Dynamic relationships between criminal offending and victimization[1]

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ABSTRACT

It is a stylized fact in criminology that those who commit crimes are more likely to be victims of crime and vice versa. However, the empirical research investigating this victim-offender overlap has largely been limited to establishing its existence and investigating population heterogeneity explanations. While the economics of crime literature has explored the possibility of a dynamic relationship, whereby current victimization (offending) leads to future offending (victimization), this has been limited due to a lack of population-wide administrative data with detailed information on the timing of offending and victimization incidents. We, therefore, use a monthly panel of all police investigations in New Zealand between 2014 and 2020 to examine the possibility of a dynamic relationship. We first follow previous literature and, pooling data over time, use recursive bivariate probit methods. This provides evidence of a small, but fully simultaneous, relationship between victimization and offending. We next use event study and dynamic panel data methods to explore the intertemporal relationships between victimization and offending. This analysis reveals that the victim-offender overlap primarily reflects population heterogeneity. Moreover, the dynamic relationship that does exist is driven primarily by 1) criminal incidents occurring close together in time and 2) simultaneous incidents where individuals are both offenders and victims (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: These results are not official statistics. They have been created for research purposes from the Integrated Data Infrastructure (IDI) which is carefully managed by Stats NZ. For more information about the IDI please visit https://www.stats.govt.nz/integrated-data/.

The results are based in part on tax data supplied by Inland Revenue to Stats NZ under the Tax Administration Act 1994 for statistical purposes. Any discussion of data limitations or weaknesses is in the context of using the IDI for statistical purposes, and is not related to the data's ability to support Inland Revenue's core operational requirements.

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1. INTRODUCTION

Becker's (1968) seminal work in the economics of crime models the decision to engage in crime as a trade-off between expected costs and benefits. Building on this notion, the empirical economics of crime examines a range of determinants and consequences of crime.

One area that is potentially important to understanding the determinants and consequences of crime that has not yet received much attention in the economics of crime literature is the overlap between victimization and offending. Yet, the reciprocal relationship between victims and offenders has long been a stylized fact in criminology with von Hentig (1940, p. 303) describing it as "*one of the most curious phenomena of criminal life*" in his seminal work over 80 years ago.

This paper, therefore, fills this gap by examining the nature of the victim-offender overlap using data from Stats NZ's Integrated Data Infrastructure (IDI). The IDI links data from various sources, including monthly records on all police incidents of alleged offending and victimization in New Zealand between 2014 and 2020. This administrative database appears to be unique internationally as it not only provides high-frequency data with universal coverage, it identifies both the alleged offenders and victims involved in each police incident and has rich information on the nature of the incident, such as the type and severity of the alleged offense. Analysis using New Zealand data is also internationally relevant due to its moderate crime rates[6] as well as the close similarity of its criminal justice system to those of the UK and other former British colonies, including the United States, Canada and Australia.[7]

After establishing the existence of a victim-offender overlap, these data allow us to examine the nature of this relationship. In particular, we ask if it is driven by time-invariant

[6] Data from the United Nations Gallup World Poll shows that New Zealand has comparable crime rates for certain offenses compared to the US and UK. 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 US 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 et al., 2021).

[7] Due to New Zealand's history as a British colony, the justice system is not just similar to the UK system, but was actually modelled on it. For example, the New Zealand criminal justice system, like that of the UK, US, Canada and Australia, follows case law, based on a common law system (as opposed to a civil law system which is common in e.g. continental Europe).

population heterogeneity or if there is dynamic component. That is, does an individual's characteristics, lifestyle and/or neighborhood make them more likely to be both a victim and offender? Or, does being an offender increase the likely of becoming a victim in the future, and/or vice versa? The answers to these questions may provide insights into the determinants and consequences of crime. Specifically, whether offending (victimization) is a determinant of later victimization (offending), as well as whether a potential cost of offending (victimization) is an increased risk of later victimization (offending). Given the high direct and indirect costs of crime, understanding the nature of the victim-offender relationship may, therefore, provide insights into effective and appropriate policy interventions to reduce the incidence and costs of crime.

In examining the nature of the relationship between victimization and offending, we make a contribution to three related strands of literature. First, we make a major contribution to the victim-offender overlap literature, which is a prominent topic in criminology but less explored in the economics of crime. Second, we contribute to the growing empirical economics of crime literature that examines the determinants and consequences of crime. This literature considers a wide range of factors, such as labor market conditions (e.g. Bindler & Ketel, 2021), education (e.g. Machin et al., 2011), the likelihood of detection and severity of punishment (see Chalfin & McCrary, 2017 for a summary) and so forth. A dynamic relationship between victimization and offending would suggest that victimization (offending) is a determinant and/or consequence of offending (victimization). Lastly, it contributes the emerging empirical literature on the cost of victimization (e.g. Bindler & Ketel, 2021). An elevated risk of future offending may be a potential cost of victimization which has not been examined to date.

In terms of the victim-offender overlap literature, the documentation of the existence of this overlap is extensive in the criminology literature (Berg et al., 2012; Berg & Mulford, 2020 for comprehensive literature overviews; Jennings et al., 2012; see e.g. Lauritsen & Laub, 2007).[8] However, the focus in the criminology literature has been 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.

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

With the rise of the empirical economics of crime literature, it was especially economists who first attempted to identify dynamic relationships between victims and offenders with their focus being on the economic rationale behind criminal behavior (Balkin & McDonald, 1981; Deadman & MacDonald, 2004; Entorf, 2013). 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 since they are often more exposed. On the other hand, the 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 some progress in isolating population heterogeneity from dynamic effects in recent years, it still lacks a clear and generalizable conclusion. The major reason for this is a lack of good administrative data with detailed population-level information on the timing of victimization and offending.

In contrast, we have a unique high-frequency panel dataset of victims and offenders. This provides at least three advantages over the existing literature. First, we use data covering the entire resident population of New Zealand whereas existing research relies on survey data covering a specific sub-group of the population (e.g. youth), meaning our results are more generalizable. Second, our administrative data does not rely on survey participants' recall of past victimization and offending over a specific time period, which may be subject to recall and perception errors. Third, and most importantly, our use of longitudinal administrative data means the precise timing of victimization and offending incidents can be examined in a way that is not possible with cross-sectional survey data. This allows us to make significant methodological advance in this area via the application of dynamic panel techniques in order to estimate the intertemporal relationship between victimization and offending. Overall, our use of detailed population-level panel data provides an opportunity to shed empirical light on the theoretical explanations behind the overlap. Specifically, whether this overlap is explained by an individual's lifestyle and characteristics, or whether a dynamic relationship exists, whereby past victimization (offending) leads to future offending (victimization).

Following previous literature, we first identify a small but fully simultaneous relationship between offending and victimization by pooling our data over time and using recursive bivariate probits. We next explore the intertemporal relationship between victimization and offending.

Event study models with fixed effects 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 few months immediately before offending (victimization). These results are further corroborated by dynamic panel models. The dynamic link is also largely driven by simultaneous events where an individual is both an alleged offender and victim (e.g. mutually combative assaults), and becomes very weak when these events are excluded. The remaining consecutive overlap between victimization and offending can, in very large part, be explained by time-invariant individual characteristics. This adds empirical weight to the theoretical explanations that emphasize the importance of population heterogeneity in the widely observed victim-offender overlap.

Delving into the nature of this victim-offender relationship not only sheds empirical light on the theories from the economics of crime and criminology, it also has the potential to provide policy insights. Since our findings give weight to the population heterogeneity argument, this is consistent with the commonly-held view that early life-course interventions will be most effective. If the dynamic relationship was instead more important, this might suggest that it would be more appropriate to time interventions at the point of the first offending or victimization incident.

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

2. EXISTING LITERATURE AND THEORETICAL BACKGROUND

The positive association between victimization and offending 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 offenders 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 & 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 determinants of crime in general (Berg & Mulford, 2020; Reiss, 1981).

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

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 chances of being exposed to crime (Cohen & Felson, 1979; Foreman-Peck & Moore, 2010; Osgood et al., 1996). These theoretical considerations were supported in multiple empirical studies finding a strong link in the socio-demographic profiles of victims and offenders (Broidy et al., 2006; Sampson & Lauritsen, 1990; Silver et al., 2011; Singer, 1981; Turanovic et al., 2015; Wittebrood & Nieuwbeerta, 1999). 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

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

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 (Flexon et al., 2016; Gottfredson & Hirschi, 1990; Piquero et al., 2005; Turanovic et al., 2015; van Gelder et al., 2015).

Population heterogeneity in the economics of crime

While the victim-offender 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 and informal punishment rates are low (Agnew, 1992; Akers, 2009; Berg et al., 2012; Jensen & Brownfield, 1986). An extreme example for this idea is the analysis of gang memberships and its role in explaining the victim-offender overlap (Pyrooz et al., 2014).

Dynamic relationships between victimization and offending

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 victimization and offending. 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 their lifestyle, their risk-preferences, or their 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 a willingness to retaliate even if this is costly to themselves in the short run (Fehr & Gächter, 2002). This is confirmed by the findings of experimental economics (Fehr & Schmidt, 2006). This suggests that retaliation by victims results in 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; Jacobs & Wright, 2010; Kubrin & Weitzer, 2003; Simons & 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 & Riedl, 2008). It should also be noted that these retaliatory motives explanations imply 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 theoretical explanations of the victim-offender overlap, particularly in terms of the possibility of a dynamic relationship. One major reason for the gap in the empirical literature which attempts to identify a dynamic relationship between offending and victimization was the lack of good longitudinal data which allows for such a perspective.

Lauritsen et al. (1991) was among the first studies to use longitudinal survey data in order to identify the sequencing of victimization and offending in more detail. They applied OLS regressions which included one-period lagged victimisation and delinquency measures as explanatory variables but did not employ specific panel-data econometric techniques. They found a strong dynamic relationship between victimization and offending 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 et al., 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, the paper comes to a very similar conclusion as the other two studies.

Nevertheless, these studies 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 et al., 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 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 theoretical explanations for the observed stylized fact that offending and victimization overlap, with a focus on differentiating between population heterogeneity and dynamic state-dependency arguments. We are also able to explore the role of simultaneous victim/offending incidents and retaliation. Moreover, the ability to examine different crime types to an extent previous survey-based research has not been able 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 resembles the prison population. For example, it is, on average, younger and less educated than the general German population as well as predominantly male.

allows us to provide additional insights into the hypotheses behind the victim-offender overlap. For example, as discussed, the rational choice theory implies that the victim-offender overlap would be more evident for violent crimes than property crimes.

3. DATA

Integrated Data Infrastructure

For our empirical analysis, we use New Zealand administrative data available within Stats NZ's Integrated Data Infrastructure (IDI).[11] The IDI is a comprehensive centralized research database, which 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.

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 version of the offender database used in this analysis collects information on every alleged offender reported from July 2009 to June 2020. Detailed information is available on each criminal incidence, including: the type of alleged offense committed[12], a standardized measure of its seriousness[13] and the police action taken (e.g. whether the police proceeded with the offense and how, such as informal/formal warning, arrest, and prosecution etc.). Similarly, the recorded victims database includes information on all alleged 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 identifier, allowing us to see who was involved in each incident as either an offender or victim (or both). Since the police records are comprehensive, they include very minor infractions. We, therefore, exclude incidents involving

[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 seriousness scores are based on the average sentences that such an offense would carry. For details, see McRae, Sullivan and Ong (2017).

very minor offenses that are not punishable by imprisonment, such as minor traffic offenses (i.e. those categorized as having the “lowest” seriousness).[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 offenses as well as offenses that did not involve police proceedings against the offender (where proceedings can involve minor actions such as informal warnings or small fines as well as more serious actions such as arrests and prosecutions). 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 seven 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, we construct an indicator of parent criminal history based on the longer available time-series of Ministry of Justice Court Charges data, which may partially remedy this (particularly if the perpetrator of a childhood victimization was the parent).

Sample definition and variables of interest

To define our population of interest, we use a 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, social welfare and 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 et al., 2016 for details.)

[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 do not contain information on the victims of burglaries.

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 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 offenses. For example, an armed robbery may involve both theft and firearm offenses. 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 offense 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 offense 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 (90.5%) were not involved in any incident as either an offender or victim. About 5.1% were involved in at least one incident as a victim, and 3.8% as an offender. 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 rounded to the nearest 100.

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

		victim			
		no	yes	total	
	no	353,800	20,200	374,000	$\Pr(V_i\!=\!1 \mid O_i = 0)$
	(cell %)	*(90.53%)*	*(5.14%)*	*(95.17%)*	5.40%
offender	yes	15,000	4,000	19,000	$\Pr(V_i\!=\!1 \mid O_i = 1)$
	(cell %)	*(3.82%)*	*(1.02%)*	*(4.83%)*	21.05%
	total	368,800	24,300	393,000	
	(cell %)	*(93.84%)*	*(6.18%)*		
		$\Pr(O_i = 1 \mid V_i = 0)$	$\Pr(O_i = 1 \mid V_i = 1)$		
		4.07%	16.46%		

Source: Authors' calculations using New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS). Counts are from a random sample of 10% 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', 'moderate' or 'high' seriousness. 'Lowest' seriousness incidents are excluded. Counts have been rounded to the nearest 100 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 victimization and offending. For those who were not offenders over the 2014 to 2020 period, there is a 5.4% probability that they are victims. If the individual was an offender, this probability of being a victim increases almost four-fold to 21.1%. Similarly, for those who were not victims, the probability of offending is 4.1%, compared with a probability of offending of 16.5% for those who had been a victim.

Table 2 gives an overview of 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. 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 the lowest 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 Pacific Peoples. 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

	1. $V_i = 0, O_i = 0$	2. $V_i = 0, O_i = 1$	3. $V_i = 1, O_i = 0$	4. $V_i = 1, O_i = 1$
	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 Peoples	.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: Authors' calculations using New Zealand Police Recorded Crime – Victims Statistics (RCVS), Recorded Crime – Offenders Statistics (RCOS), Inland Revenue, Stats NZ personal details and Ministry of Justice Court Charges data. "Parent charged" equals one if any parent was charged with a crime since 1992 (when the data series begins) and zero otherwise. Counts have been rounded to the nearest 100 in accordance with the Stats NZ confidentiality protocol.

Table 3 describes the observed criminal incidents separately for 1) only offenders, 2) only victims and 3) simultaneous offenders and victims. The characteristics of simultaneous victims and offenders are different for the offense and the victimization because the two crimes can still differ.

We see that in the overlap group the individuals are more likely to be repeated offenders (52.2%) than repeated victims (30.9%) and offenses are less likely to be violent (57.1%) than victimizations (61.0%). The share of those 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 also more likely to be involved in violent, intimate partner crimes, crimes involving family members and crimes involving weapons than those who are only victims or only offenders. Also in line with expectations, violent crimes are the most prevalent type of incident among those who are offenders only or both victims and offenders, while property crimes are the most prevalent among those who are only victims.

Table 3. Proportions of crime and victimization types

	$V_i = 0, O_i = 1$	$V_i = 1, O_i = 0$	$V_i = 1, O_i = 1$
Offender:			
Retaliatory	-	-	.056
Simultaneous victim/offender	-	-	.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 victim/offender	-	-	.026
Repeat victimization	-	.142	.309
Violent	-	.321	.610
Property	-	.714	.502
Family	-	.089	.204
Intimate partner violence	-	.090	.211
Sexual	-	.045	.050
Weapon	-	.063	.183
Observations	15,000	20,200	4,000

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

Two special cases of criminal incidents warrant attention when examining victim-offender overlap. First, incidents of simultaneous victimization and offending where a person is an alleged victim and offender 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 individuals in the overlap group have been involved in at least one such incident as offenders, and 2.6% individuals have been involved as victims.

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 individuals in the overlap group have been involved in at least one retaliatory incident as offenders and 4.1% as victims.

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. It also allows us to compare our results to existing literature, which predominantly uses this technique.

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

and

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

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

(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 a victim or an 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 $\varepsilon_j \ \forall j = 1 \dots 4 \sim N(0,1)$. 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 & 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 (Greene, 2012; Maddala, 1983; Wilde, 2000; Wooldridge, 2010). 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 the data to be pooled over time. This prevents us from investigating 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

[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).

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

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

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 & Hsiao, 1981, 1982). Additionally, equations (7) and (8) do not allow for correlated disturbances. Maddala (1983) 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 & Bond, 1991).

Dynamic panel models 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 & Bover, 1995; Blundell & Bond, 1998). We utilize generalized method 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 socio-economic status 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 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)

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

	$Pr(O = 1, V = 1 \mid \boldsymbol{X})$	$Pr(O = 1, V = 1 \mid \boldsymbol{X}, O = 1)$	$Pr(O = 1, V = 1 \mid \boldsymbol{X}, V = 1)$
Offender		-.1720*** (.0511)	
Victim			.0195*** (.0049)
$\hat{\rho}$	.3311*** (.0057)	.4662*** (.0322)	-.4145*** (.0272)
Observations	393,000	393,000	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 a10% random sample of the estimated resident population from 2014 to 2020. Observations have been randomly rounded to the nearest 100 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 Appendix Table A.1.

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 probit 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, victim-offender overlap 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 & Farrington, 2014) (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 0.11 (crimes of a sexual nature) to 0.45 (repeat offending and repeat victimization). This suggests a positive amount of overlap across crime types, although the relationship is less precisely measured for crimes of a sexual nature.

Also unsurprisingly, the victim-offender relationship is stronger for repeated crime, 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 victim-offender overlap 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 victim-offender 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 panel nature of our dataset, which provides monthly, population-wide offending and victimization records, allows 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 victim-offender overlap observed in the bivariate probit results.

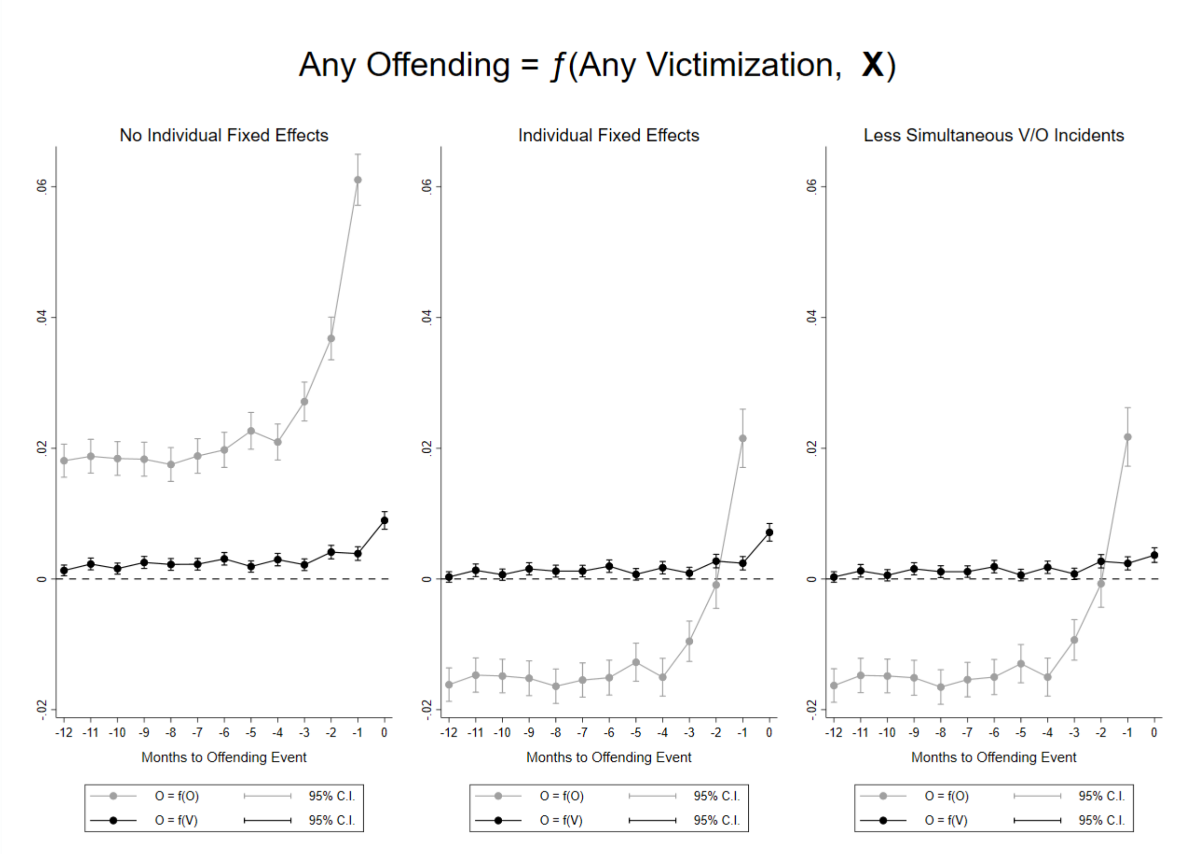
Figure 1 presents results for equation (7), where offending at time zero is a function of current and lagged victimization (black), as well as lagged offending (grey) and time-varying individual characteristics (namely age and income). Vertical bars represent 95% confidence intervals. Panel A (left) 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 (black), as well as lagged victimization (grey) and time-varying individual characteristics. Full estimation results are shown in Appendix Tables A.3 and A.4.

Figure 1A 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.

However, the magnitude of this greater likelihood of victimization is small, particularly compared with the relationship between current and past offending. The inclusion of fixed effects in 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. The negative relationship between long-run past offending and current offending could e.g. be explained by incarcerations and other detention which decrease offending opportunities. 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 small 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.

To explore the possibility that the remaining relationship is driven by simultaneous incidents where the individual is both an alleged offender and victim, 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 also presents the results without retaliatory events, and the results are very similar to those without simultaneous events.

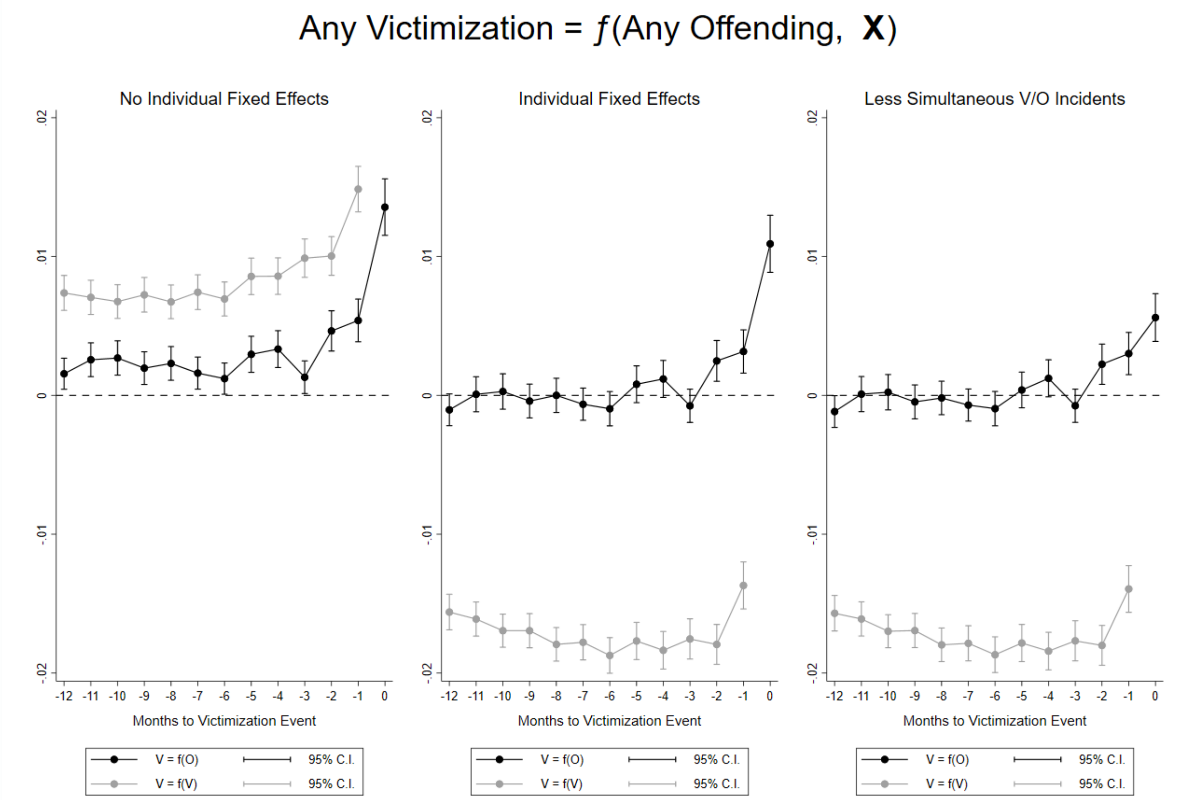
Figure 1. Main estimation results (outcome: offending)



Source: Authors' illustration and calculations using New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS). The population consists of a 10% random sample of the estimated resident population from 2014 to 2020.

We now turn to Figure 2 showing the relationship between current victimization and past offending (black) and victimization (grey). 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 victim-offender events are removed from the analysis, this magnitude of this short-term positive relationship decreases.

Figure 2. Main estimation results (outcome: victimization)



Source: Authors' illustration and calculations using New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS). The population consists of a 10% random sample of the estimated resident population from 2014 to 2020.

Once population heterogeneity is removed, i.e. time-invariant determinants of both events are controlled for with the individual fixed-effects, 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.

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, the overlap is only signficant for the current month. There is a small but 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 events where those involved are considered both victims and offenders. Also 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 victim-offender events, there is little evidence of overlap when it comes to crimes involving weapons.

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.

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*** (.004)		.194*** (.065)	
Offender (*t-1*)	.010*** (.005)	.066*** (.007)	-.005 (.034)	.039*** (.011)
Offender (*t-2*)	.013*** (.003)	.027*** (.005)	.024 (.025)	.025*** (.008)
Offender (*t*-3)	-.004 (.004)	.012*** (.004)	.015 (.030)	.013** (.005)
Victim(*t*)		.006** (.002)		.194** (.092)
Victim (*t-1*)	.010*** (. 003)	.009*** (.002)	.005** (.002)	-.019 (.0082)
Victim (*t-2*)	.008*** (.003)	-.003 (.002)	.004* (.002)	-.087 (.093)
Victim (*t-3*)	.006** (.003)	.0004 (.002)	.002* (.001)	-.005 (.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
Observations	2,926,600	2,926,600	2,926,600	2,926,600

Source: Authors' calculations using 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 2019 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.

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.

In columns (1) and (2), only the lagged dependent variables are assumed to be exogenous. In columns (3) and (4) all independent victimization and offending variables are considered endogenous. Note that these models are 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.

6. CONCLUSION

Identifying whether, and explaining why, victims are more likely to be offenders and offenders are more likely to be victims of crime, is important to understanding criminal dynamics. Although the victim-offender relationship is frequently referred to in the previous literature, it lacks a thorough empirical analysis of the dynamic relationship between offenders and victims. Existing research on this topic, especially in criminology, mainly focuses on the descriptive relationship and hypotheses an important role of time-invariant population heterogeneity for the positive correlation between both events. First attempts of identifying causal effects in the dynamic relationship, especially by researchers in the field of the economics of crime, were limited largely by a lack of suitable administrative data. Existing studies such as e.g. by Entorf (2013), Deadman and MacDonald (2004) make use of survey data covering specific sub-populations and are thus very limited in their external validity. Their lack of information on the exact timing of incidents also greatly limits their ability to identify a dynamic causal relationship.

This is where our study makes a major contribution. We are the first to systematically identify the dynamic relationship between offending and victimization using administrative data. Specifically, we use the universe of police investigations in New Zealand between 2014 and 2020 which include unique identifiers for both the offenders as well as the victims of the crimes. We are thus able to identify alleged offending as well as alleged victimization for all members of the residential population in New Zealand on a monthly basis. Using this data, we analyse the victim-offender overlap using three distinct empirical methods: 1) recursive bivariate probit models, 2) panel fixed effects models as well as 3) dynamic panel models.

Using recursive bivariate probit models, we find a small but fully simultaneous relationship between criminal offending and victimization, which is broadly in line with existing studies. As these models disregard the exact timing of events, we estimate panel models with individual fixed effects in a second step. The first finding is that these models provide empirical evidence of the importance of population heterogeneity, as put forward by numerous theories, particularly in the criminology literature. Further, these models enable us to identify a very distinct feature of the victim-offender overlap which has been hidden by the pooled time periods in existing empirical literature. We find that victimization and offending are indeed positively linked in both directions even if time-invariant population heterogeneity is controlled for, but that these links can only be observed over a short time span of up to three months. A large majority of overlaps occur within the same month and many of these even within the same event. Simultaneous events as well as events lying close together are thus found to be primary drivers of the dynamic relationship between victimization and offending. These findings are also supported by the results of the Arellano-Bond dynamic panel models and are found especially for non-sexual violent crimes.

In terms of rational choice theory, expected costs and benefits of crime depends on individual characteristics and these are largely time invariant, at least over the short- to medium-term. Experiencing victimization or undertaking offending does not seem to change these expected costs and benefits (e.g. due to revealing new information in the presence of imperfect info). Small exceptions for some types of crime exist in the very short run, but these also fit with rational choice theory. For example, some short-term dynamic relationships for violent crimes may be expected due to rational retaliation in a repeated game setting. But there is 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 is little reason to expect these victims to retaliate given the relatively low expected payoff vs. high expected costs to them doing so.

Due to a lack of understanding of the mechanisms behind the stylized fact of a victim-offender overlap, this paper thus makes a major contribution to the understanding of criminal dynamics. As such, it not only adds to the literature but also provides valuable insights into law and order policies. For example, our empirical findings add weight to the notion that population heterogeneity accounts for almost all of the victim-offender overlap, and reinforces the commonly-held view that early lifecourse interventions would be most effective in reducing the incident and costs of crime.

REFERENCES

Agnew, R. (1992). Foundation for a general strain theory of crime and delinquency. *Criminology*, *30*(1), 47–88.

Akers, R. L. (2009). *Social Learning and Social Structure: A General Theory of Crime and Deviance*. Routledge. https://doi.org/10.4324/9781315129587

Anderson, T. W., & Hsiao, C. (1981). Estimation of dynamic models with error components. *Journal of the American Statistical Association*, *76*(375), 598–606. https://doi.org/10.2307/2287517

Anderson, T. W., & Hsiao, C. (1982). Formulation and estimation of dynamic models using panel data. *Journal of Econometrics*, *18*(1), 47–82. https://doi.org/10.1016/0304-4076(82)90095-1

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, *58*(2), 277–297. https://doi.org/10.2307/2297968

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, *68*(1), 29–51. https://doi.org/10.1016/0304-4076(94)01642-D

Balkin, S., & McDonald, J. F. (1981). The market for street crime: An economic analysis of victim-offender interaction. *Journal of Urban Economics*, *10*(3), 390–405. https://doi.org/10.1016/0094-1190(81)90009-7

Berg, M. T., & Mulford, C. F. (2020). Reappraising and redirecting research on the victim–offender overlap. *Trauma, Violence, & Abuse*, *21*(1), 16–30. https://doi.org/10.1177/1524838017735925

Berg, M. T., Stewart, E. A., Schreck, C. J., & Simons, R. L. (2012). The victim-offender overlap in context: Examining the role of neighborhood street culture. *Criminology*, *50*(2), 359–390. https://doi.org/10.1111/j.1745-9125.2011.00265.x

Bindler, A., & Ketel, N. (2021). Scaring or scarring? Labour market effects of criminal victimisation. *Journal of Labor Economics*. https://doi.org/10.1086/718515

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*(1), 115–143. https://doi.org/10.1016/S0304-4076(98)00009-8

Broidy, L. M., Daday, J. K., Crandall, C. S., Sklar, D. P., & Jost, P. F. (2006). Exploring demographic, structural, and behavioral overlap among homicide offenders and victims. *Homicide Studies*, *10*(3), 155–180. https://doi.org/10.1177/1088767906288577

Chalfin, A., & McCrary, J. (2017). Criminal deterrence: A review of the literature. *Journal of Economic Literature*, *55*(1), 5–48. https://doi.org/10.1257/jel.20141147

Cohen, L. E., & Felson, M. (1979). Social change and crime rate trends: A routine activity approach. *American Sociological Review*, *44*(4), 588–608.

Daday, J. K., Broidy, L. M., Crandall, C. S., & Sklar, D. P. (2005). Individual, neighborhood, and situational factors associated with violent victimization and offending. *Criminal Justice Studies*, *18*(3), 215–235.

Deadman, D., & MacDonald, Z. (2004). Offenders as victims of crime?: An investigation into the relationship between criminal behaviour and victimization. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *167*(1), 53–67. https://doi.org/10.1111/j.1467-985X.2004.00291.x

Egas, M., & Riedl, A. (2008). The economics of altruistic punishment and the maintenance of cooperation. *Proceedings of the Royal Society B: Biological Sciences*, *275*(1637), 871–878. https://doi.org/10.1098/rspb.2007.1558

Entorf, H. (2013). Criminal victims, victimized criminals, or both? A deeper look at the victim-offender overlap. *IZA Discussion Paper*, *7686*.

Fehr, E., & Gächter, S. (2002). Altruistic punishment in humans. *Nature*, *415*(6868), 137–140.

Fehr, E., & Schmidt, K. M. (2006). Chapter 8 The Economics of Fairness, Reciprocity and Altruism – Experimental Evidence and New Theories. In S.-C. Kolm & J. M. Ythier (Eds.), *Handbook of the Economics of Giving, Altruism and Reciprocity* (Vol. 1, pp. 615–691). Elsevier. https://doi.org/10.1016/S1574-0714(06)01008-6

Filippini, M., Greene, W. H., Kumar, N., & Martinez-Cruz, A. L. (2018). A note on the different interpretation of the correlation parameters in the bivariate probit and the recursive bivariate probit. *Economics Letters*, *167*, 104–107. https://doi.org/10.1016/j.econlet.2018.03.018

Flexon, J. L., Meldrum, R. C., & Piquero, A. R. (2016). Low self-control and teh victim-offender overlap: A gendered analysis. *Journal of Interpersonal Violence*, *31*(11), 2052–2076. https://doi.org/10.1177/0886260515572471

Foreman-Peck, J., & Moore, S. C. (2010). Gratuitous violence and the rational offender model. *International Review of Law and Economics*, *30*(2), 160–172. https://doi.org/10.1016/j.irle.2010.03.003

Gibb, S., Bycroft, C., & Matheson-Dunning, N. (2016). *Identifying the New Zealand resident population in the Integrated Data Infrastructure (IDI)*. Stats New Zealand. https://www.stats.govt.nz/assets/Research/Identifying-the-New-Zealand-resident-population-in-the-Integrated-Data-Infrastructure/identifying-nz-resident-population-in-idi.pdf

Gottfredson, M. R., & Hirschi, T. (1990). *A General Theory of Crime*. Stanford University Press.

Greene, W. H. (2012). *Greene, W. H. (2012). Econometric Analysis. 7th Ed. New Jersey: Prentice-Hall.* Prentice-Hall.

Hindelang, M. J., Gottfredson, M. R., & Garofalo, J. (1978). *Victims of Personal Crime: An Empirical Foundation for a Theory of Personal Victimization*. Ballinger Cambridge, MA.

Holtz-Eakin, D., Newey, W., & Rosen, H. S. (1988). Estimating vector autoregressions with panel data. *Econometrica*, *56*(6), 1371–1395. https://doi.org/10.2307/1913103

Jacobs, B. A., & Wright, R. (2010). Bounded rationality, retaliation, and the spread of urban violence. *Journal of Interpersonal Violence*, *25*(10), 1739–1766.

Jennings, W. G., Higgins, G. E., Tewksbury, R., Gover, A. R., & Piquero, A. R. (2010). A longitudinal assessment of the victim-offender overlap. *Journal of Interpersonal Violence*, *25*(12), 2147–2174. https://doi.org/10.1177/0886260509354888

Jennings, W. G., Piquero, A. R., & Reingle, J. M. (2012). On the overlap between victimization and offending: A review of the literature. *Aggression and Violent Behavior*, *17*(1), 16–26. https://doi.org/10.1016/j.avb.2011.09.003

Jensen, G. F., & Brownfield, D. (1986). Gender, lifestyles, and victimization: Beyond routine activity. *Violence and Victims*, *1*(2), 85–99.

Knapp, L. G., & Seaks, T. G. (1998). A Hausman test for a dummy variable in probit. *Applied Economics Letters*, *5*(5), 321–323. https://doi.org/10.1080/758524410

Kubrin, C. E., & Weitzer, R. (2003). Retaliatory homicide: Concentrated disadvantage and neighborhood culture. *Social Problems*, *50*(2), 157–180. https://doi.org/10.1525/sp.2003.50.2.157

Lauritsen, J. L., & Laub, J. H. (2007). Understanding the link between victimization and offending: New reflections on an old idea. *Crime Prevention Studies*, *22*, 55–75.

Lauritsen, J. L., Sampson, R. J., & Laub, J. H. (1991). The link between offending and victimization among adolescents. *Criminology*, *29*(2), 265–292.

Loeber, R., & Farrington, D. P. (2014). Age-Crime Curve. In G. Bruinsma & D. Weisburd (Eds.), *Encyclopedia of Criminology and Criminal Justice* (pp. 12–18). Springer. https://doi.org/10.1007/978-1-4614-5690-2_474

Machin, S., Marie, O., & Sunčica, V. (2011). The crime reducing effect of education. *The Economic Journal*, *121*(552), 463–484.

Maddala, G. S. (1983). *Limited-Dependent and Qualitative Variables in Econometrics*. Cambridge University Press. https://doi.org/10.1017/CBO9780511810176

McRae, R., Sullivan, C., & Ong, S.-W. (2017). *Justice sector seriousness score (2016 update): FAQs* (Justice Sector Working Paper). New Zealand Police, Ministry of Justice, Department of Corrections. https://www.justice.govt.nz/assets/Documents/Publications/2016-FAQs-Seriousness-Scores2.pdf

Ministry of Justice. (2021). *New Zealand Crime and Victims Survey: Key findings: Descriptive statistics: June 2021: Results drawn from Cycle 3 (2019/20) of the New Zealand Crime and Victims Survey*. Ministry of Justice. https://www.justice.govt.nz/assets/Documents/Publications/Cycle-3-Core-Report-20210611-v1.5-for-release.pdf

Osgood, D. W., Wilson, J. K., O'Malley, P. M., Bachman, J. G., & Johnston, L. D. (1996). Routine activities and individual deviant behavior. *American Sociological Review*, *61*(4), 635--655.

Ousey, G. C., Wilcox, P., & Fisher, B. S. (2011). Something old, something new: Revisiting competing hypotheses of the victimization-offending relationship among adolescents. *Journal of Quantitative Criminology*, *27*(1), 53–84. https://doi.org/10.1007/s10940-010-9099-1

Piquero, A. R., MacDonald, J., Dobrin, A., Daigle, L. E., & Cullen, F. T. (2005). Self-control, violent offending, and homicide victimization: Assessing the general theory of crime. *Journal of Quantitative Criminology*, *21*(1), 55–71.

Pyrooz, D. C., Moule, R. K., & Decker, S. H. (2014). The contribution of gang membership to the victim-offender overlap. *Journal of Research in Crime and Delinquency*, *51*(3), 315–348. https://doi.org/10.1177/0022427813516128

Reiss, A. J. (1981). Towards a revitalization of theory and research on victimization by crime. *J. Crim. L. & Criminology*, *72*, 704.

Roodman, D. (2009). How to do Xtabond2: An Introduction to Difference and System GMM in Stata. *The Stata Journal*, *9*(1), 86–136.

Sampson, R. J., & Lauritsen, J. L. (1990). Deviant lifestyles, proximity to crime, and the offender-victim link in personal violence. *Journal of Research in Crime and Delinquency*, *27*(2), 110–139. https://doi.org/10.1177/0022427890027002002

Schreck, C. J., Stewart, E. A., & Osgood, D. W. (2008). A reappraisal of the overlap of violent offenders and victims. *Criminology*, *46*(4), 871–906. https://doi.org/10.1111/j.1745-9125.2008.00127.x

Silver, E., Piquero, A. R., Jennings, W. G., Piquero, N. L., & Leiber, M. (2011). Assessing the violent offending and violent victimization overlap among discharged psychiatric patients. *Law and Human Behavior*, *35*(1), 49–59. https://doi.org/10.1007/s10979-009-9206-8

Simons, R. L., & Burt, C. H. (2011). Learning to be bad: Adverse social conditions, social schemas, and crime. *Criminology*, *49*(2), 553. https://doi.org/10.1111/j.1745-9125.2011.00231.x

Singer, S. I. (1981). Homogeneous victim-offender populations: A review and some research implications. *Journal of Criminal Law and Criminology, 72*(2), 779–788.

Statistics New Zealand. (2016a). *IDI Data Dictionary: Recorded crime offenders data (May 2016 edition)* (p. 29). Available from www.stats.govt.nz

Statistics New Zealand. (2016b). *IDI Data Dictionary: Recorded crime victims data (May 2016 edition)*. Available from www.stats.govt.nz.

Turanovic, J. J., Reisig, M. D., & Pratt, T. C. (2015). Risky lifestyles, low self-control, and violent victimization across gendered pathways to crime. *Journal of Quantitative Criminology*, *31*(2), 183–206. https://doi.org/10.1007/s10940-014-9230-9

van Dijk, J., Nieuwbeerta, P., & Joudo Larsen, J. (2021). Global crime patterns: An analysis of survey data from 166 countries around the world, 2006–2019. *Journal of Quantitative Criminology*. https://doi.org/10.1007/s10940-021-09501-0 van Gelder, J.-L., Averdijk, M., Eisner, M., & Ribaud, D. (2015). Unpacking the victim-offender overlap: On role differentiation and socio-psychological characteristics. *Journal of Quantitative Criminology*, *31*(4), 653–675. https://doi.org/10.1007/s10940-014-9244-3

von Hentig, H. (1940). Remarks on the interaction of perpetrator and victim. *Journal of the American Institute of Criminal Law and Criminology*, *31*(3), 303–309.

Von Hentig, H. (1948). *The Criminal and his Victim: Studies in the Sociobiology of Crime* (pp. viii, 461). Yale University Press.

Weisburd, D., Groff, E. R., & Yang, S.-M. (2012). *The Criminology of Place: Street Segments and our Understanding of the Crime Problem*. Oxford University Press.

Weisburd, D., Groff, E. R., & Yang, S.-M. (2014). Understanding and controlling hot spots of crime: The importance of formal and informal social controls. *Prevention Science*, *15*(1), 31–43.

Wilde, J. (2000). Identification of multiple equation probit models with endogenous dummy regressors. *Economics Letters*, *69*(3), 309–312. https://doi.org/10.1016/S0165-1765(00)00320-7

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics*, *126*(1), 25–51. https://doi.org/10.1016/j.jeconom.2004.02.005

Wittebrood, K., & Nieuwbeerta, P. (1999). Wages of Sin? The Link Between Offending, Lifestyle and Violent Victimisation. *European Journal on Criminal Policy and Research*, *7*, 63–80.

Wolfgang, M. E. (1958). Patterns in Criminal Homicide. In *Patterns in Criminal Homicide*. University of Pennsylvania Press. https://www.degruyter.com/document/doi/10.9783/9781512808728/html

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data* (Second edition.). MIT Press,.

APPENDIX

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

	(1) Pr(O = 1, V = 1 | $\boldsymbol{X}$)	(2) Pr(O = 1, V = 1 | $\boldsymbol{X}$, O = 1)	(3) Pr(O = 1, V = 1 | $\boldsymbol{X}$, 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	

Source: Authors' calculations using 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.. *, **, 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 since 1992 (when the data series begins) 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)
Intimate partner violence	.321*** (.015)
Sexual	.110** (.045)
Weapon	.430*** (.014)

Source: Authors' calculations 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***	.0109***	.0056***	.0052***
	(.0010)	(.0010)	(.0009)	(.0009)
t – 1	.0054***	.0032***	.0030***	.0030***
	(.0008)	(.0008)	(.0008)	(.0008)
t – 2	.0046***	.0025***	.0022***	.0021***
	(.0007)	(.0007)	(.0007)	(.0007)
t – 3	.0013**	-.0007	-.0007	-.0008
	(.0006)	(.0006)	(.0006)	(.0006)
t – 4	.0033***	.0012*	.0012*	.0009
	(.0007)	(.0007)	(.0007)	(.0007)
t – 5	.0030***	.0008	.0004	.0005
	(.0007)	(.0007)	(.0007)	(.0007)
t – 6	.0012**	-.0010	-.0009	-.0010
	(.0006)	(.0006)	(.0006)	(.0006)
t – 7	.0016**	-.0006	-.0007	-.0004
	(.0006)	(.0006)	(.0006)	(.0006)
t – 8	.0023***	< .0001	-.0002	.0001
	(.0006)	(.0006)	(.0006)	(.0006)
t – 9	.0020***	-.0004	-.0005	-.0005
	(.0006)	(.0006)	(.0006)	(.0006)
t – 10	.0027***	.0003	.0002	.0003
	(.0006)	(.0007)	(.0006)	(.0006)
t – 11	.026***	< .0001	< .0001	.0002
	(.0006)	(.0006)	(.0006)	(.0006)
t – 12	.0016***	-.0010*	-.0012**	-.0013**
	(.0006)	(.0006)	(.0006)	(.0006)
victim				
t – 1	.0149***	-.0137***	-.0139***	-.0140***
	(.0008)	(.0009)	(.0009)	(.0009)
t – 2	.0100***	-.0179***	-.0180***	-.0180***

	(.0007)	(.0007)	(.0007)	(.0007)
t – 3	.0099**	-.0175***	-.0177***	-.0179***
	(.0007)	(.0007)	(.0007)	(.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: Authors' calculations using New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS). Robust standard errors are shown in parentheses. Marginal effects are calculated at variable means. *, **, and *** denote statistical significance at the 10, 5, and 1 percent-level.

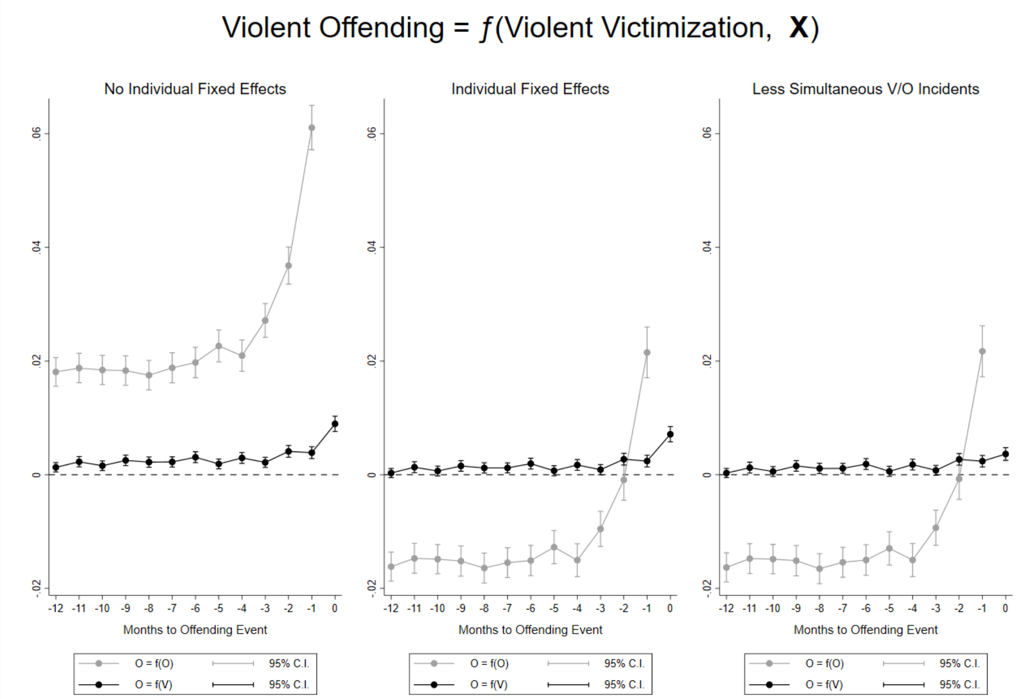
Table A.4. Full estimation results, any offending as the dependent variable

	No Individual Fixed Effects	Individual Fixed Effects	Less Simultaneous V/O Offenders	Less Potential Retaliatory Offenders
offending				
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)
victim				
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*** (.0005)	.0009** (.0005)	.0008* (.0004)	.0007* (.0004)
$t-4$	.0030*** (.0005)	.0017*** (.0005)	.0018*** (.0005)	.0018*** (.0005)
$t-5$	.0019*** (.0004)	-.0007 (.0005)	.0006 (.0004)	.0005 (.0004)
$t-6$	.0031** (.0005)	.0020*** (.0005)	.0019*** (.0005)	.0018*** (.0005)
$t-7$	.0023*** (.0005)	.0012*** (.0005)	.0011** (.0004)	.0011** (.0004)
$t-8$	.0022*** (.0005)	.0012*** (.0005)	.0011** (.0005)	.0009** (.0004)
$t-9$	.0025*** (.0005)	.0016*** (.0005)	.0016*** (.0005)	.0014*** (.0005)
$t-10$	.0016*** (.0004)	.0007 (.0004)	.0006 (.0004)	.0006 (.0004)
$t-11$	.0023*** (.0005)	.0013*** (.0005)	.0013** (.0005)	.0014*** (.0005)
$t-12$	.0013*** (.0004)	.0003 (.0004)	.0003 (.0004)	.0002 (.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

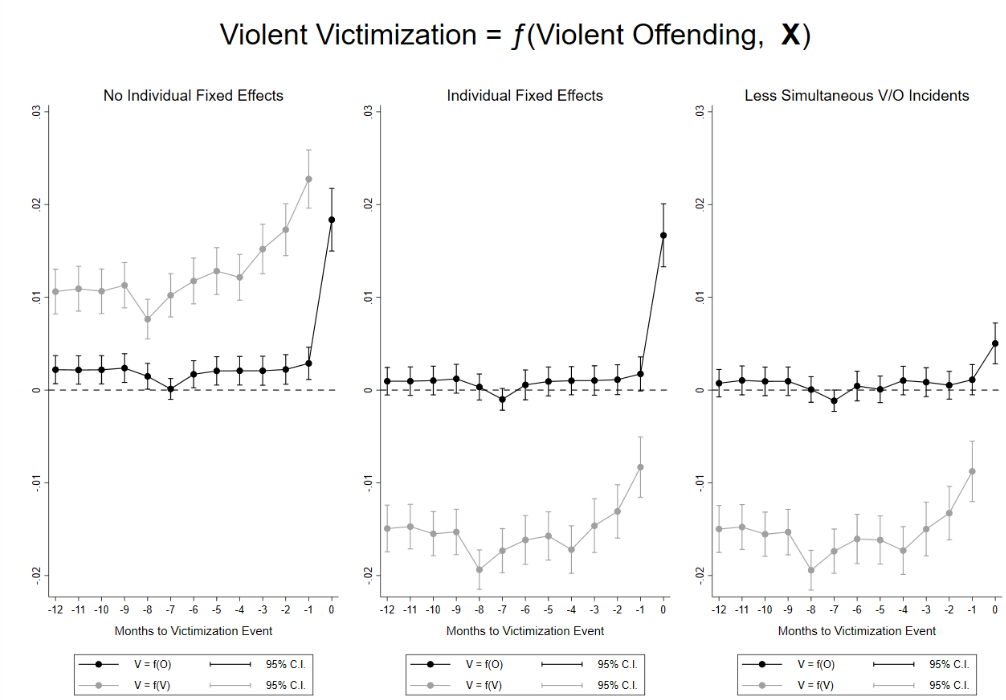
Source: New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS). Robust standard errors are shown in parentheses. Marginal effects are calculated at variable means. *, **, and *** denote statistical significance at the 10, 5, and 1 percent-levels, respectively.

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



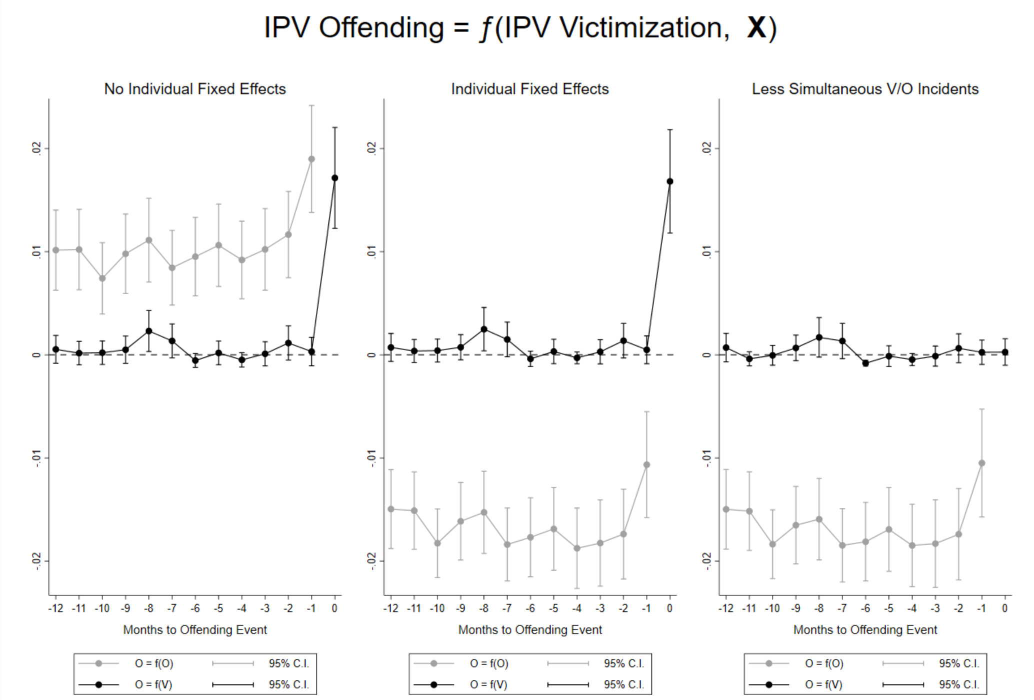
Source: Authors' illustration and calculations using New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS).

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



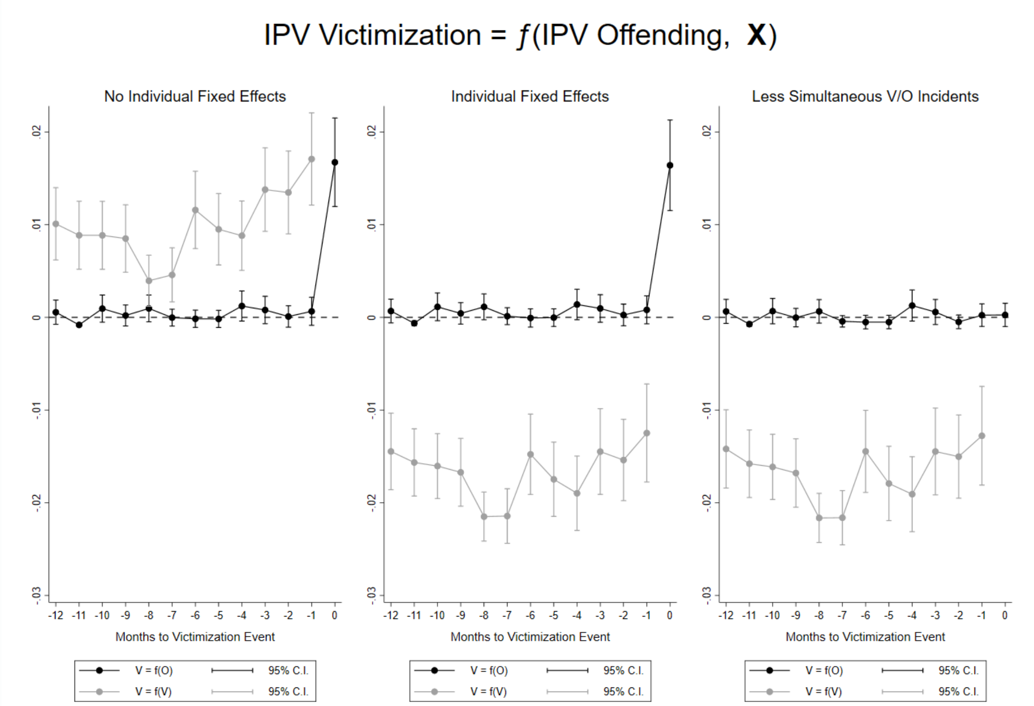
Source: Authors' illustration and calculations using New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS).

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



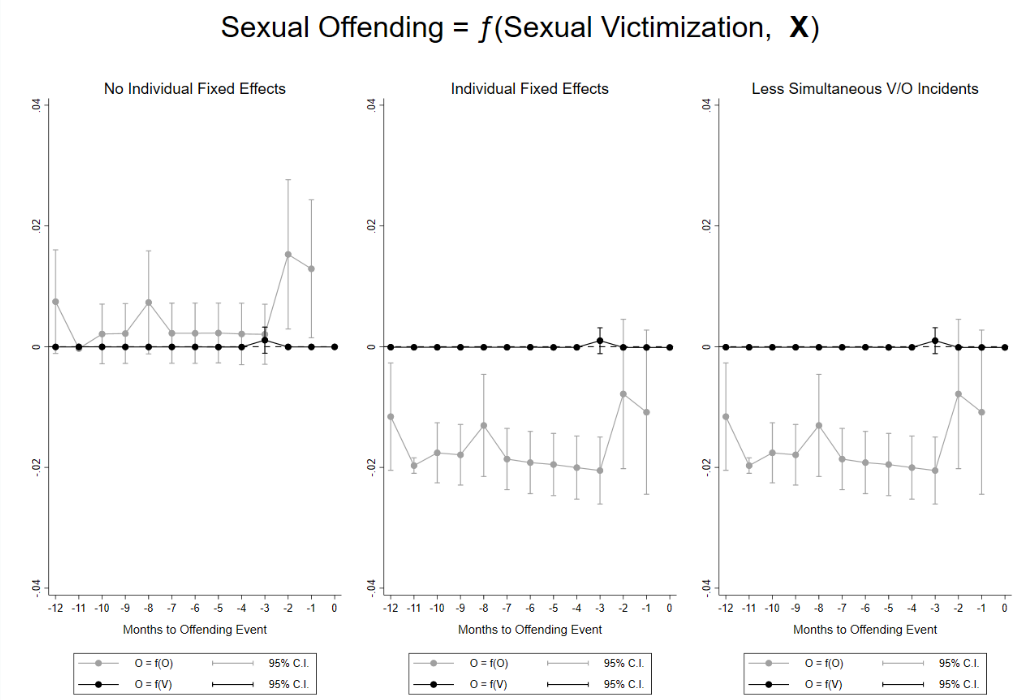
Source: Authors' illustration and calculations using New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS).

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



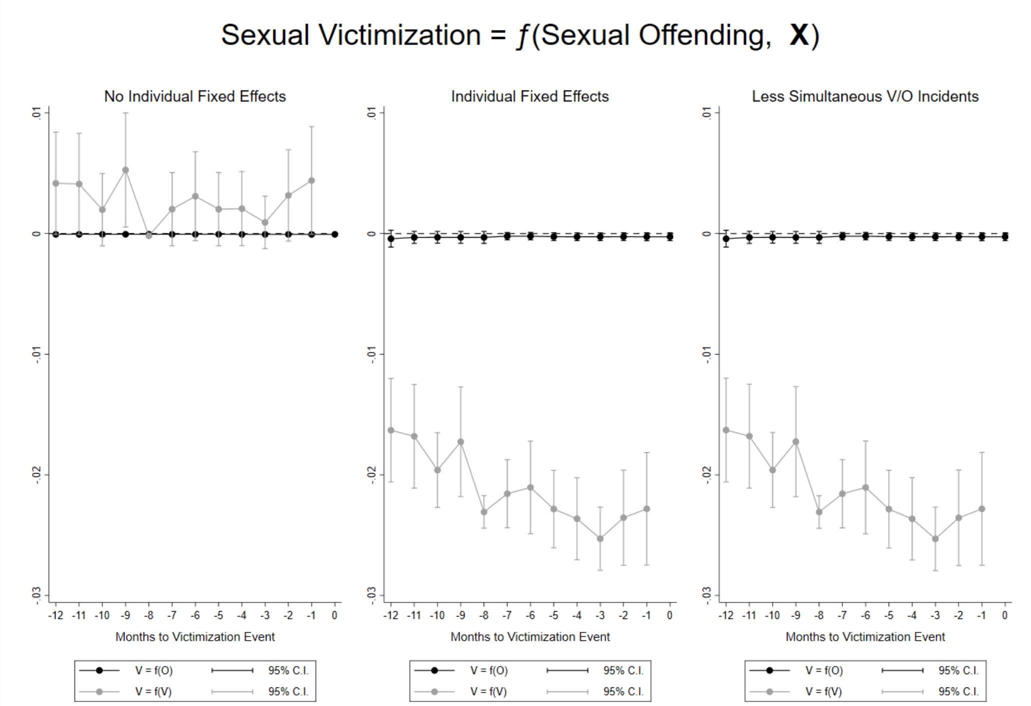
Source: Authors' illustration and calculations using New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS).

Figure A.5. Results by offense type, sexual crime offending



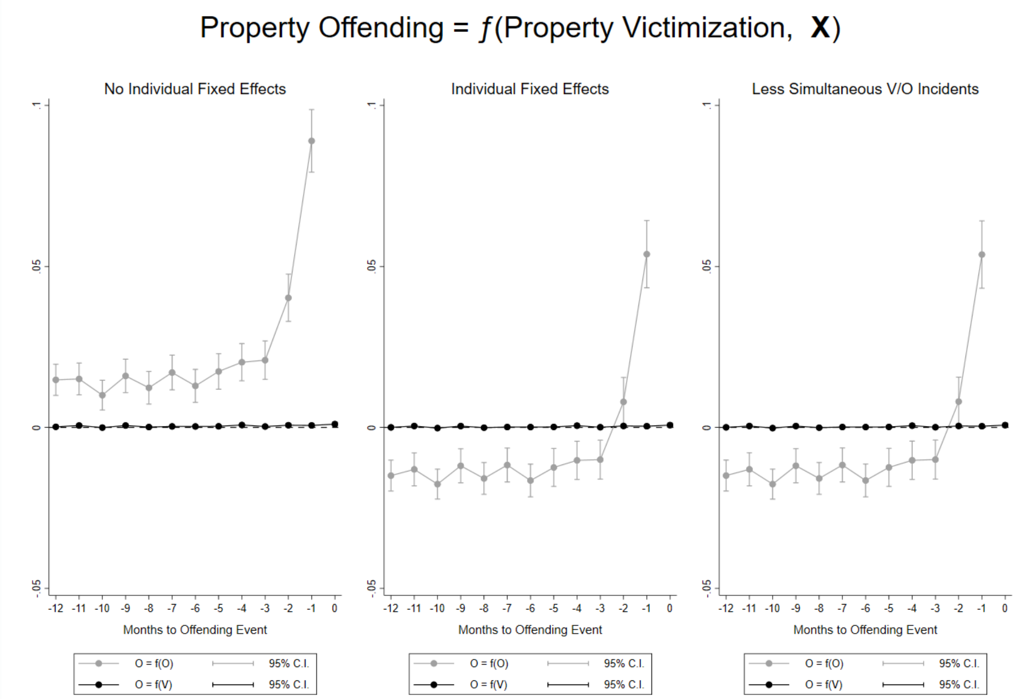
Source: Authors' illustration and calculations using New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS).

Figure A.6. Results by offense type, sexual crime victimization



Source: Authors' illustration and calculations using New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS).

Figure A.7. Results by offense type, property crime offending



Source: Authors' illustration and calculations using New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS).

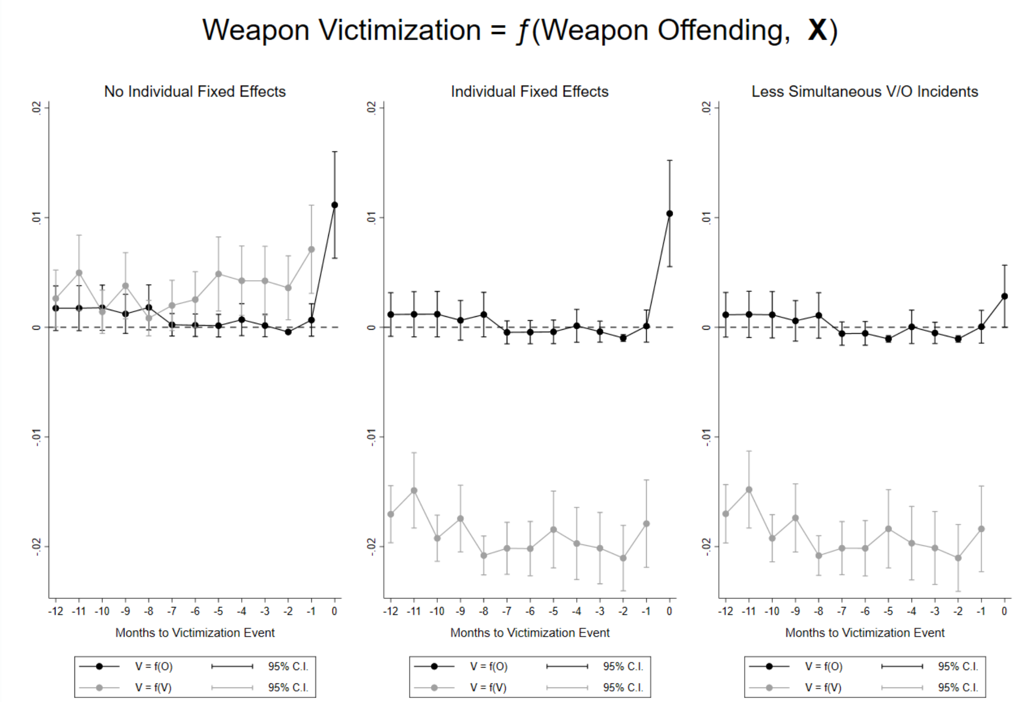
Figure A.8. Results by offense type, property crime victimization

Source: Authors' illustration and calculations using New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS).

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

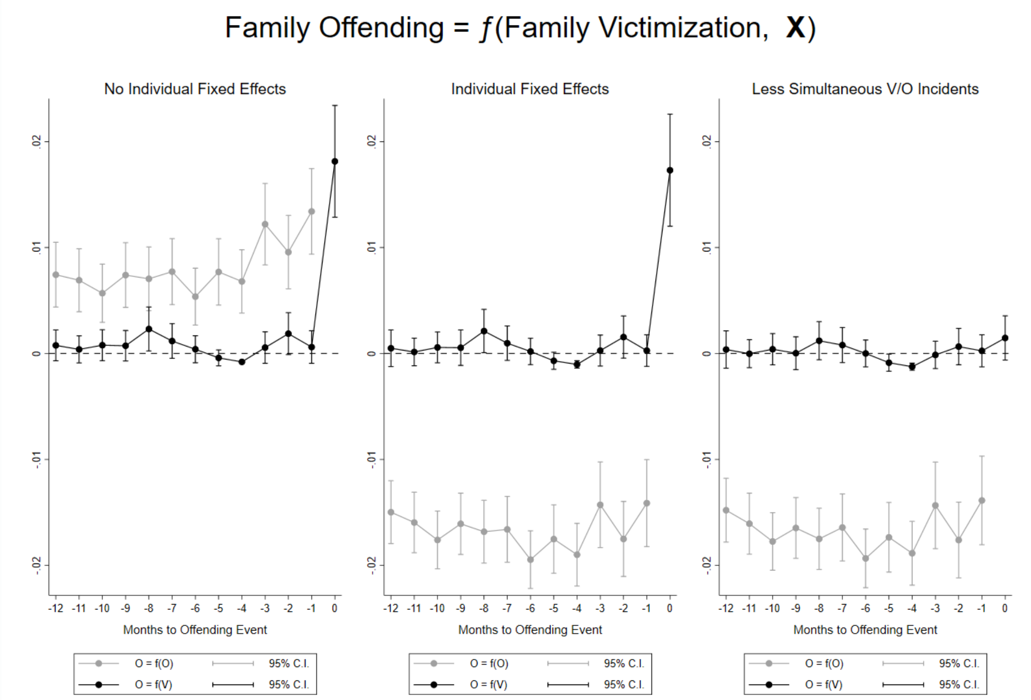
Source: Authors' illustration and calculations using New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS).

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



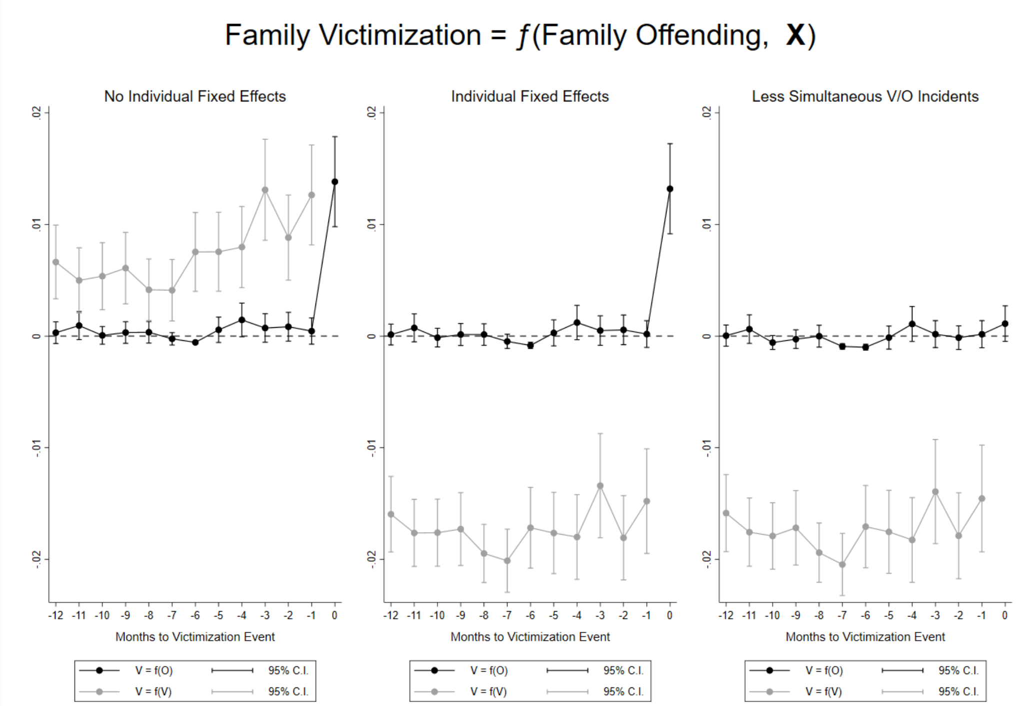
Source: Authors' illustration and calculations using New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS).

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



Source: Authors' illustration and calculations using New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS).

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



Source: Authors' illustration and calculations using New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS).