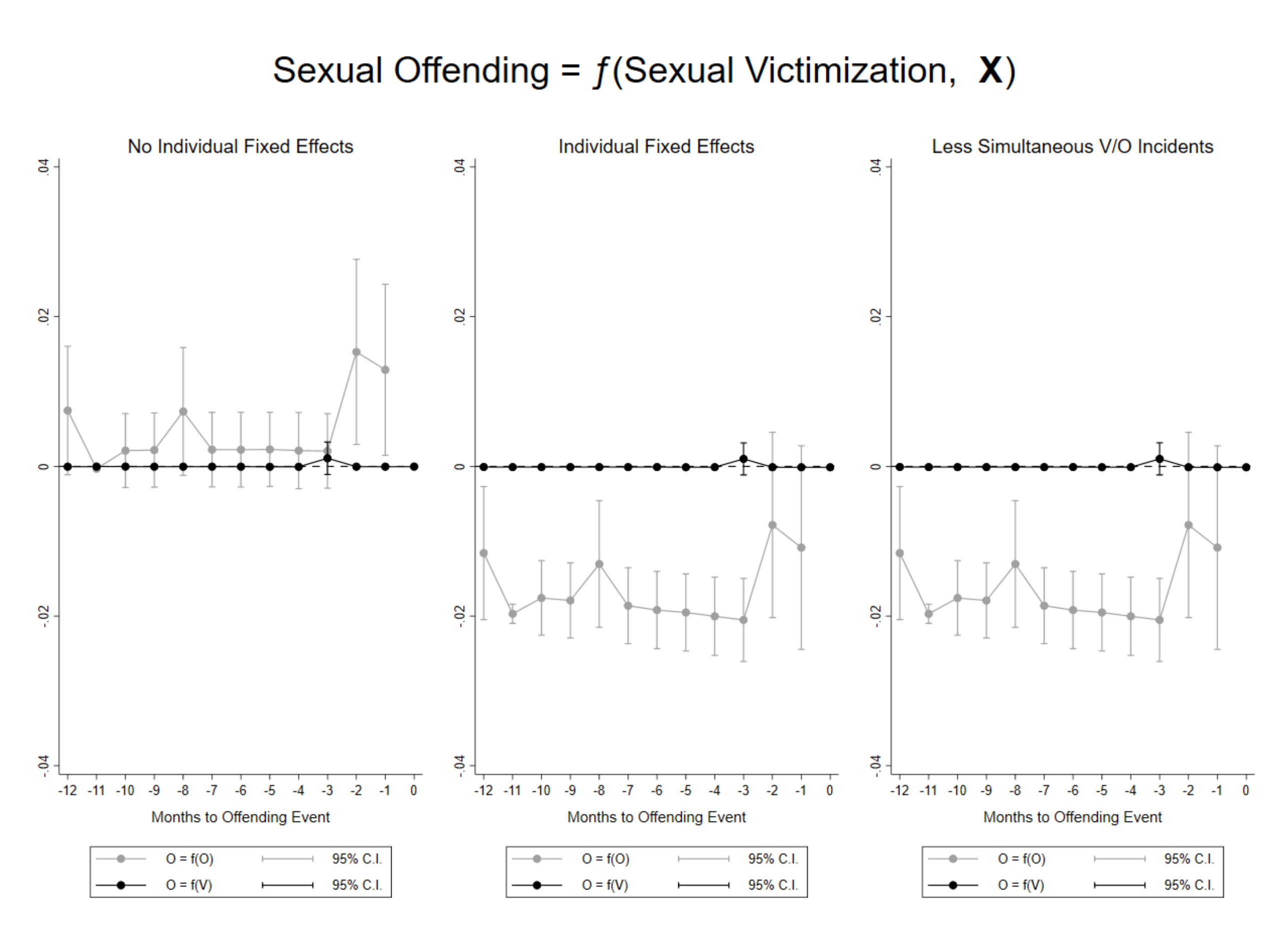

Figure A.6 - Results by offense type, sexual crime offending

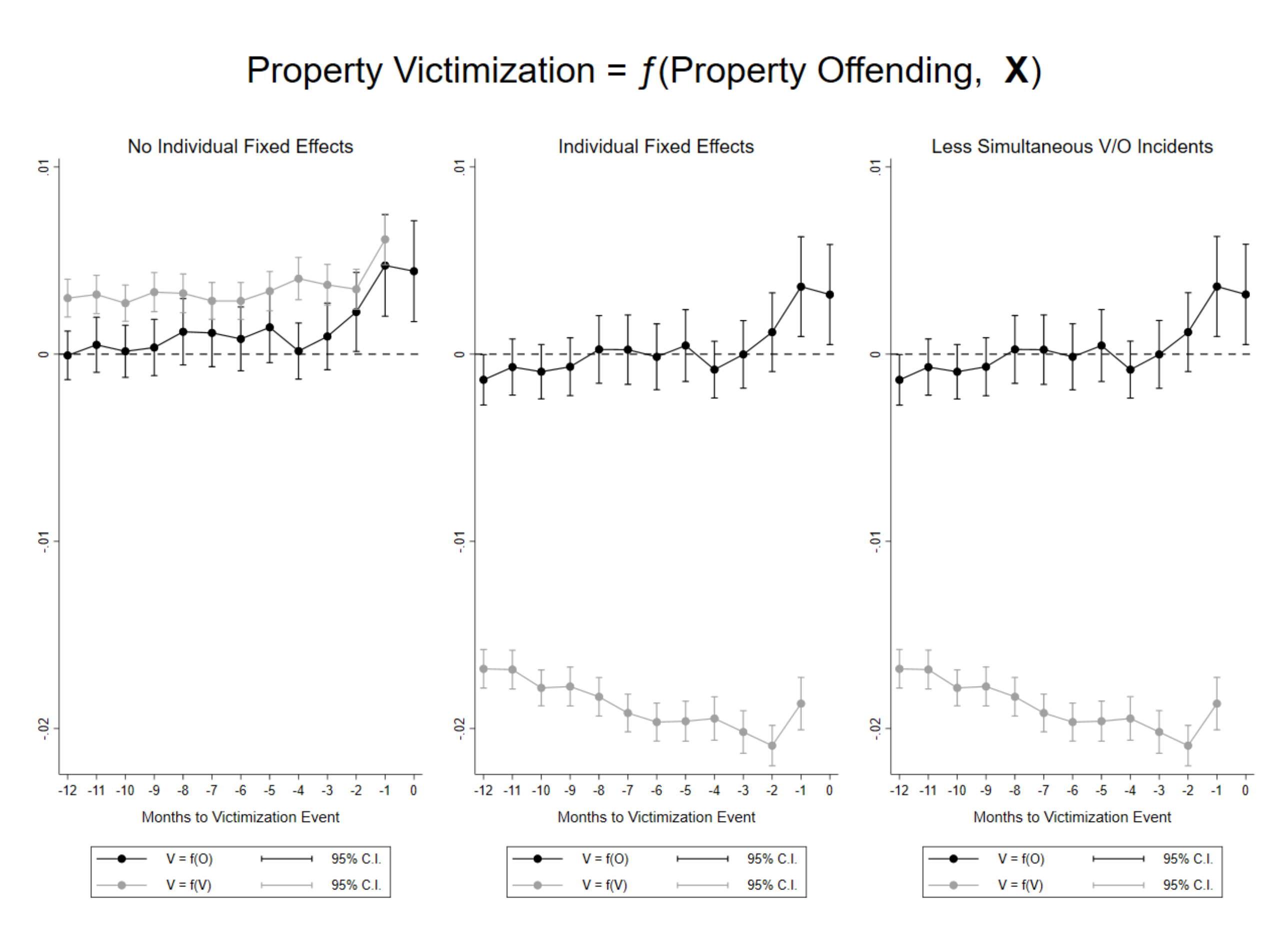

Figure A.7 - Results by offense type, property crime victimization

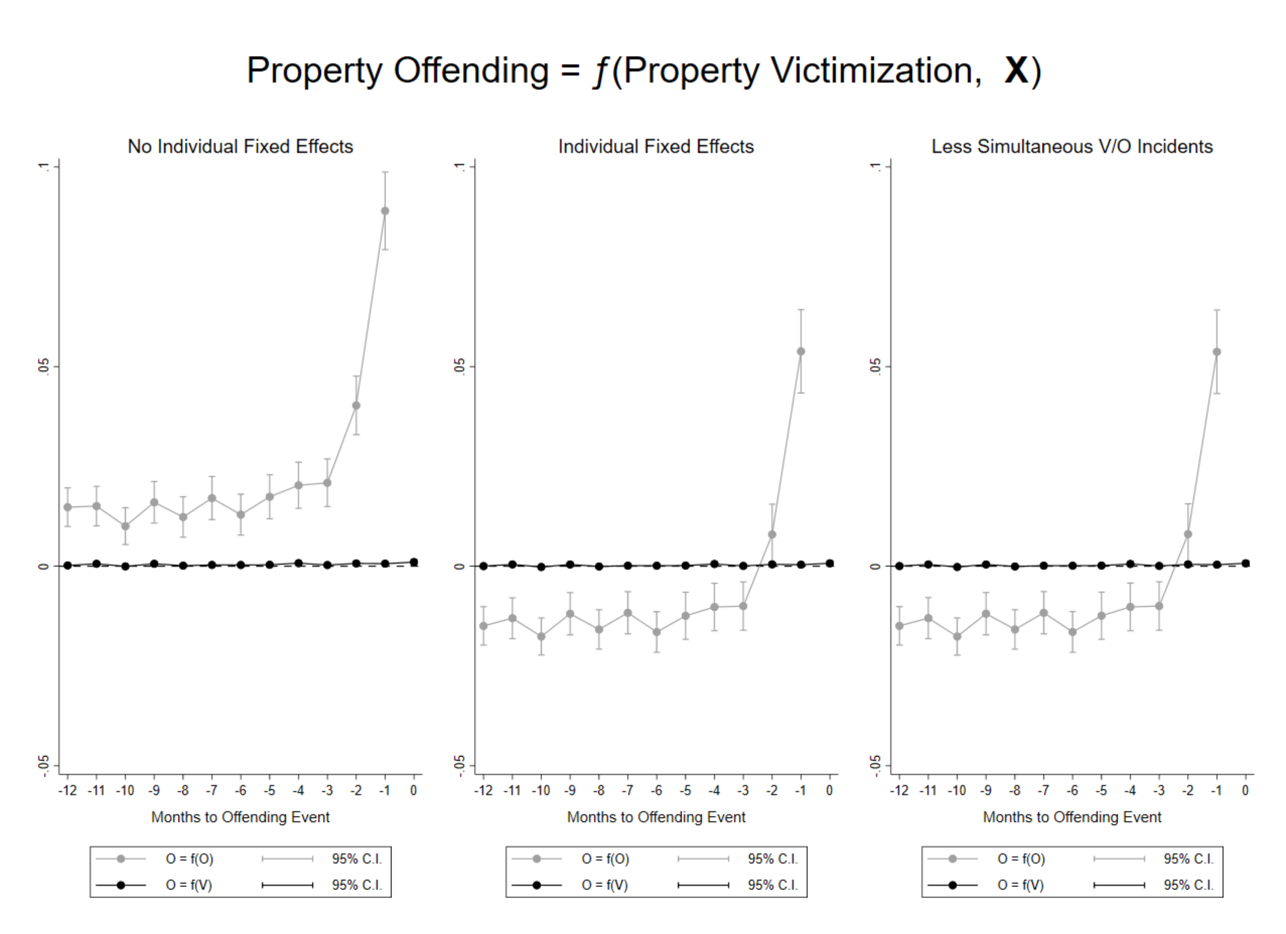

Figure A.8 - Results by offense type, property crime offending

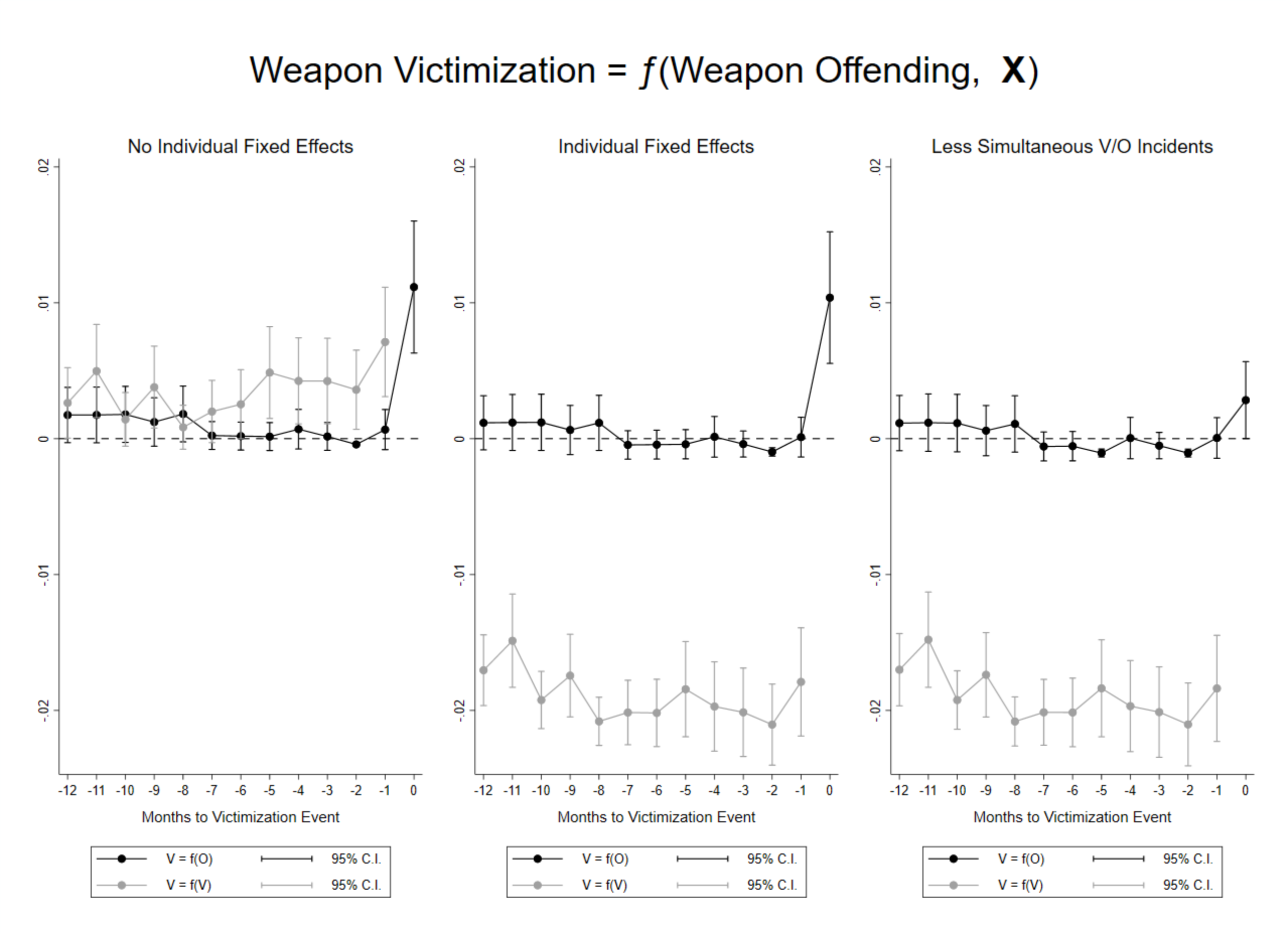

Figure A.9 - Results by offense type, crimes involving weapons victimization

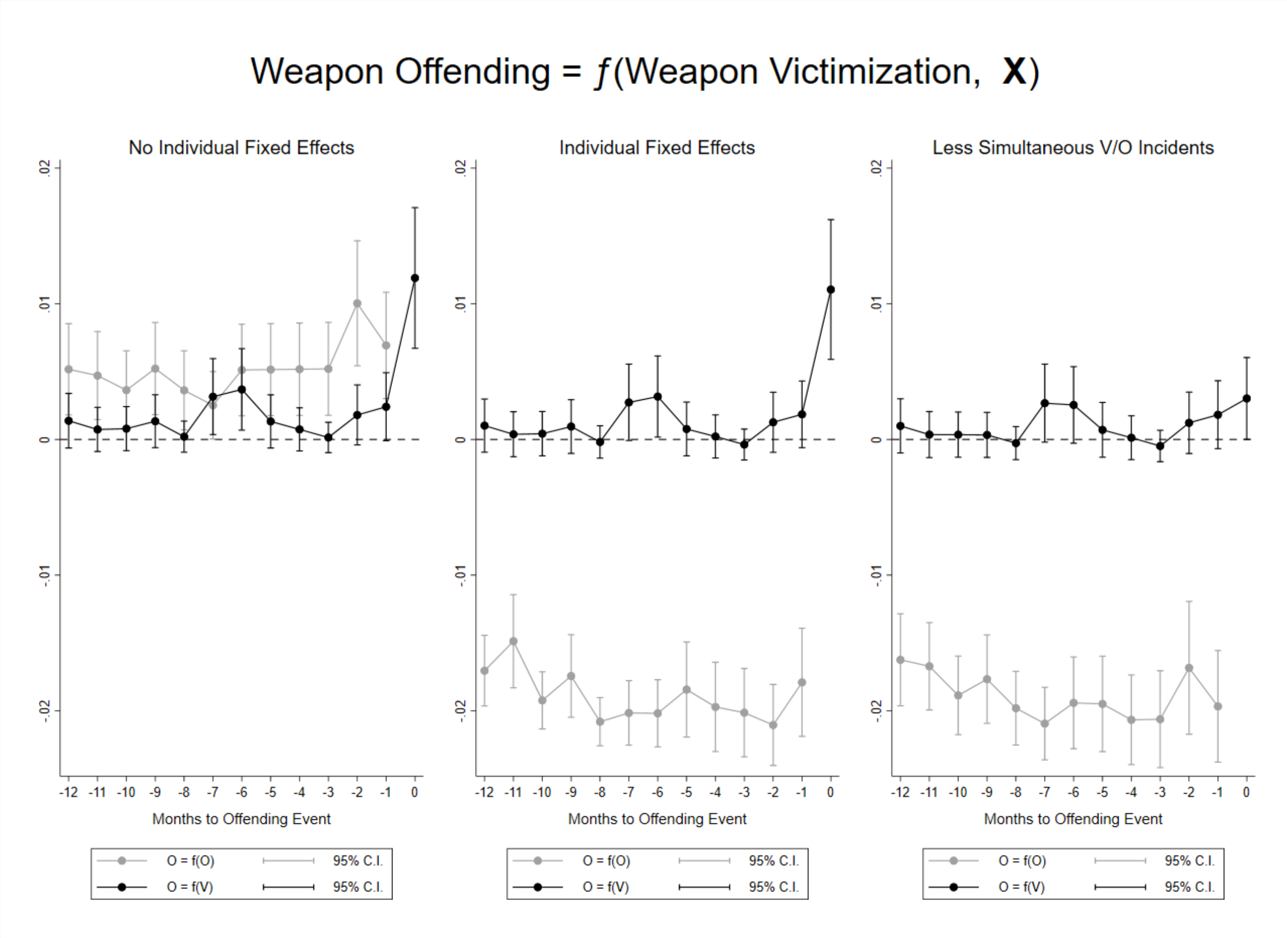

Figure A.10 - Results by offense type, crimes involving weapons offending

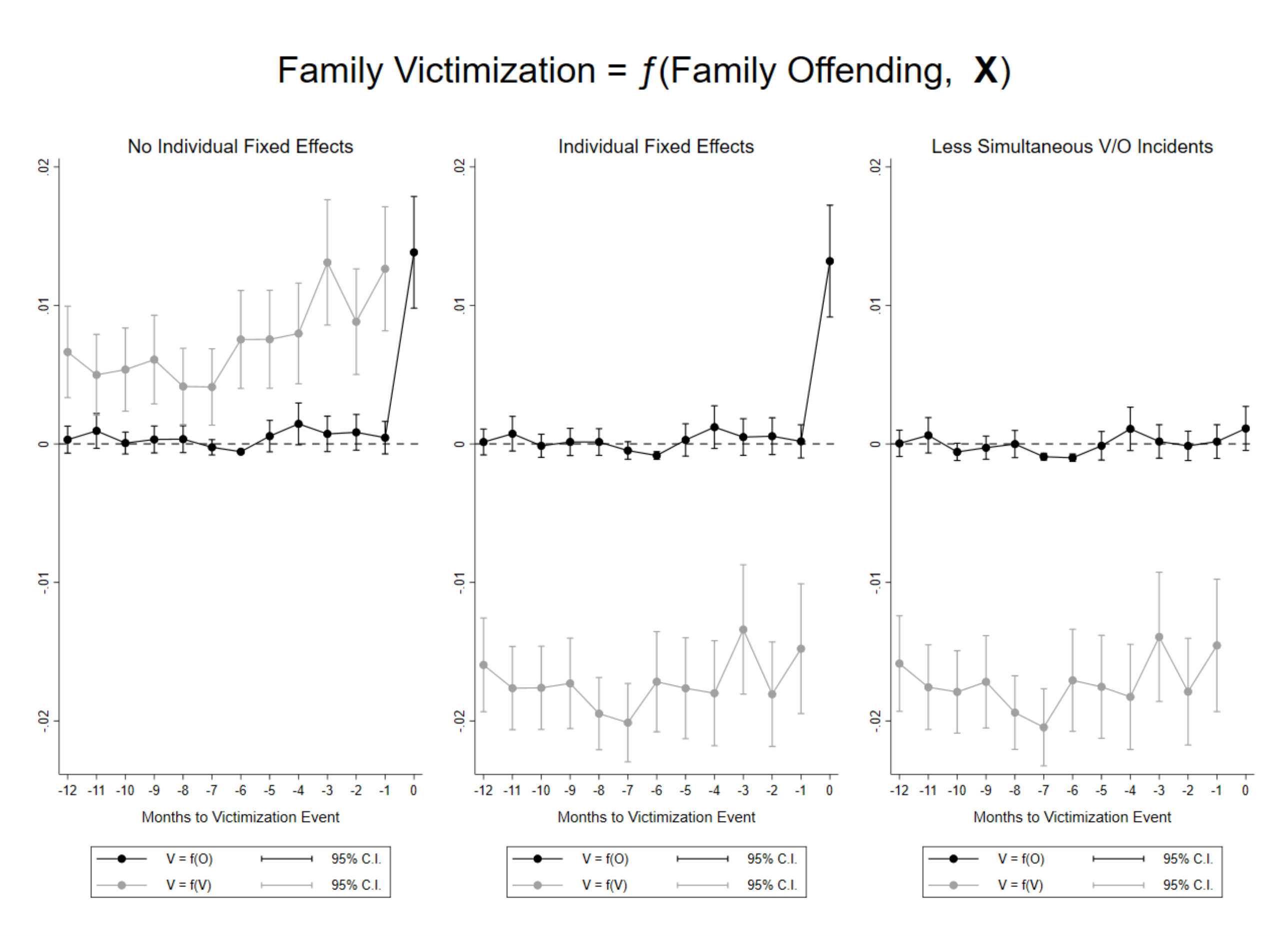

Figure A.11 - Results by offense type, crimes against family victimization

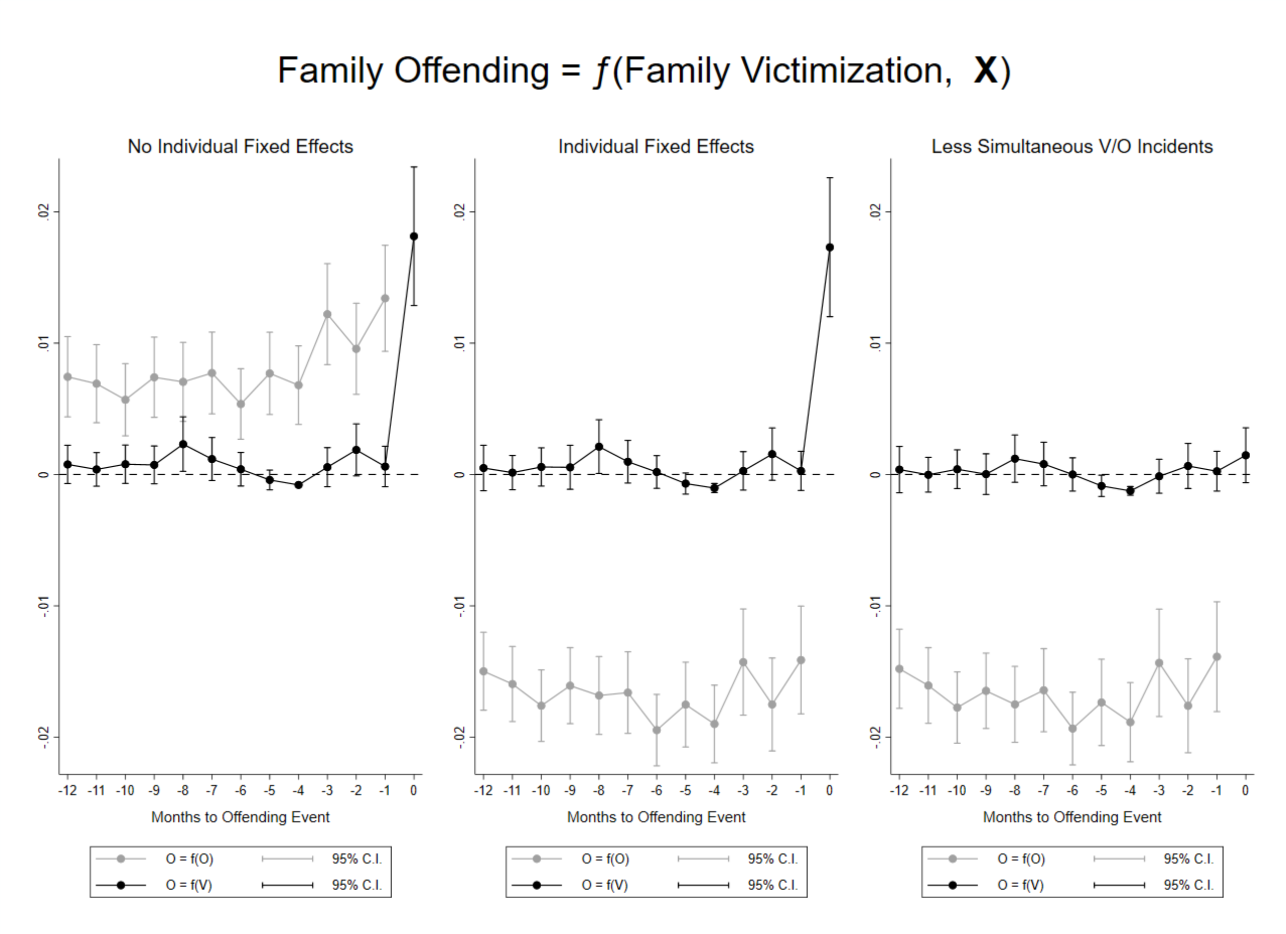

Figure A.12 - Results by offense type, crimes against family offending

Table A.1. Full Estimation Results: Seemingly unrelated and recursive bivariate probit models (marginal effects)

	(1) $\Pr(O = 1, V = 1 \mid \boldsymbol{X})$	(2) $\Pr(O = 1, V = 1 \mid \boldsymbol{X}, O = 1)$	(3) $\Pr(O = 1, V = 1 \mid \boldsymbol{X}, V = 1)$
Offender		-.1720*** (.0511)	
Victim			.0195*** (.0049)
Female	-.6154*** (.0134)	-.9320*** (.0910)	-.0115*** (.0034)
Age	.0670*** (.0016)	.0982*** (.0086)	.0013*** (< .0001)
Age^2	-.0944*** (.0020)	-.1376*** (.0004)	-.0018*** (< .0001)
Prioritized Ethnicity			
Māori	.6383*** (.0150)	.9454*** (.0858)	.0117*** (.0035)
Pacific	.2365*** (.0129)	.3610*** (.0398)	.0044*** (.0013)
Asian	-.3896*** (.0142)	-.5802*** (.0563)	-.0074*** (.0022)
MELAA	-.1603*** (.0281)	-.2384*** (.0462)	-.0030*** (.0010)
Other	-1.1605*** (.1294)	-1.6902*** (.2385)	-.0221*** (.0069)
Annual earnings	-.0875*** (.0021)	-.1283*** (.0114)	-.0017*** (< .0001)
Parent charged	.1646*** (.0142)	.2445*** (.0299)	.0029*** (< .0001)
$\hat{\rho}$	.3311*** (.0057)	.4662*** (.0322)	-.4145*** (.0272)
Observations	393,000	393,000	393,000

Source: New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS). Probabilistic point estimates are presented in percentage terms. Robust standard errors are reported. The population consists of all victims and offenders investigated within New Zealand, as well as all persons counted in the estimated resident population from 2014 to 2020. Observations have been randomly rounded to the nearest hundred in accordance with the Stats NZ confidentiality protocol. *, **, and *** denote statistical significance at the 10, 5, and 1 percent-levels, respectively. "Parent charged" equals one if any parent was charged with a crime, and zero otherwise. Annual earnings is divided by $10,000 and the square of age is divided by 100.

Table A.2. Tetrachoric correlations from unadjusted seemingly unrelated bivariate probit models by crime type

	Seemingly Unrelated Bivariate Probit
Crime Type	$\hat{\rho}$ (SE)
All	.383*** (.005)
Repeated	.446*** (.009)
Violent	.439*** (.007)
Property	.234*** (.009)
Family	.378*** (.013)
IPV	.321*** (.015)
Sexual	.110** (.045)
Weapon	.430*** (.014)

Source: New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS). *, **, and *** denote statistical significance at the 10, 5, and 1 percent-levels, respectively.

Table A.3. Full estimation results, any victimization as the dependent variable

	No Individual Fixed Effects	Individual Fixed Effects	Less Simultaneous V/O Offenders	Less Potential Retaliatory Offenders
offending				
t	.0136*** (.0010)	.0109*** (.0010)	.0056*** (.0009)	.0052*** (.0009)
t – 1	.0054*** (.0008)	.0032*** (.0008)	.0030*** (.0008)	.0030*** (.0008)
t – 2	.0046*** (.0007)	.0025*** (.0007)	.0022*** (.0007)	.0021*** (.0007)
t – 3	.0013** (.0006)	-.0007 (.0006)	-.0007 (.0006)	-.0008 (.0006)
t – 4	.0033*** (.0007)	.0012* (.0007)	.0012* (.0007)	.0009 (.0007)
t – 5	.0030*** (.0007)	.0008 (.0007)	.0004 (.0007)	.0005 (.0007)
t – 6	.0012** (.0006)	-.0010 (.0006)	-.0009 (.0006)	-.0010 (.0006)
t – 7	.0016** (.0006)	-.0006 (.0006)	-.0007 (.0006)	-.0004 (.0006)
t – 8	.0023*** (.0006)	< .0001 (.0006)	-.0002 (.0006)	.0001 (.0006)
t – 9	.0020*** (.0006)	-.0004 (.0006)	-.0005 (.0006)	-.0005 (.0006)
t – 10	.0027*** (.0006)	.0003 (.0007)	.0002 (.0006)	.0003 (.0006)
t – 11	.026*** (.0006)	< .0001 (.0006)	< .0001 (.0006)	.0002 (.0006)
t – 12	.0016*** (.0006)	-.0010* (.0006)	-.0012** (.0006)	-.0013** (.0006)
victim				
t – 1	.0149*** (.0008)	-.0137*** (.0009)	-.0139*** (.0009)	-.0140*** (.0009)
t – 2	.0100*** (.0007)	-.0179*** (.0007)	-.0180*** (.0007)	-.0180*** (.0007)
t – 3	.0099** (.0007)	-.0175*** (.0007)	-.0177*** (.0007)	-.0179*** (.0007)

$t-4$	.0086***	-.0184***	-.0184***	-.0184***
	(.0007)	(.0007)	(.0007)	(.0007)
$t-5$	.0086***	-.0177***	-.0178***	-.0179***
	(.0007)	(.0007)	(.0007)	(.0007)
$t-6$	.0069**	-.0187***	-.0187***	-.0187***
	(.0006)	(.0007)	(.0007)	(.0007)
$t-7$	.0074***	-.0178***	-.0179***	-.0180***
	(.0006)	(.0006)	(.0006)	(.0006)
$t-8$	.0067***	-.0179***	-.0180***	-.0180***
	(.0006)	(.0006)	(.0006)	(.0006)
$t-9$	.0073***	-.0169***	-.0169***	-.0171***
	(.0006)	(.0006)	(.0006)	(.0006)
$t-10$	.0068***	-.0169***	-.0170***	-.0170***
	(.0006)	(.0006)	(.0006)	(.0006)
$t-11$	.0071***	-.0161***	-.0161***	-.0163***
	(.0006)	(.0006)	(.0006)	(.0006)
$t-12$	.0074***	-.0156***	-.0157***	-.0156***
	(.0006)	(.0007)	(.0007)	(.0007)
Individual Fixed Effects	NO	YES	YES	YES
Monthly Fixed Effects	YES	YES	YES	YES
Observations	20,467,500	20,467,500	20,461,500	20,456,900

Source: New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS). Robust standard errors are shown in parentheses. The population consists of all victims and offenders investigated within New Zealand, as well as all persons counted in the estimated resident population from 2014 to 2019. Marginal effects are calculated at variable means. *, **, and *** denote statistical significance at the 10, 5, and 1 percent-levels, respectively.

Table A.4. Full estimation results, any offending as the dependent variable

	No Individual Fixed Effects	Individual Fixed Effects	Less Simultaneous V/O Offenders	Less Potential Retaliatory Offenders
<u>offending</u>				
t – 1	.0611***	.0215***	.0217***	.0219***
	(.0020)	(.0023)	(.0023)	(.0023)
t – 2	.0368***	-.0009	-.0007	-.0007
	(.0017)	(.0018)	(.0018)	(.0019)
t – 3	.0272***	-.0095***	-.0007	-.0096***
	(.0015)	(.0016)	(.0016)	(.0015)
t – 4	.0210***	.0150***	-.0150***	-.0150***
	(.0014)	(.0015)	(.0015)	(.0015)
t – 5	.0227***	-.0127***	-.0130***	-.0129***
	(.0014)	(.0015)	(.0015)	(.0015)
t – 6	.0198***	-.0151***	-.0150***	-.0150***
	(.0014)	(.0014)	(.0014)	(.0014)
t – 7	.0189***	-.0155***	-.0154***	-.0152***
	(.0013)	(.0013)	(.0013)	(.0014)
t – 8	.0175***	.0164***	-.0165***	-.0166***
	(.0013)	(.0013)	(.0013)	(.0013)
t – 9	.0183***	-.0152***	-.0151***	-.0150***
	(.0013)	(.0014)	(.0014)	(.0014)
t – 10	.0184***	-.0148***	-.0148***	-.0149***
	(.0013)	(.0013)	(.0013)	(.0013)
t – 11	.0188***	-.0147***	-.0148***	-.0148***
	(.0013)	(.0013)	(.0013)	(.0013)
t – 12	.0181***	-.0162***	-.0163***	-.0162***
	(.0013)	(.0013)	(.0013)	(.0013)
<u>victim</u>				
t	.0090***	.0071***	.0037***	.0034***

	(.0007)	(.0007)	(.0006)	(.0006)
$t-1$	.0039***	.0024***	.0024***	.0022***
	(.0005)	(.0005)	(.0005)	(.0005)
$t-2$	.0041***	.0027***	.0027***	.0025***
	(.0005)	(.0005)	(.0005)	(.0005)
$t-3$	.0022***	.0009**	.0008*	.0007*
	(.0005)	(.0005)	(.0004)	(.0004)
$t-4$	.0030***	.0017***	.0018***	.0018***
	(.0005)	(.0005)	(.0005)	(.0005)
$t-5$	.0019***	-.0007	.0006	.0005
	(.0004)	(.0005)	(.0004)	(.0004)
$t-6$	.0031**	.0020***	.0019***	.0018***
	(.0005)	(.0005)	(.0005)	(.0005)
$t-7$	.0023***	.0012***	.0011**	.0011**
	(.0005)	(.0005)	(.0004)	(.0004)
$t-8$	.0022***	.0012***	.0011**	.0009**
	(.0005)	(.0005)	(.0005)	(.0004)
$t-9$	.0025***	.0016***	.0016***	.0014***
	(.0005)	(.0005)	(.0005)	(.0005)
$t-10$	.0016***	.0007	.0006	.0006
	(.0004)	(.0004)	(.0004)	(.0004)
$t-11$	.0023***	.0013***	.0013**	.0014***
	(.0005)	(.0005)	(.0005)	(.0005)
$t-12$	.0013***	.0003 (.0004)	.0003	.0002
	(.0004)		(.0004)	(.0004)
Individual Fixed Effects	NO	YES	YES	YES
Monthly Fixed Effects	YES	YES	YES	YES
Age and income	YES	YES	YES	YES
observations	20,467,500	20,467,500	20,461,500	20,456,900

Source: New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS). Robust standard errors are shown in parentheses. The population consists of all victims and offenders investigated within New Zealand, as well as all persons counted in the estimated resident population from 2014 to 2019. Marginal effects are calculated at variable means. *, **, and *** denote statistical significance at the 10, 5, and 1 percent-levels, respectively.