

Dynamic relationships between criminal offending and victimization

Christopher Erwin

Juliane Hennecke

Lisa Meehan

Gail Pacheco*

*New Zealand Work Research Institute
Auckland University of Technology

(authors listed in alphabetical order)

Disclaimer #1

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/>.

Disclaimer #2

- Sensitive research area
 - Victim blaming
 - Esp. intimate partner violence, crimes of a sexual nature
- We aim to better understand the behavioral patterns that put victims and offenders into contact, not to cast any blame

Motivation

- Criminals are more likely to become victims (and vice-versa)
 - Long history in criminological and sociological studies (Von Hentig, 1948; Wolfgang, 1958).
 - Less studied in economics (Deadman and MacDonald, 2004; Entorf, 2013; Ousey, Wilcox, and Fisher, 2010)
- Shaffer (2004)
 - Offenders are 1.5 – 7 times more likely than non-offenders to be victims
 - Victims are 2 – 7 times more likely than non-victims to be offenders

Motivation

- Why the overlap between criminals and victims of crime?
- Four intuitive reasons:
 1. Retaliation
 2. Institutionalization
 3. Simultaneous victim/offender events
 4. Risk preferences

Motivation

- From a 5% random sample of NZ residents over 2014 - 2020:

Table 1. Bivariate frequency counts of any victimization and any offending, 2014 – 2020

		victim		total
		no	yes	
offender	no	355,200	19,100	374,300
	yes	15,000	3,700	18,700
	total	370,200	22,800	393,000

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

Motivation

- From a 5% random sample of NZ residents over 2014 - 2020:

Table 1. Bivariate frequency counts of any victimization and any offending, 2014 – 2020

		victim		total
		no	yes	
offender	no	355,200	19,100	374,300
	yes	15,000	3,700	18,700
	total	370,200	22,800	393,000

~ 1:100 people

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

Motivation

- From a 5% random sample of NZ residents over 2014 - 2020:

Table 2. Unadjusted conditional probabilities of any victimization and any offending in New Zealand, 2014 – 2020

$\Pr(V_i = 1 \mid O_i = 0)$.0510
$\Pr(V_i = 1 \mid O_i = 1)$.1979
$\Pr(O_i = 1 \mid V_i = 0)$.0405
$\Pr(O_i = 1 \mid V_i = 1)$.1623

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

Research Questions

1. Is there a causal link between offending (O) and victimization (V)?
 - Is this a fully simultaneous relationship?
 - Existing literature suggests $O \rightarrow V$, but not vice versa
2. How do estimates change when controlling for individual-level fixed effects?
 - Do relationships between V and O change when we control for environmental and individual characteristics that do not change over time?

Preview of Findings

- Victimization and offending are jointly determined
- Victim/Offender overlap exists in New Zealand
 - Fixed effects are important
 - Environment and risk preferences appear to mask the causal relationship between victimization and criminal behaviour
- Events where individuals are simultaneously deemed victims and offenders drive the V/O overlap story
- Overlap is driven largely by incidents that occur close to each other in time

Contribution

- Only study to use a census of all investigated criminal and victimization incidents
- Previous studies lack external validity
 - Samples on teenagers, young adults, and samples based on the demographics of prisoners
- Previous studies rely on the accuracy of self-reported measures
- The detailed nature of NZ Police data allow us to examine simultaneity of violent crime, repeat offending/victimization, IPV, family violence, property crimes, etc.

Data

- New Zealand Police data, 2014 - 2020
 - Recorded Crime Offenders Statistics (RCOS)
 - Recorded Crime Victims Statistics (RCVS)
- Estimated resident population (ERP) from Stats NZ used as the spine
 - Victims and offenders not included in the ERP were excluded
- Only incidents linked to a person ID
- Only incidents that resulted in at least an informal warning

Data

- Excluded individuals younger than 18 years of age
- Excluded the least serious offenses
 - We used a file from MoJ that is populated in the IDI's Ad Hoc folder named "corr_offense"
- Used MoJ court charges data to flag whether an individual's parents were ever charged with a crime (data back to 1992)
- Used a 5% random sample of the ERP from 2014-2020
 - 393,000 individuals
 - Necessary to manage computational costs

Table 3. Descriptive statistics, 2014 – 2020

variable	(1) $V_i = 0, O_i = 0$	(2) $V_i = 0, O_i = 1$	(3) $V_i = 1, O_i = 0$	(4) $V_i = 1, O_i = 1$
female	.521	.172	.485	.396
age	46.84 (19.17)	37.56 (13.63)	38.44 (15.46)	34.18 (11.66)
European	.643	.402	.549	.371
Māori	.126	.434	.215	.501
Pacific	.059	.110	.064	.073
Asian	.151	.044	.156	.042
MELAA	.015	.010	.015	.013
other	.006	< .001	.001	< .001
parent charged	.034	.092	.061	.108
annual earnings	31,379 (40,704)	20,081 (24,234)	32,918 (38,983)	13,033 (19,235)
observations	355,200	15,000	19,100	3,700

Source: New Zealand Police Recorded Crime – Victims Statistics (RCVS), Recorded Crime – Offenders Statistic (RCOS), Immigration New Zealand, Inland Revenue, and Ministry of Justice. Standard deviations are shown in parentheses. The population consists of all victims and offenders investigated within New Zealand and included the country’s estimated resident population. “Parent charged” equals one if any parent was charged with a crime, and zero otherwise.

Table 3. Descriptive statistics, 2014 – 2020

variable	(1) $V_i = 0, O_i = 0$	(2) $V_i = 0, O_i = 1$	(3) $V_i = 1, O_i = 0$	(4) $V_i = 1, O_i = 1$
female	.521	.172	.485	.396
age	46.84 (19.17)	37.56 (13.63)	38.44 (15.46)	34.18 (11.66)
European	.643	.402	.549	.371
Māori	.126	.434	.215	.501
Pacific	.059	.110	.064	.073
Asian	.151	.044	.156	.042
MELAA	.015	.010	.015	.013
other	.006	< .001	.001	< .001
parent charged	.034	.092	.061	.108
annual earnings	31,379 (40,704)	20,081 (24,234)	32,918 (38,983)	13,033 (19,235)
observations	355,200	15,000	19,100	3,700

Source: New Zealand Police Recorded Crime – Victims Statistics (RCVS), Recorded Crime – Offenders Statistic (RCOS), Immigration New Zealand, Inland Revenue, and Ministry of Justice. Standard deviations are shown in parentheses. The population consists of all victims and offenders investigated within New Zealand and included the country’s estimated resident population. “Parent charged” equals one if any parent was charged with a crime, and zero otherwise.

Table 3. Descriptive statistics, 2014 – 2020

variable	(1) $V_i = 0, O_i = 0$	(2) $V_i = 0, O_i = 1$	(3) $V_i = 1, O_i = 0$	(4) $V_i = 1, O_i = 1$
female	.521	.172	.485	.396
age	46.84 (19.17)	37.56 (13.63)	38.44 (15.46)	34.18 (11.66)
European	.643	.402	.549	.371
Māori	.126	.434	.215	.501
Pacific	.059	.110	.064	.073
Asian	.151	.044	.156	.042
MELAA	.015	.010	.015	.013
other	.006	< .001	.001	< .001
parent charged	.034	.092	.061	.108
annual earnings	31,379 (40,704)	20,081 (24,234)	32,918 (38,983)	13,033 (19,235)
observations	355,200	15,000	19,100	3,700

Source: New Zealand Police Recorded Crime – Victims Statistics (RCVS), Recorded Crime – Offenders Statistic (RCOS), Immigration New Zealand, Inland Revenue, and Ministry of Justice. Standard deviations are shown in parentheses. The population consists of all victims and offenders investigated within New Zealand and included the country’s estimated resident population. “Parent charged” equals one if any parent was charged with a crime, and zero otherwise.

Table 3. Descriptive statistics, 2014 – 2020

variable	(1) $V_i = 0, O_i = 0$	(2) $V_i = 0, O_i = 1$	(3) $V_i = 1, O_i = 0$	(4) $V_i = 1, O_i = 1$
female	.521	.172	.485	.396
age	46.84 (19.17)	37.56 (13.63)	38.44 (15.46)	34.18 (11.66)
European	.643	.402	.549	.371
Māori	.126	.434	.215	.501
Pacific	.059	.110	.064	.073
Asian	.151	.044	.156	.042
MELAA	.015	.010	.015	.013
other	.006	< .001	.001	< .001
parent charged	.034	.092	.061	.108
annual earnings	31,379 (40,704)	20,081 (24,234)	32,918 (38,983)	13,033 (19,235)
observations	355,200	15,000	19,100	3,700

Source: New Zealand Police Recorded Crime – Victims Statistics (RCVS), Recorded Crime – Offenders Statistic (RCOS), Immigration New Zealand, Inland Revenue, and Ministry of Justice. Standard deviations are shown in parentheses. The population consists of all victims and offenders investigated within New Zealand and included the country’s estimated resident population. “Parent charged” equals one if any parent was charged with a crime, and zero otherwise.

Table 3. Descriptive statistics, 2014 – 2020

variable	(1) $V_i = 0, O_i = 0$	(2) $V_i = 0, O_i = 1$	(3) $V_i = 1, O_i = 0$	(4) $V_i = 1, O_i = 1$
female	.521	.172	.485	.396
age	46.84 (19.17)	37.56 (13.63)	38.44 (15.46)	34.18 (11.66)
European	.643	.402	.549	.371
Māori	.126	.434	.215	.501
Pacific	.059	.110	.064	.073
Asian	.151	.044	.156	.042
MELAA	.015	.010	.015	.013
other	.006	< .001	.001	< .001
parent charged	.034	.092	.061	.108
annual earnings	31,379 (40,704)	20,081 (24,234)	32,918 (38,983)	13,033 (19,235)
observations	355,200	15,000	19,100	3,700

Source: New Zealand Police Recorded Crime – Victims Statistics (RCVS), Recorded Crime – Offenders Statistic (RCOS), Immigration New Zealand, Inland Revenue, and Ministry of Justice. Standard deviations are shown in parentheses. The population consists of all victims and offenders investigated within New Zealand and included the country’s estimated resident population. “Parent charged” equals one if any parent was charged with a crime, and zero otherwise.

Table 4. Proportions of crime and victimization types

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

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

Table 4. Proportions of crime and victimization types

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

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

Table 4. Proportions of crime and victimization types

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

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

Empirical Model

1. Pool data over 2014-2020 and estimate seemingly unrelated bivariate probit and recursive bivariate probit models
 - We can see whether there is a truly simultaneous relationship between victimization and offending
 - This is done for several crime types (e.g., violent, property, weapon involved, etc.)

$$(1) V_i^* = \mathbf{X}_i \boldsymbol{\beta}_i + \varepsilon_{1,i}, \quad Victim_i = 1(V_i^* > 0)$$

$$(2) O_i^* = \mathbf{X}_i \boldsymbol{\beta}_i + \varepsilon_{2,i}, \quad Offender_i = 1(O_i^* > 0)$$

$$(3) \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right]$$

Empirical Model

2. Construct a monthly panel and estimate fixed effects models

$$(4) V_{it} = \alpha_0 + \sum_{j=1}^{12} \alpha_j V_{i,t-j} + \sum_{k=0}^{12} \beta_{k+1} O_{i,t-k} + \mathbf{X}_{it}\boldsymbol{\Gamma} + \delta_t + \delta_i + \varepsilon_{it}$$

$$(5) O_{it} = \gamma_0 + \sum_{m=1}^{12} \gamma_m O_{i,t-m} + \sum_{n=0}^{12} \theta_{n+1} V_{i,t-n} + \mathbf{X}_{it}\boldsymbol{\Pi} + \delta_t + \delta_i + \mu_{it}$$

- Individual fixed effects, δ_i , control for all individual characteristics that do not change over time (e.g., environment, neighborhood, risk preferences etc.)
- Time fixed effects, δ_t , control for monthly effects (e.g., holidays, summer months, etc.)

Empirical Model

$$(4) V_{it} = \alpha_0 + \sum_{j=1}^{12} \alpha_j V_{i,t-j} + \sum_{k=0}^{12} \beta_{k+1} O_{i,t-k} + \mathbf{X}_{it}\boldsymbol{\Gamma} + \delta_t + \delta_i + \varepsilon_{it}$$

$$(5) O_{it} = \gamma_0 + \sum_{m=1}^{12} \gamma_m O_{i,t-m} + \sum_{n=0}^{12} \theta_{n+1} V_{i,t-n} + \mathbf{X}_{it}\boldsymbol{\Pi} + \delta_t + \delta_i + \mu_{it}$$

- Models estimate the impact of current offending (victimization) on current victimization (offending), controlling for previous behaviour
- We estimate with and without individual fixed effects to see how much impact environment and risk preference has on V/O overlap
- We also remove individuals that experienced incidents that simultaneously made them victims and offenders

Empirical Model

- We also estimate dynamic panel (i.e., Arellano-Bond) estimates to verify results
- Using various lags in the dependent variable as instruments, results appear similar
- We report estimated parameters as well as tests of the identifying assumption
 - No autocorrelation in the idiosyncratic error terms

	(1)	(2)	(3)	(4)
variable	$Pr(V_i = 1 X_i)$	$Pr(V_i = 1 O_i, X_i)$	$Pr(O_i = 1 X_i)$	$Pr(O_i = 1 V_i, X_i)$
offending		.0597*** (.0012)		
victimization				.0244*** (.0006)
female	-.0092*** (.0007)	-.0033*** (.0007)	-.0332*** (.0005)	-.0325*** (.0005)
age	.0019*** (.0001)	.0014*** (.0001)	.0035*** (.0001)	.0033*** (.0001)
age ²	-.0035*** (.0001)	-.0028*** (.0001)	-.0047*** (.0001)	-.0043*** (.0001)
Māori	.0288*** (.0009)	.0208*** (.0009)	.0285*** (.0005)	.0263*** (.0005)
Pacific	-.0001 (.0001)	-.0028** (.0014)	.0132*** (.0006)	.0130*** (.0006)
Asian	-.0072*** (.0010)	-.0040*** (.0010)	-.0212*** (.0007)	-.0202*** (.0007)
MELAA	-.0055** (.0028)	-.0041 (.0027)	-.0080*** (.0014)	-.0076*** (.0013)
other	-.0663*** (.0084)	-.0611*** (.0083)	-.0494*** (.0071)	-.04657*** (.0068)
annual earnings	-.0016*** (.0001)	-.0009*** (.0001)	-.0049*** (.0001)	-.0045*** (.0001)
parent charged	.0081*** (.0015)	.0061*** (.0015)	.0074*** (.0007)	.0068*** (.0006)
observations	393,000	393,000	393,000	393,000

	(1)	(2)	(3)	(4)
variable	$Pr(V_i = 1 X_i)$	$Pr(V_i = 1 O_i, X_i)$	$Pr(O_i = 1 X_i)$	$Pr(O_i = 1 V_i, X_i)$
offending		.0597*** (.0012)		
victimization				.0244*** (.0006)
female	-.0092*** (.0007)	-.0033*** (.0007)	-.0332*** (.0005)	-.0325*** (.0005)
age	.0019*** (.0001)	.0014*** (.0001)	.0035*** (.0001)	.0033*** (.0001)
age ²	-.0035*** (.0001)	-.0028*** (.0001)	-.0047*** (.0001)	-.0043*** (.0001)
Māori	.0288*** (.0009)	.0208*** (.0009)	.0285*** (.0005)	.0263*** (.0005)
Pacific	-.0001 (.0001)	-.0028** (.0014)	.0132*** (.0006)	.0130*** (.0006)
Asian	-.0072*** (.0010)	-.0040*** (.0010)	-.0212*** (.0007)	-.0202*** (.0007)
MELAA	-.0055** (.0028)	-.0041 (.0027)	-.0080*** (.0014)	-.0076*** (.0013)
other	-.0663*** (.0084)	-.0611*** (.0083)	-.0494*** (.0071)	-.04657*** (.0068)
annual earnings	-.0016*** (.0001)	-.0009*** (.0001)	-.0049*** (.0001)	-.0045*** (.0001)
parent charged	.0081*** (.0015)	.0061*** (.0015)	.0074*** (.0007)	.0068*** (.0006)
observations	393,000	393,000	393,000	393,000

	(1)	(2)	(3)	(4)
variable	$Pr(V_i = 1 X_i)$	$Pr(V_i = 1 O_i, X_i)$	$Pr(O_i = 1 X_i)$	$Pr(O_i = 1 V_i, X_i)$
offending		.0597*** (.0012)		
victimization				.0244*** (.0006)
female	-.0092*** (.0007)	-.0033*** (.0007)	-.0332*** (.0005)	-.0325*** (.0005)
age	.0019*** (.0001)	.0014*** (.0001)	.0035*** (.0001)	.0033*** (.0001)
age ²	-.0035*** (.0001)	-.0028*** (.0001)	-.0047*** (.0001)	-.0043*** (.0001)
Māori	.0288*** (.0009)	.0208*** (.0009)	.0285*** (.0005)	.0263*** (.0005)
Pacific	-.0001 (.0001)	-.0028** (.0014)	.0132*** (.0006)	.0130*** (.0006)
Asian	-.0072*** (.0010)	-.0040*** (.0010)	-.0212*** (.0007)	-.0202*** (.0007)
MELAA	-.0055** (.0028)	-.0041 (.0027)	-.0080*** (.0014)	-.0076*** (.0013)
other	-.0663*** (.0084)	-.0611*** (.0083)	-.0494*** (.0071)	-.04657*** (.0068)
annual earnings	-.0016*** (.0001)	-.0009*** (.0001)	-.0049*** (.0001)	-.0045*** (.0001)
parent charged	.0081*** (.0015)	.0061*** (.0015)	.0074*** (.0007)	.0068*** (.0006)
observations	393,000	393,000	393,000	393,000

	(1)	(2)	(3)	(4)
variable	$Pr(V_i = 1 X_i)$	$Pr(V_i = 1 O_i, X_i)$	$Pr(O_i = 1 X_i)$	$Pr(O_i = 1 V_i, X_i)$
offending		.0597*** (.0012)		
victimization				.0244*** (.0006)
female	-.0092*** (.0007)	-.0033*** (.0007)	-.0332*** (.0005)	-.0325*** (.0005)
age	.0019*** (.0001)	.0014*** (.0001)	.0035*** (.0001)	.0033*** (.0001)
age ²	-.0035*** (.0001)	-.0028*** (.0001)	-.0047*** (.0001)	-.0043*** (.0001)
Māori	.0288*** (.0009)	.0208*** (.0009)	.0285*** (.0005)	.0263*** (.0005)
Pacific	-.0001 (.0001)	-.0028** (.0014)	.0132*** (.0006)	.0130*** (.0006)
Asian	-.0072*** (.0010)	-.0040*** (.0010)	-.0212*** (.0007)	-.0202*** (.0007)
MELAA	-.0055** (.0028)	-.0041 (.0027)	-.0080*** (.0014)	-.0076*** (.0013)
other	-.0663*** (.0084)	-.0611*** (.0083)	-.0494*** (.0071)	-.04657*** (.0068)
annual earnings	-.0016*** (.0001)	-.0009*** (.0001)	-.0049*** (.0001)	-.0045*** (.0001)
parent charged	.0081*** (.0015)	.0061*** (.0015)	.0074*** (.0007)	.0068*** (.0006)
observations	393,000	393,000	393,000	393,000

Table 5. Bivariate predicted probabilities from a seemingly unrelated bivariate probit model of any criminal victimization and any offending in New Zealand, 2014 – 2020

variable	$\Pr(V_i = 1, O_i = 1)$
female	-.0057*** (.0001)
age	.0006*** ($<$.0001)
age ²	-.0009*** ($<$.0001)
Māori	.0057*** (.0001)
Pacific	.0021*** (.0001)
Asian	-.0036*** (.0001)
MELAA	-.0015*** (.0003)
other	-.0107*** (.0012)
annual earnings	-.0008*** ($<$.0001)
parent charged	.0015*** (.0001)
$\hat{\rho}$.3203*** (.0058)
observations	393,000

Table 5. Bivariate predicted probabilities from a seemingly unrelated bivariate probit model of any criminal victimization and any offending in New Zealand, 2014 – 2020

variable	$\Pr(V_i = 1, O_i = 1)$
female	-.0057*** (.0001)
age	.0006*** ($< .0001$)
age ²	-.0009*** ($< .0001$)
Māori	.0057*** (.0001)
Pacific	.0021*** (.0001)
Asian	-.0036*** (.0001)
MELAA	-.0015*** (.0003)
other	-.0107*** (.0012)
annual earnings	-.0008*** ($< .0001$)
parent charged	.0015*** (.0001)
$\hat{\rho}$.3203*** (.0058)
observations	393,000

Table 6. Tetrachoric correlations from seemingly unrelated bivariate probit models, by crime type in New Zealand, 2014 – 2020

Crime Type	$\hat{\rho}$ (SE)
All	.320*** (.006)
Violent	.477*** (.005)
Property	.215*** (.007)
Family	.517*** (.009)
Partner	.585*** (.010)
IPV	.583*** (.011)
Weapon	.363*** (.013)
Firearm	.280*** (.046)
Sexual	.327*** (.047)
Repeated	.451*** (.006)
Observations	393,000

Source: New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS). Robust standard errors are reported. The population consists of all victims and offenders investigated within New Zealand, as well as all persons counted in the estimated resident population from 2014 to 2018. Observations have been randomly rounded to the nearest hundred in accordance with the Stats NZ confidentiality protocol. *, **, and *** denote statistical significance at the 10, 5, and 1 percent-levels, respectively. Models include controls or ethnicity, age, gender, income, and parents’ criminal record.

Table 6. Tetrachoric correlations from seemingly unrelated bivariate probit models, by crime type in New Zealand, 2014 – 2020

Crime Type	$\hat{\rho}$ (SE)
All	.320*** (.006)
Violent	.477*** (.005)
Property	.215*** (.007)
Family	.517*** (.009)
Partner	.585*** (.010)
IPV	.583*** (.011)
Weapon	.363*** (.013)
Firearm	.280*** (.046)
Sexual	.327*** (.047)
Repeated	.451*** (.006)
Observations	393,000

Source: New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS). Robust standard errors are reported. The population consists of all victims and offenders investigated within New Zealand, as well as all persons counted in the estimated resident population from 2014 to 2018. Observations have been randomly rounded to the nearest hundred in accordance with the Stats NZ confidentiality protocol. *, **, and *** denote statistical significance at the 10, 5, and 1 percent-levels, respectively. Models include controls or ethnicity, age, gender, income, and parents’ criminal record.

Table 6. Tetrachoric correlations from seemingly unrelated bivariate probit models, by crime type in New Zealand, 2014 – 2020

Crime Type	$\hat{\rho}$ (SE)
All	.320*** (.006)
Violent	.477*** (.005)
Property	.215*** (.007)
Family	.517*** (.009)
Partner	.585*** (.010)
IPV	.583*** (.011)
Weapon	.363*** (.013)
Firearm	.280*** (.046)
Sexual	.327*** (.047)
Repeated	.451*** (.006)
Observations	393,000

Source: New Zealand Police Recorded Crime – Victims Statistics (RCVS) and Recorded Crime – Offenders Statistics (RCOS). Robust standard errors are reported. The population consists of all victims and offenders investigated within New Zealand, as well as all persons counted in the estimated resident population from 2014 to 2018. Observations have been randomly rounded to the nearest hundred in accordance with the Stats NZ confidentiality protocol. *, **, and *** denote statistical significance at the 10, 5, and 1 percent-levels, respectively. Models include controls or ethnicity, age, gender, income, and parents’ criminal record.

Results Pt. 2

- Recall that we are predicting current-month offending (victimization) using previous victimization and offending behaviour

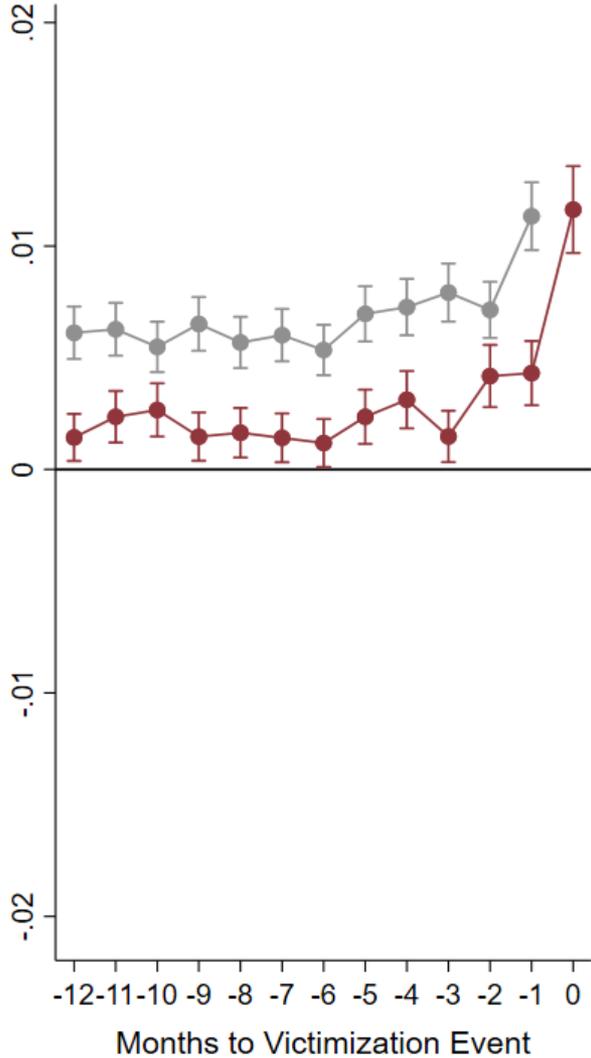
$$(4) V_{it} = \alpha_0 + \sum_{j=1}^{12} \alpha_j V_{i,t-j} + \sum_{k=0}^{12} \beta_{k+1} O_{i,t-k} + \mathbf{X}_{it}\mathbf{\Gamma} + \delta_t + \delta_i + \varepsilon_{it}$$

$$(5) O_{it} = \gamma_0 + \sum_{m=1}^{12} \gamma_m O_{i,t-m} + \sum_{n=0}^{12} \theta_{n+1} V_{i,t-n} + \mathbf{X}_{it}\mathbf{\Pi} + \delta_t + \delta_i + \mu_{it}$$

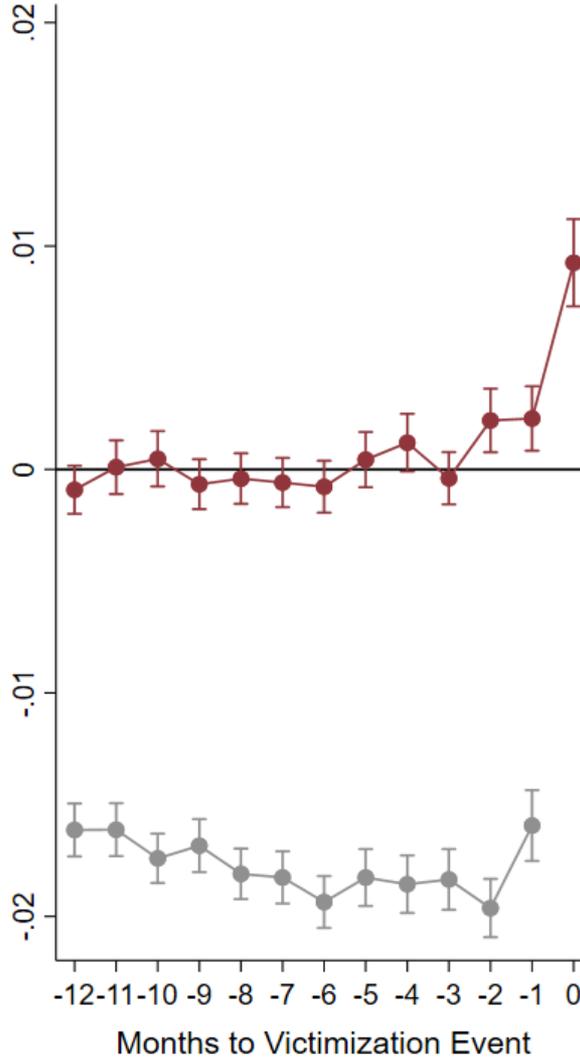
- Point estimates and 95% confidence intervals are shown graphically
- On the x-axis is months to criminal incident ($t = 0$ is the current month)

Any Victimization = $f(\text{Any Offending, } \mathbf{X})$

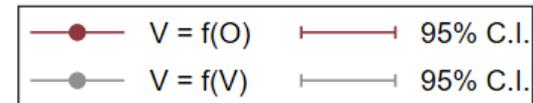
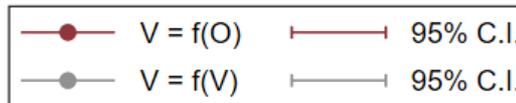
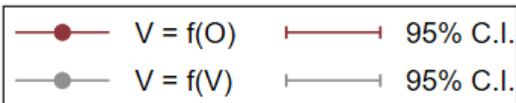
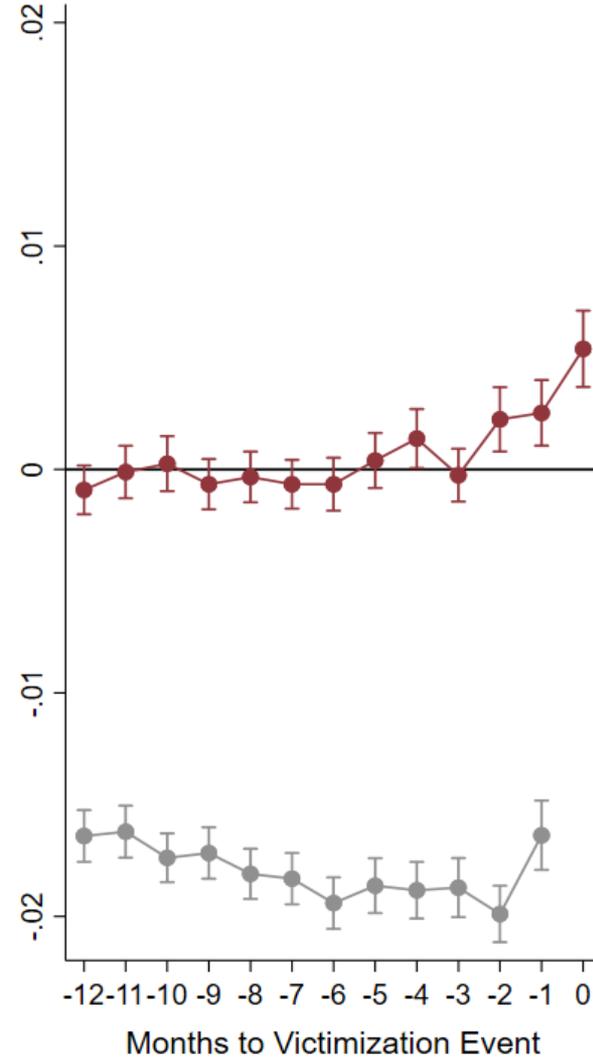
No Individual Fixed Effects



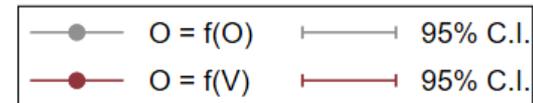
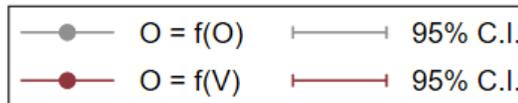
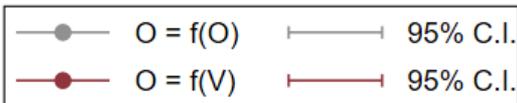
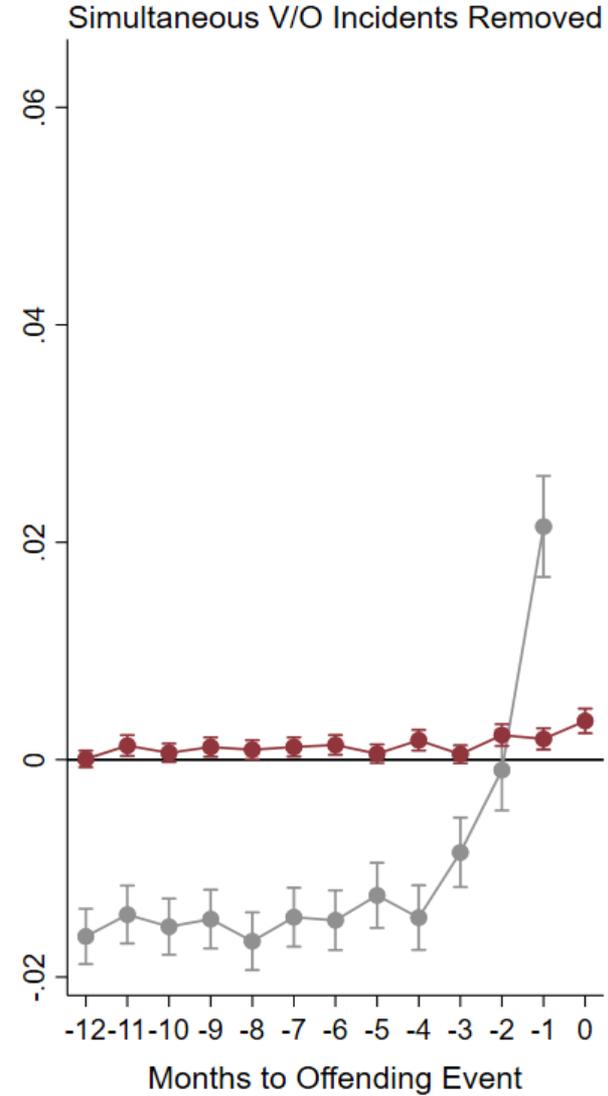
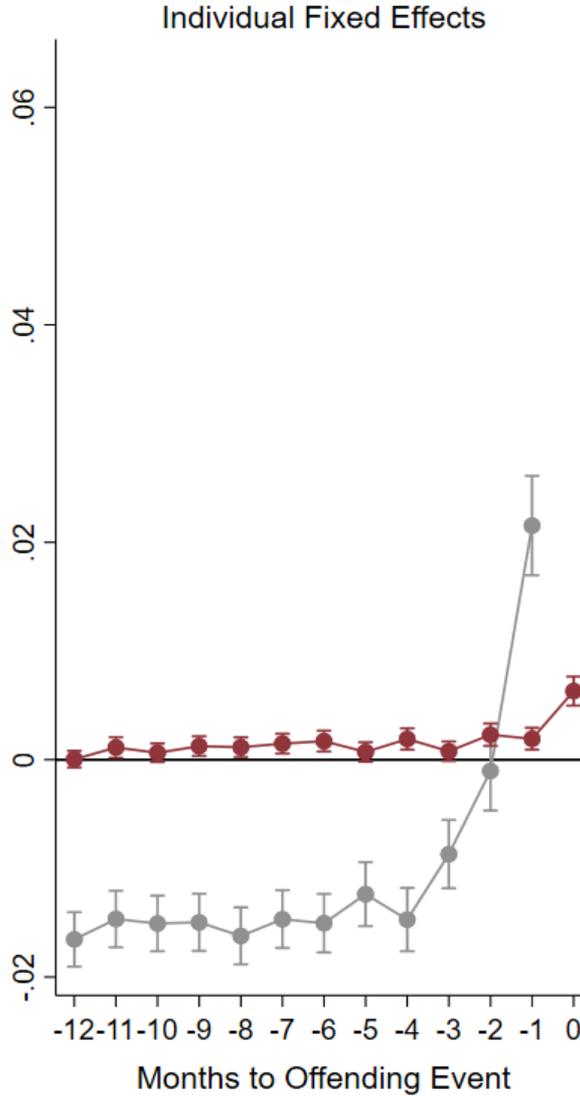
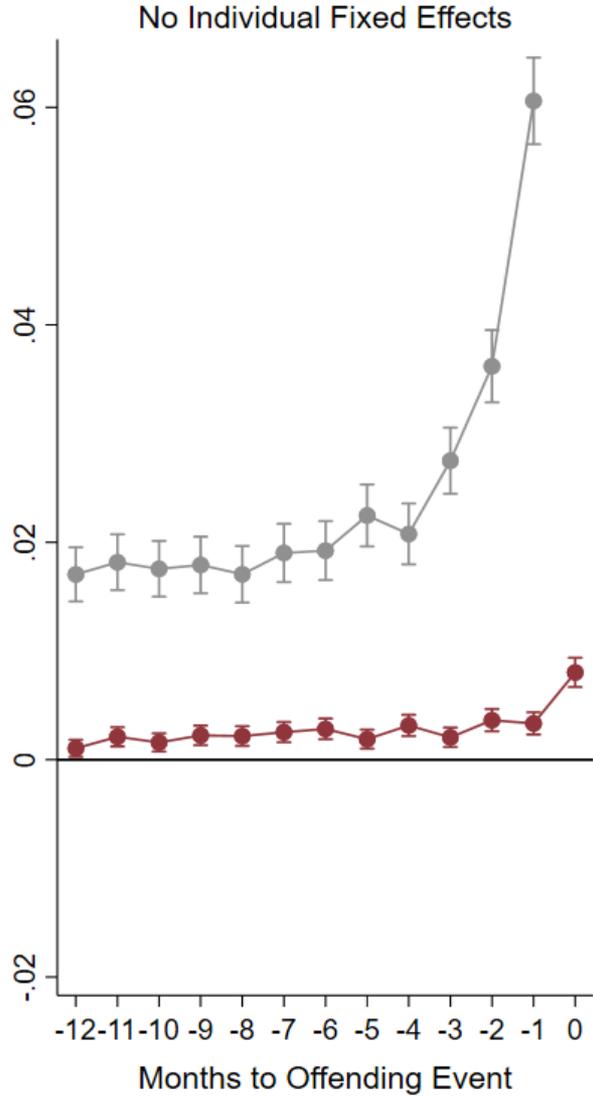
Individual Fixed Effects



Less Simultaneous V/O Incidents

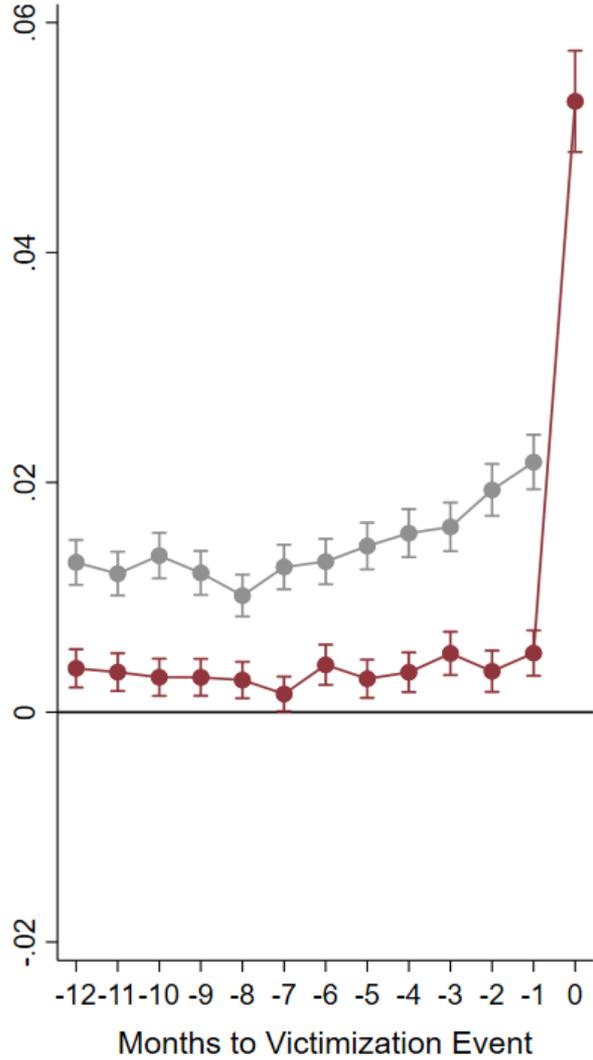


Any Offending = $f(\text{Any Victimization, X})$

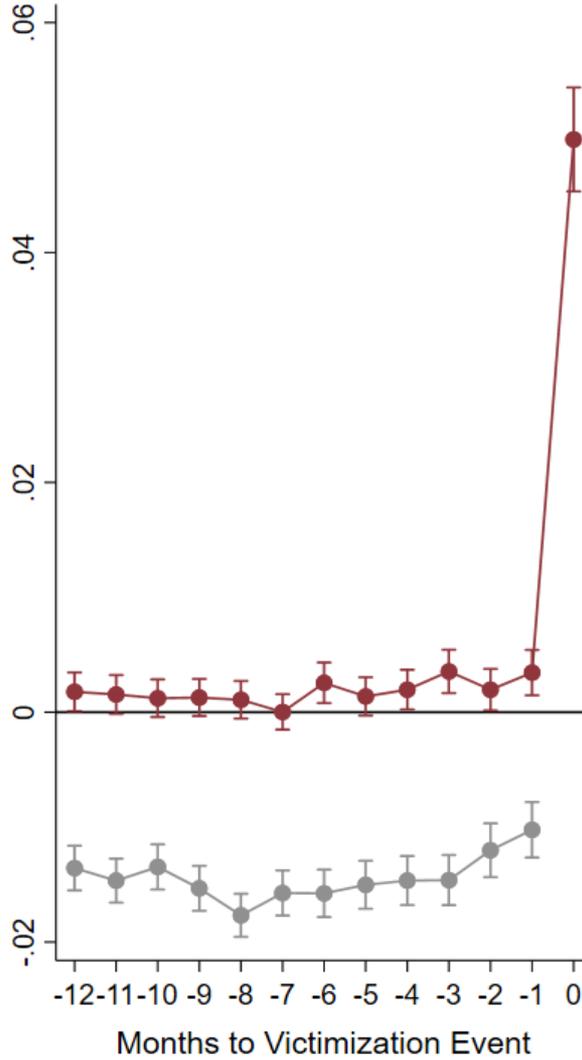


Violent Victimization = $f(\text{Violent Offending, } \mathbf{X})$

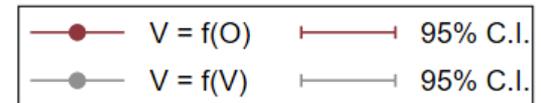
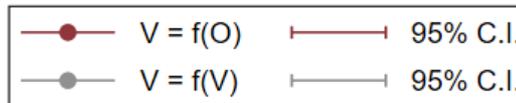
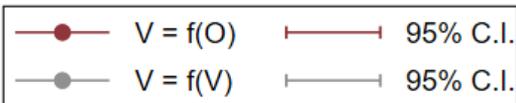
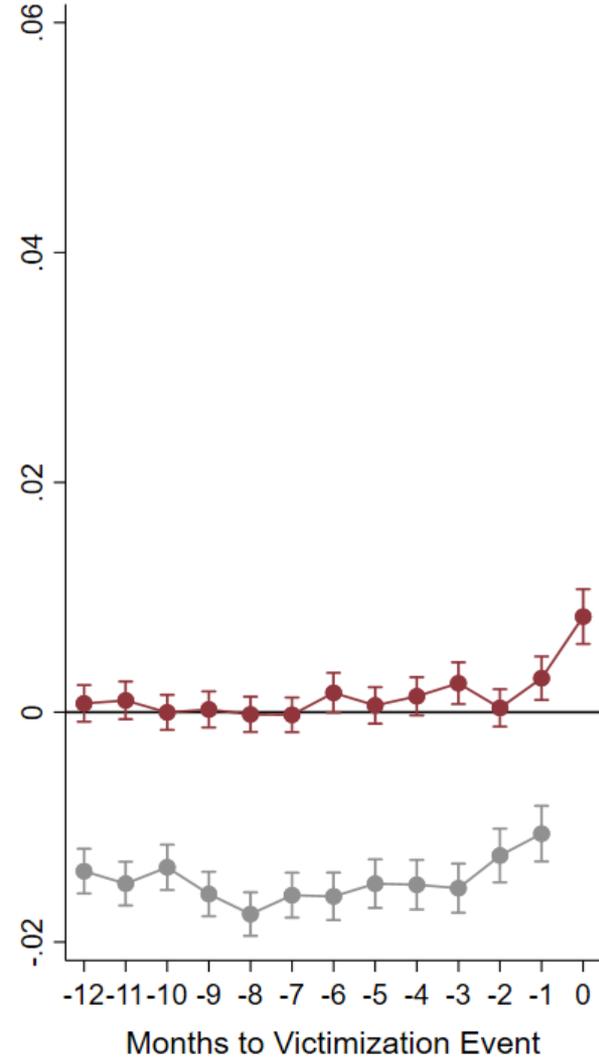
No Individual FE



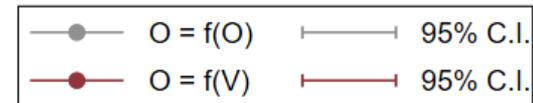
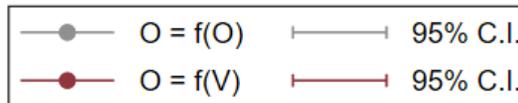
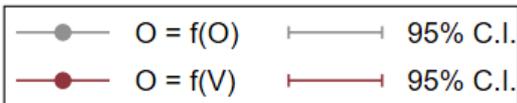
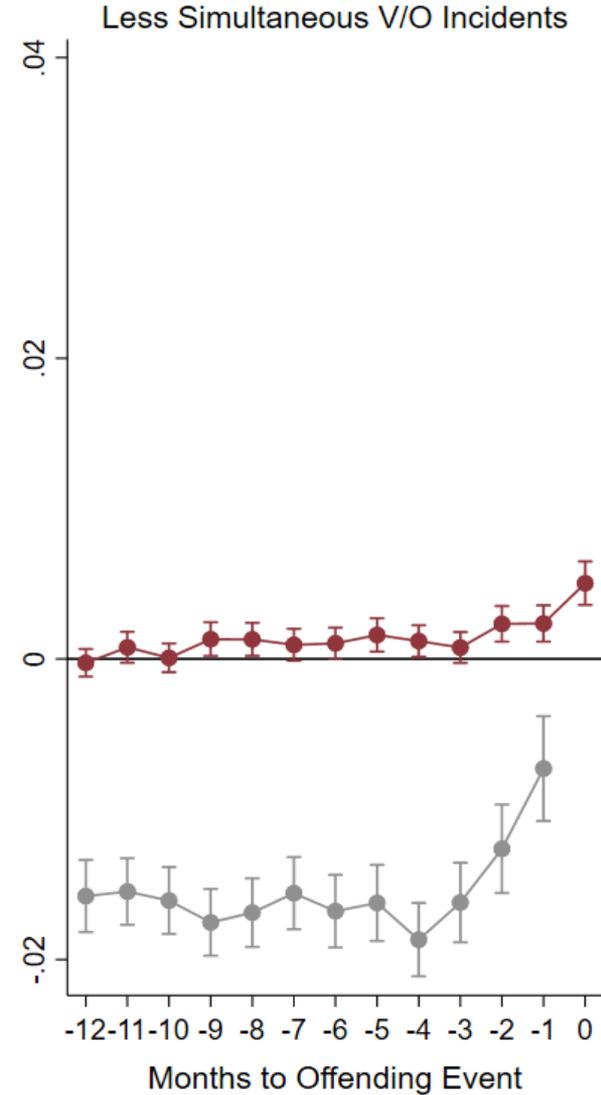
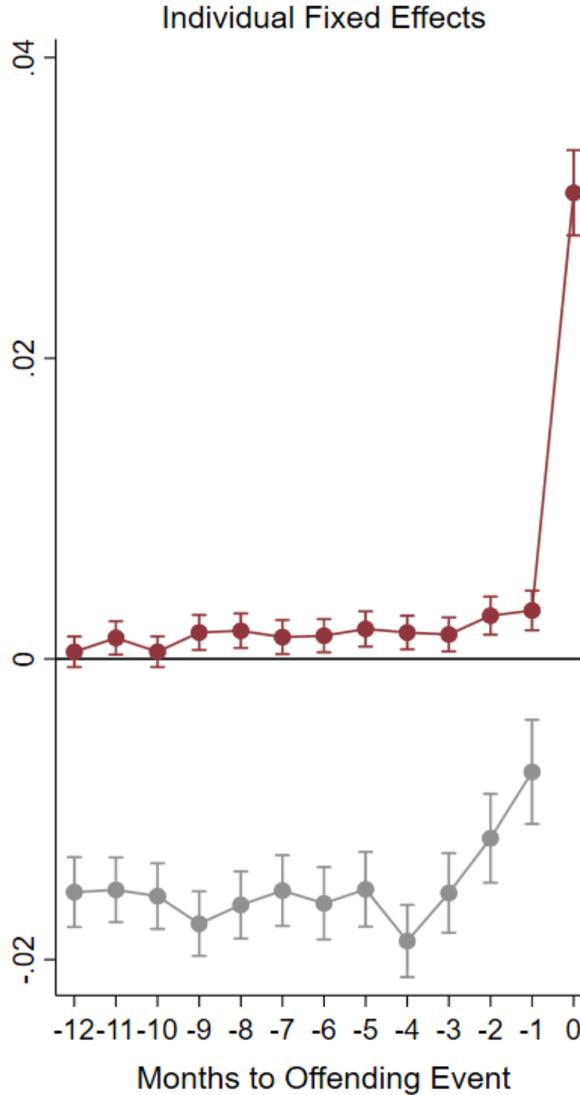
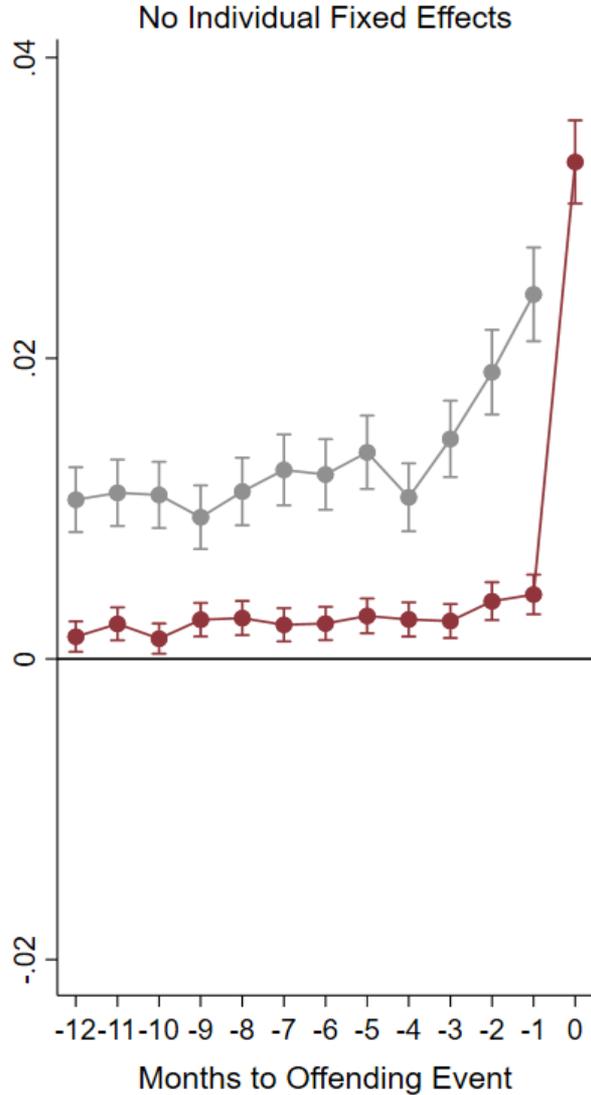
Individual & Month FE



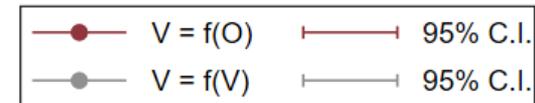
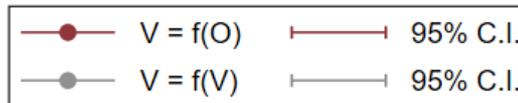
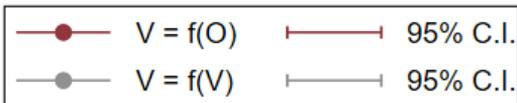
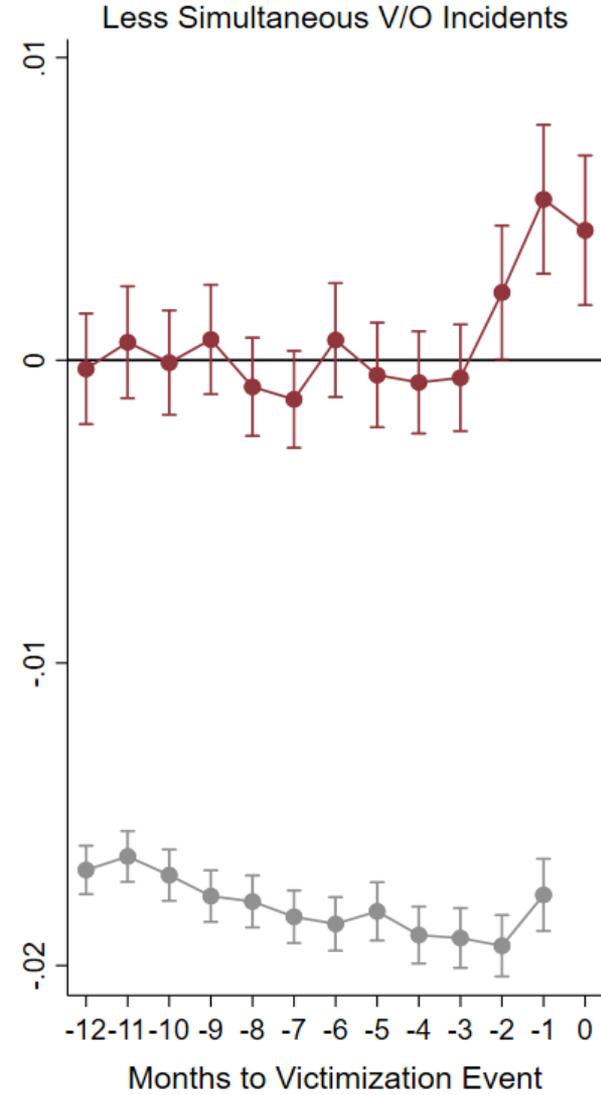
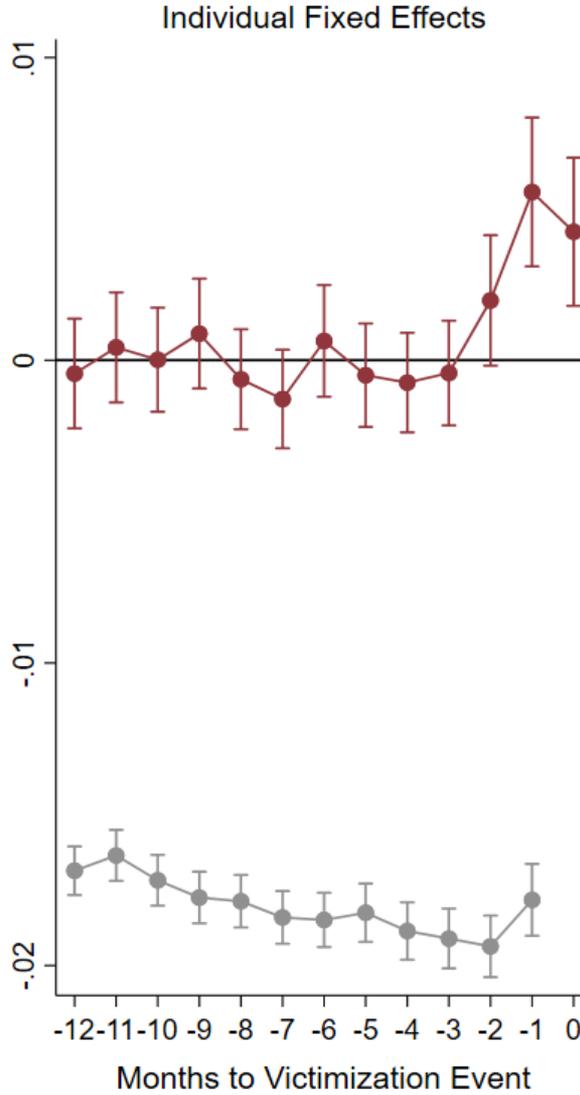
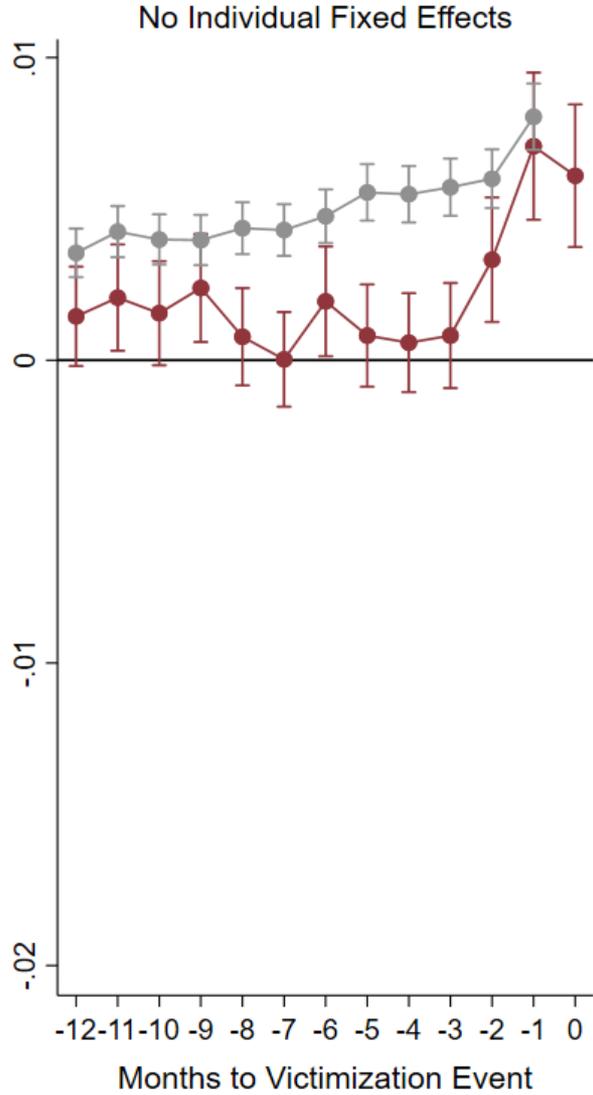
Less Simultaneous V/O Incidents



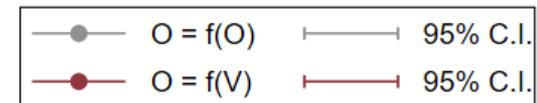
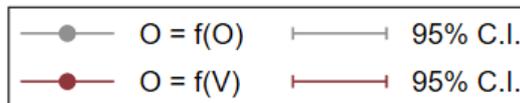
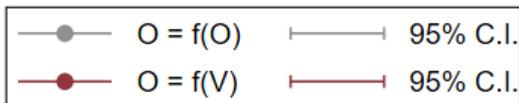
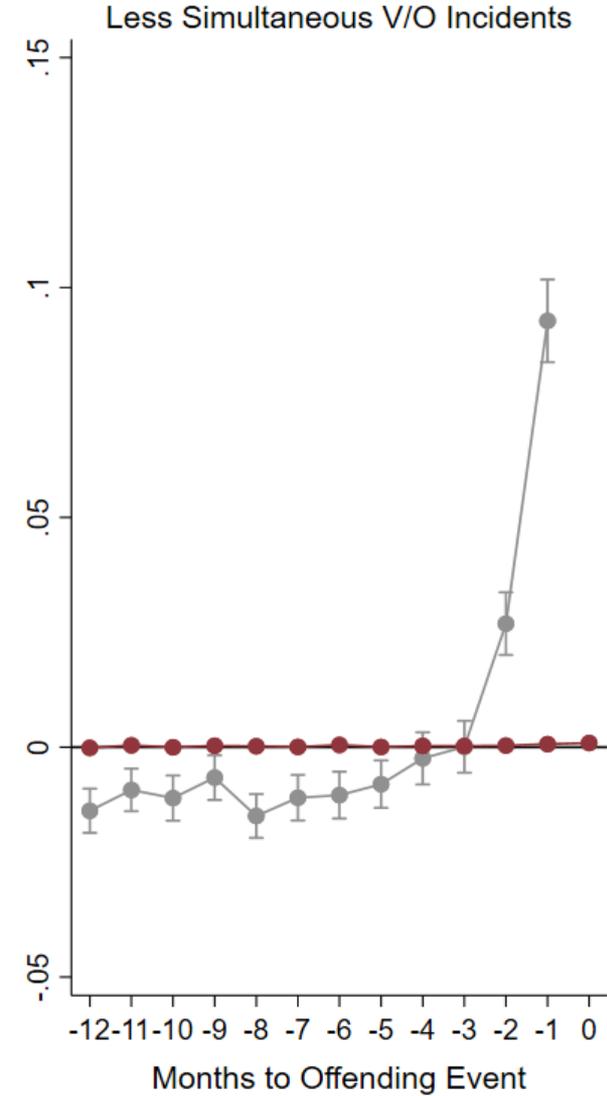
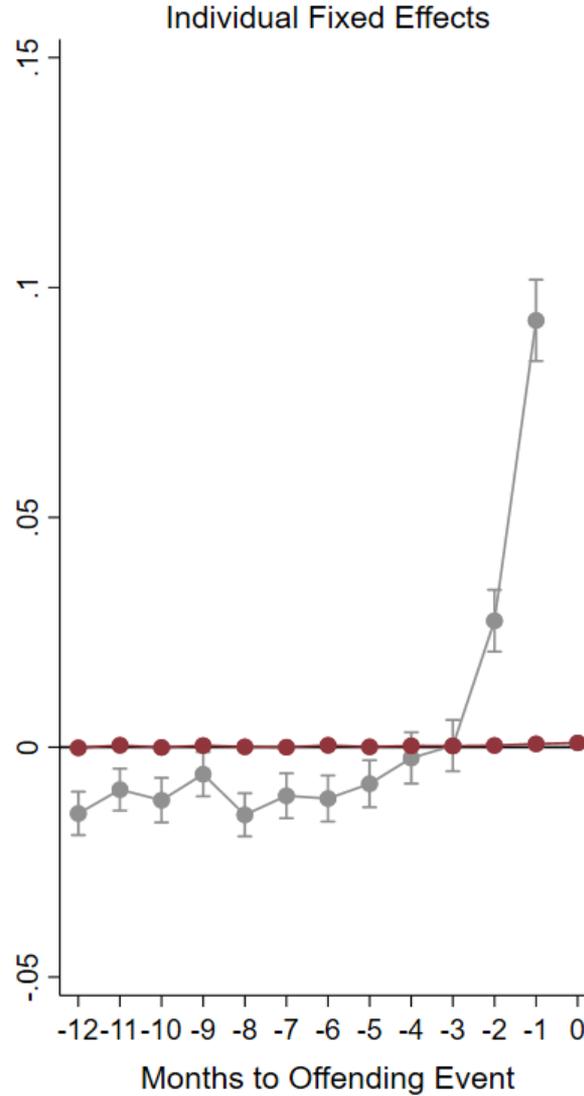
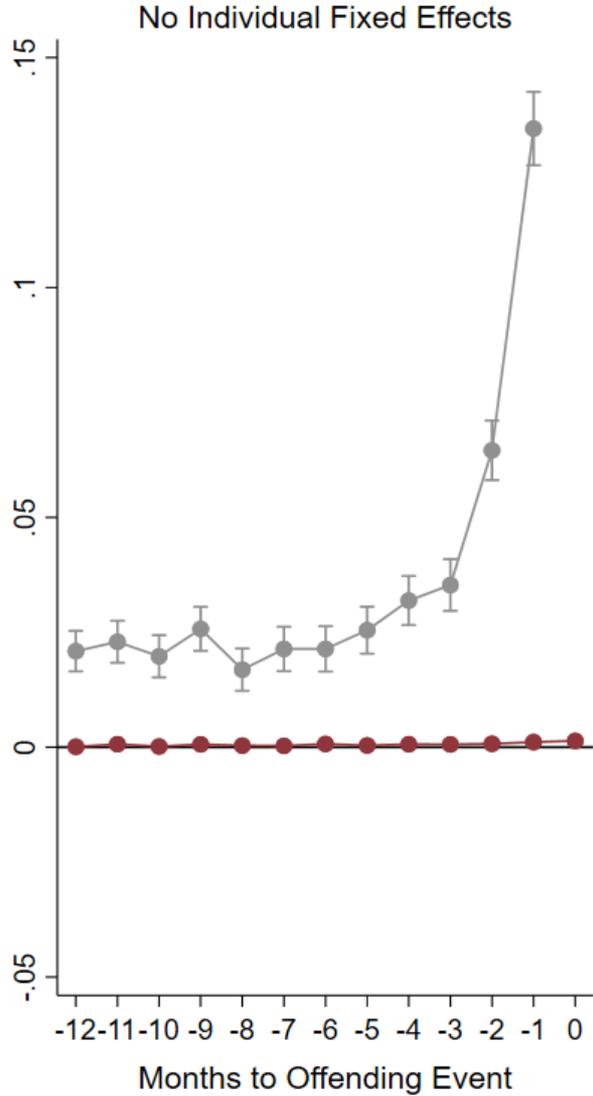
Violent Offending = $f(\text{Violent Victimization, } \mathbf{X})$



Property Victimization = $f(\text{Property Offending, } \mathbf{X})$

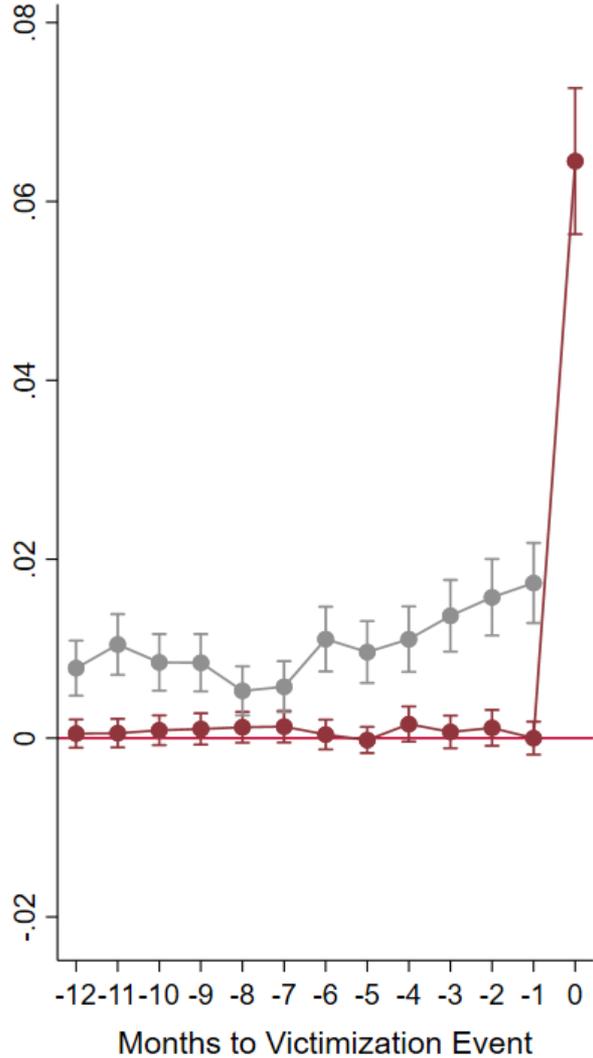


Property Offending = $f(\text{Property Victimization, } \mathbf{X})$

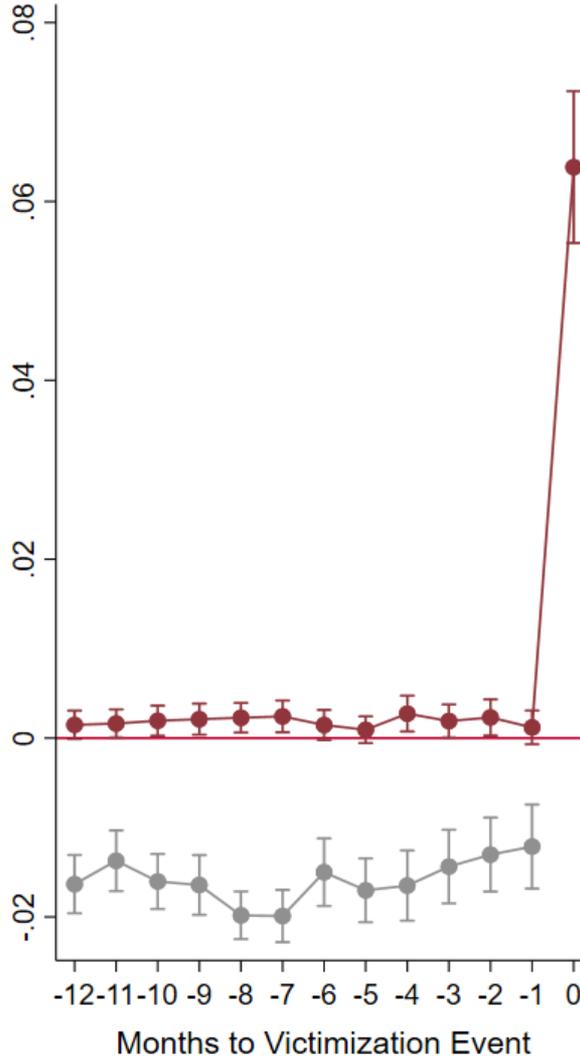


IPV Victimization = $f(\text{IPV Offending, } \mathbf{X})$

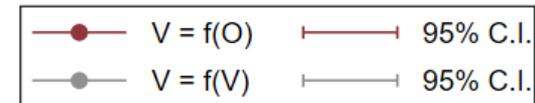
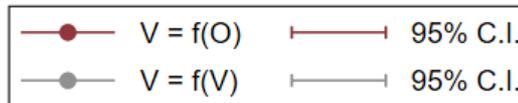
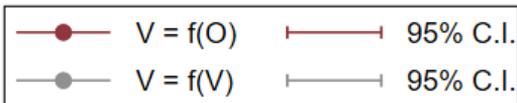
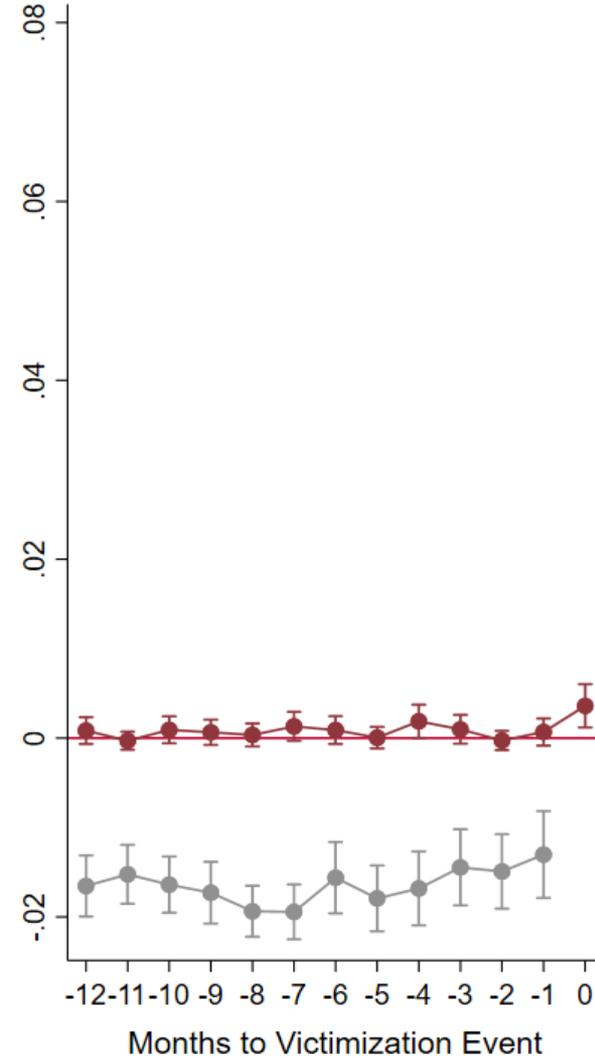
No Individual Fixed Effects



Individual Fixed Effects

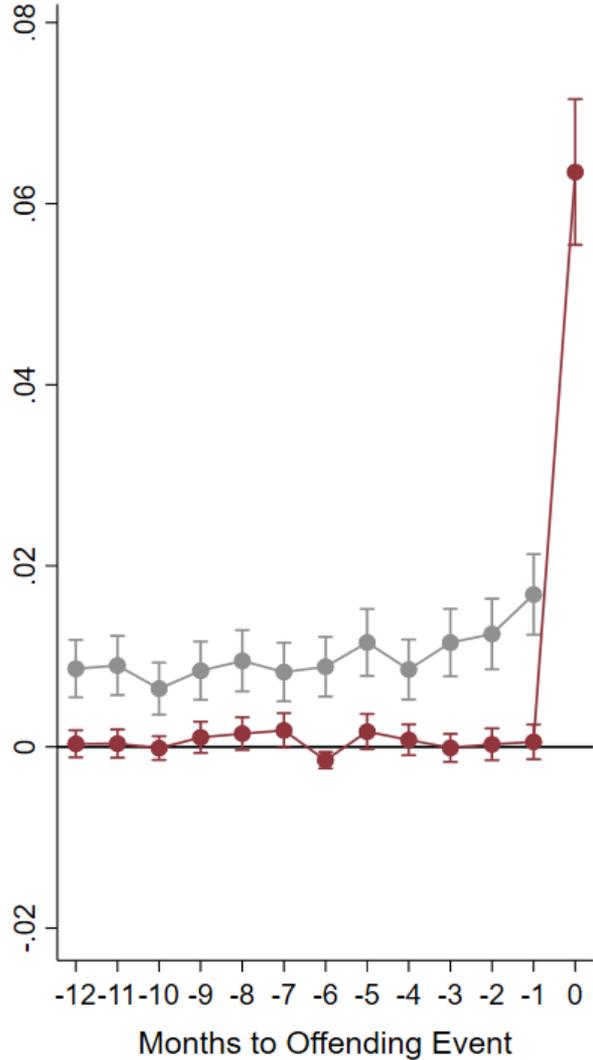


Less Simultaneous V/O Incidents

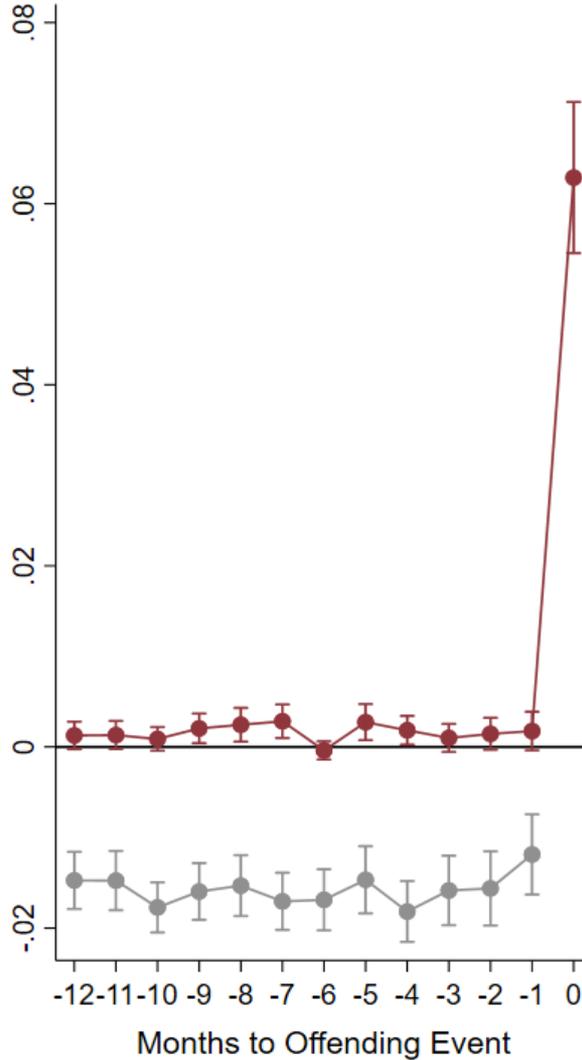


IPV Offending = $f(\text{IPV Victimization, } \mathbf{X})$

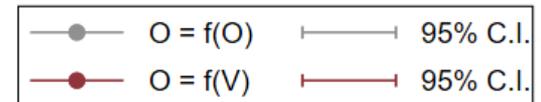
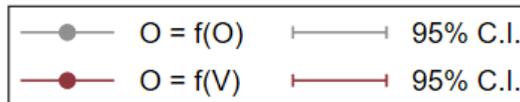
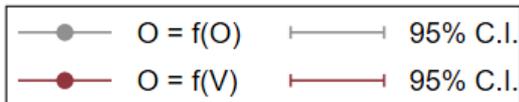
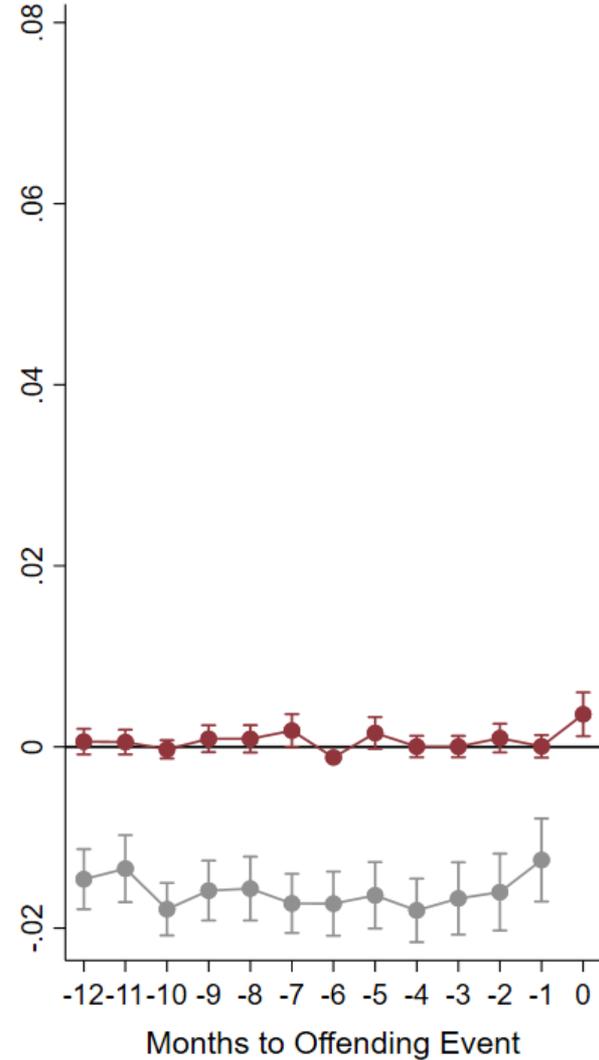
No Individual Fixed Effects



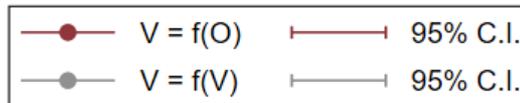
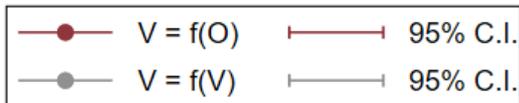
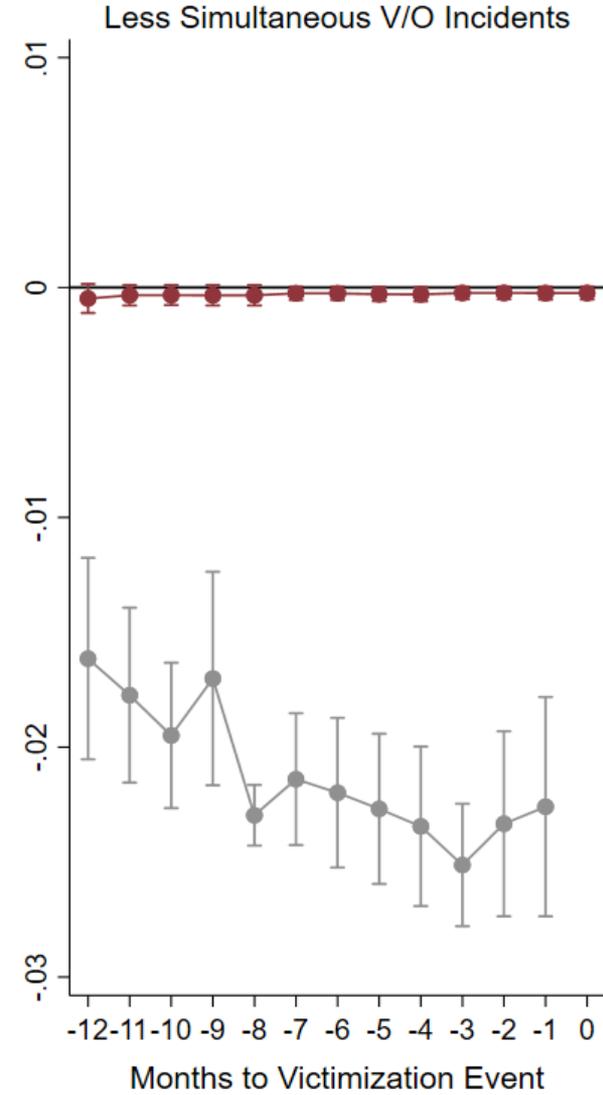
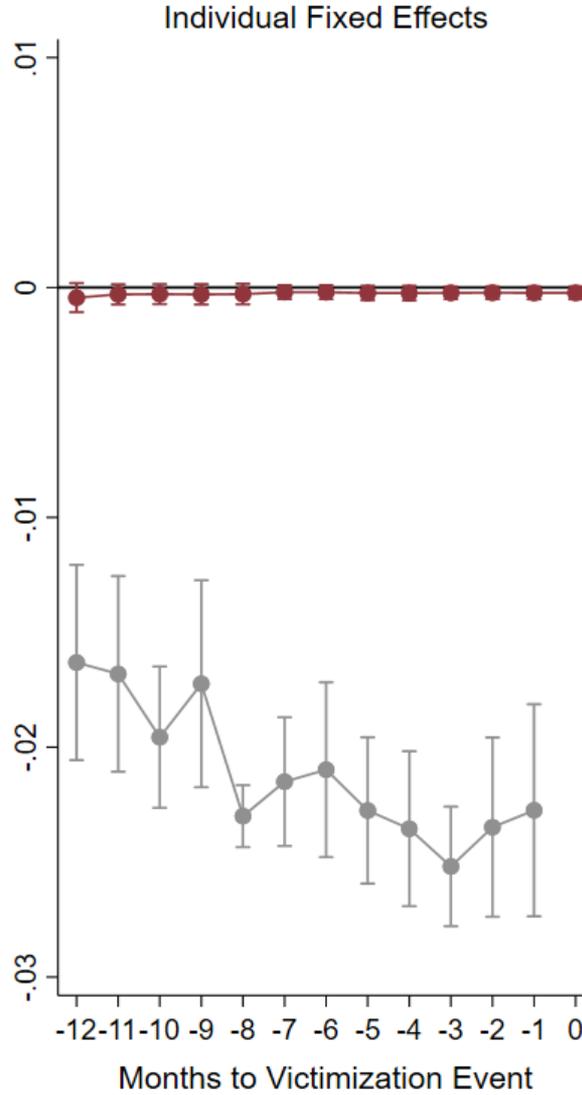
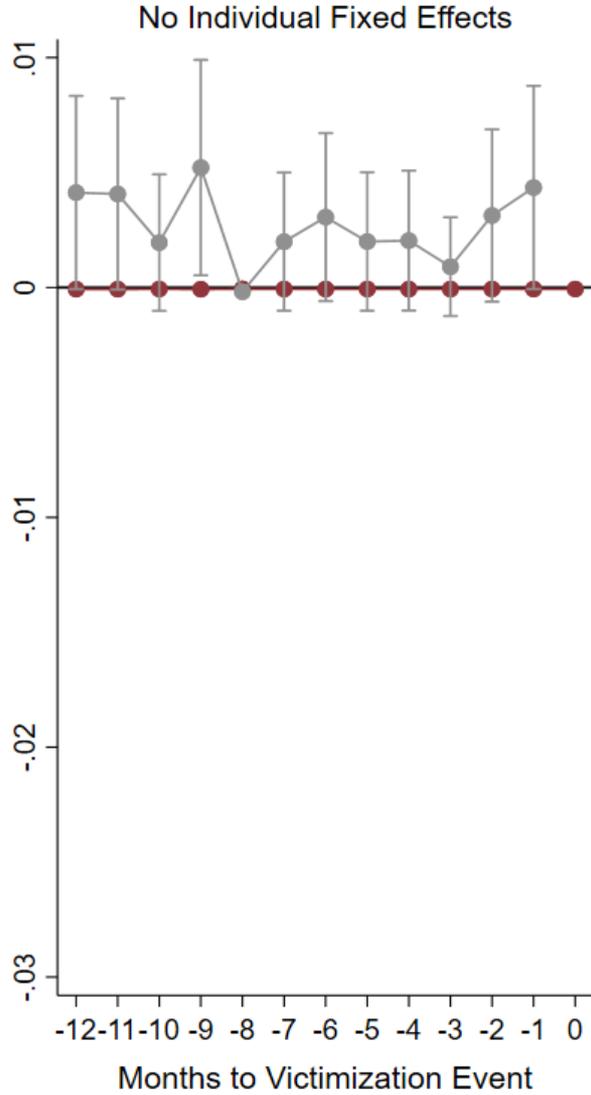
Individual Fixed Effects



Less Simultaneous V/O Incidents

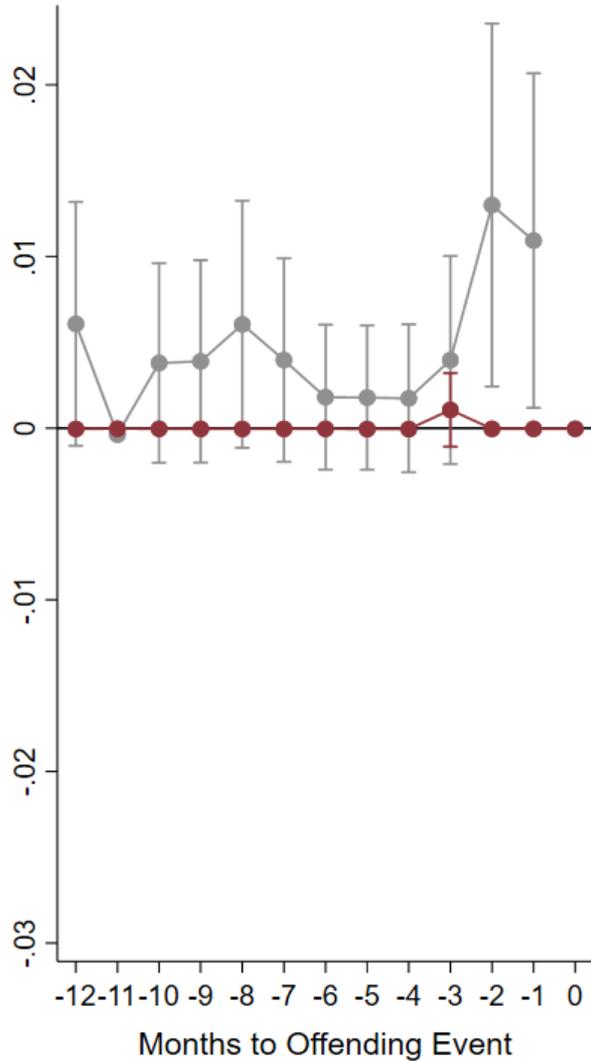


Sexual Victimization = $f(\text{Sexual Offending, } \mathbf{X})$

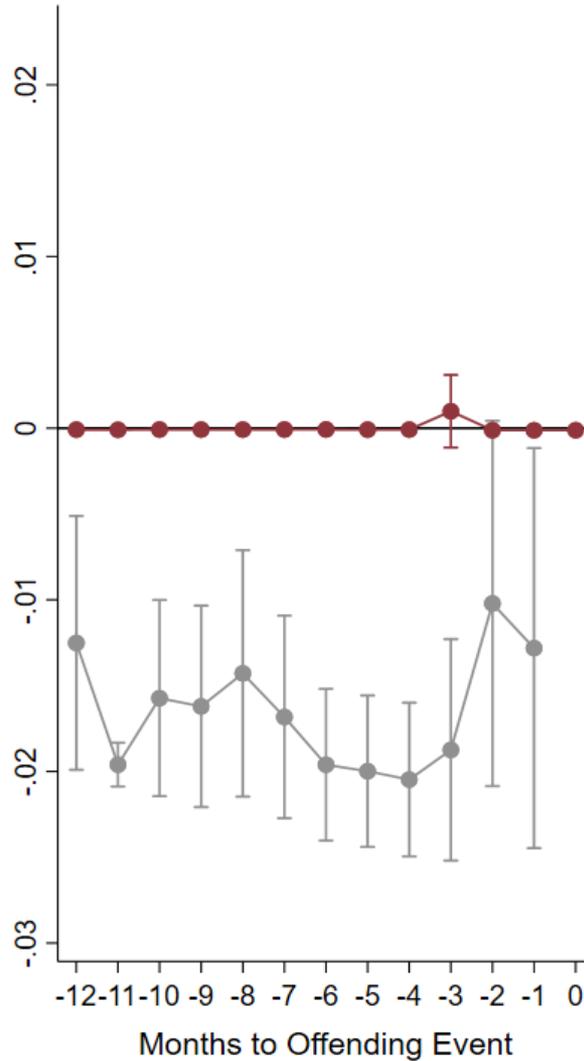


Sexual Offending = $f(\text{Sexual Victimization, } \mathbf{X})$

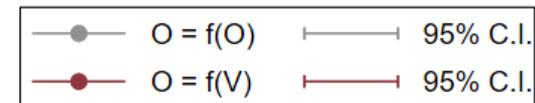
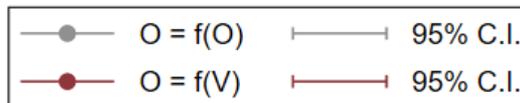
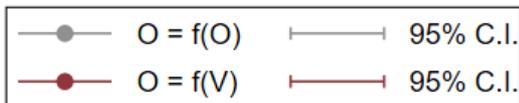
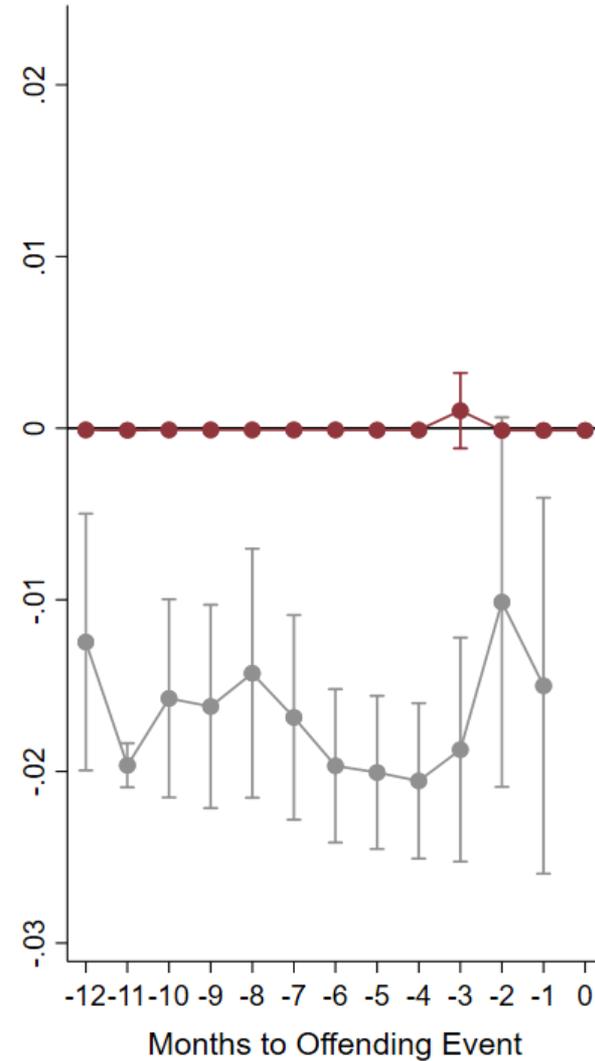
No Individual Fixed Effects



Individual Fixed Effects

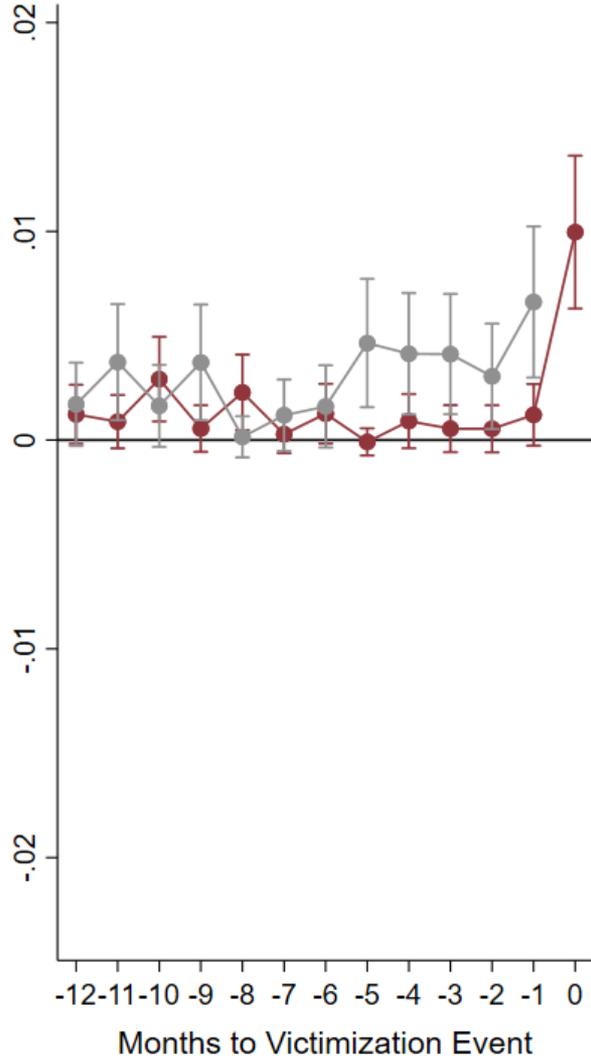


Less Simultaneous V/O Incidents

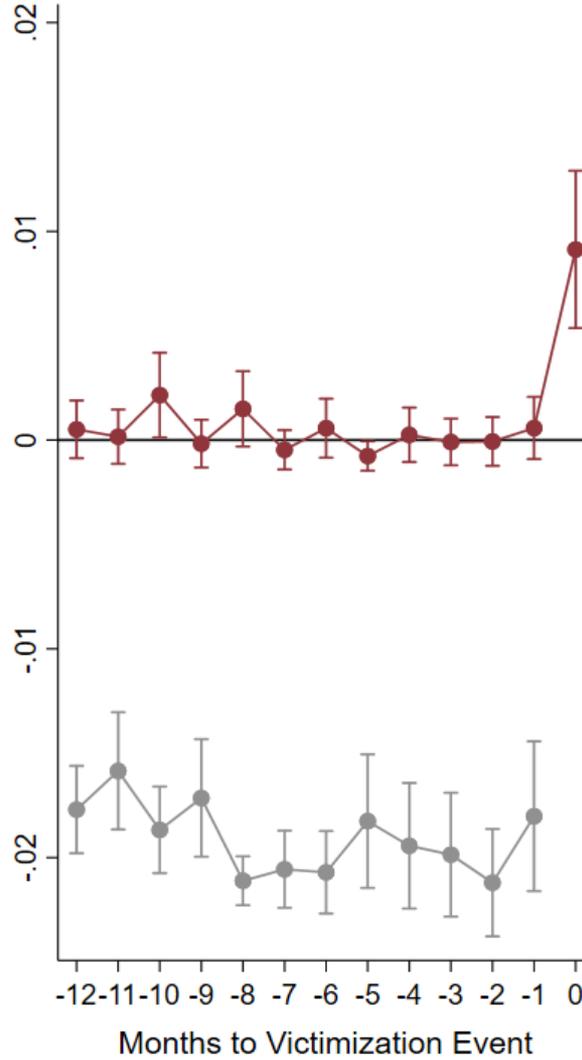


Weapon Victimization = $f(\text{Weapon Offending, } \mathbf{X})$

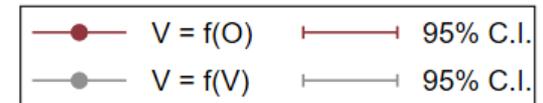
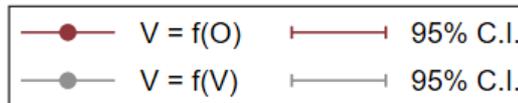
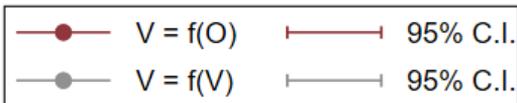
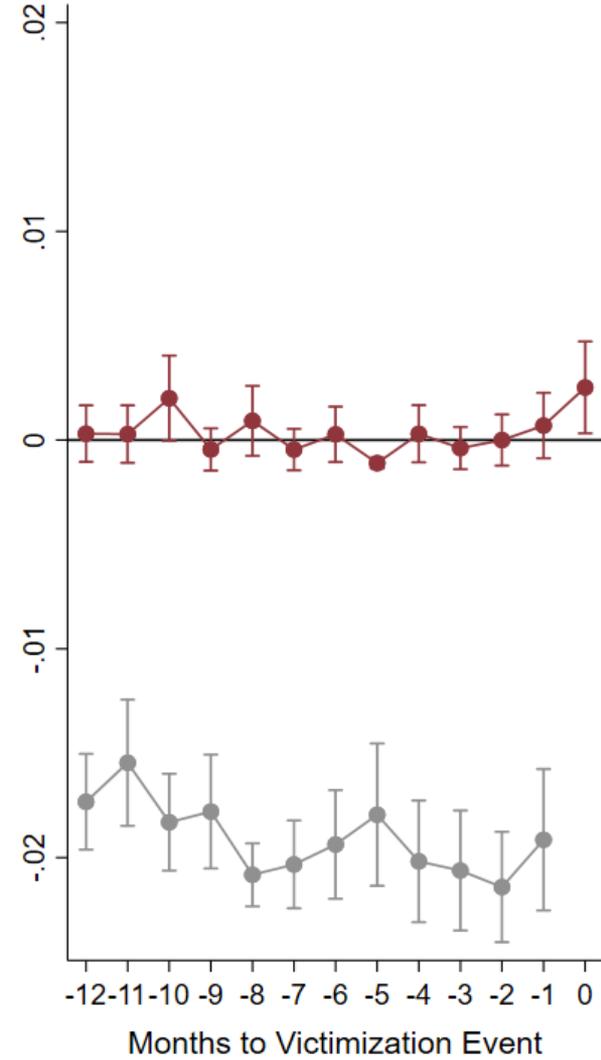
No Individual Fixed Effects



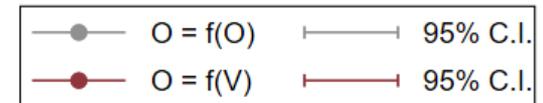
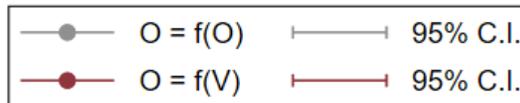
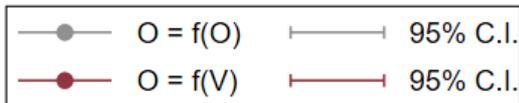
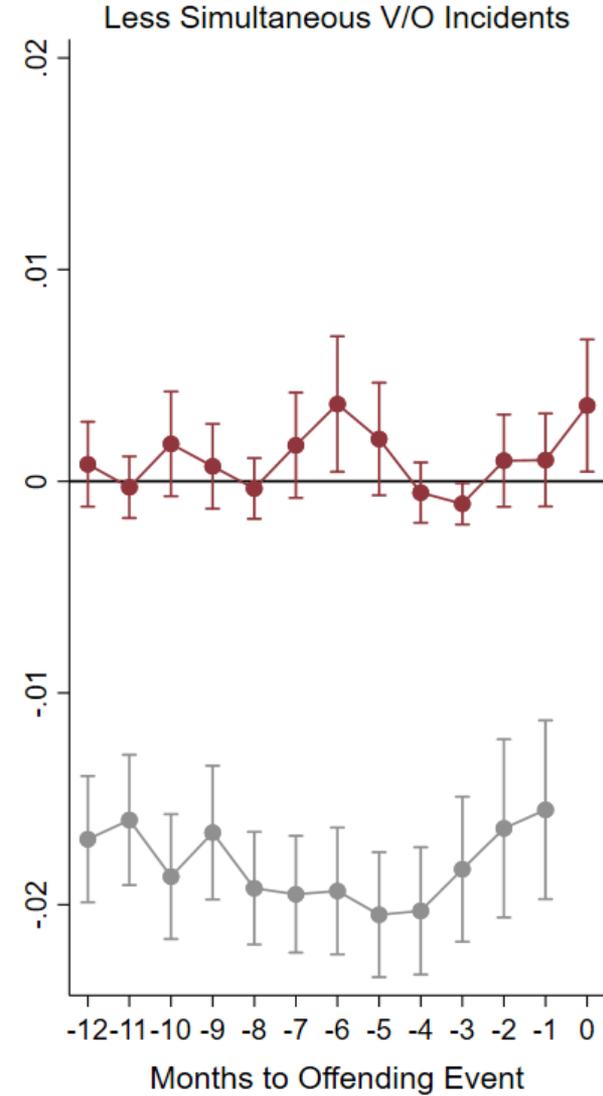
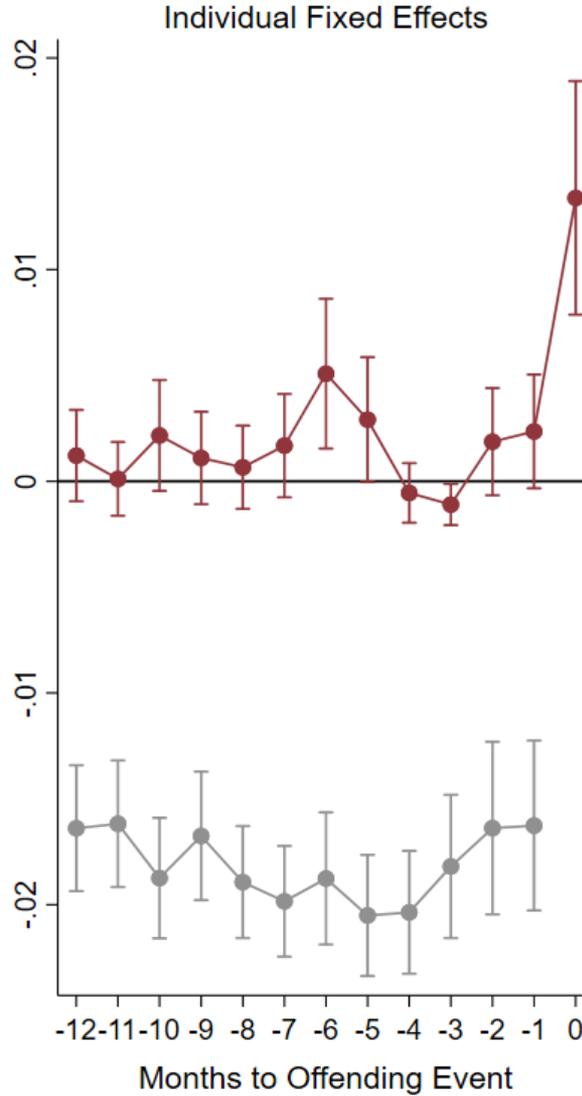
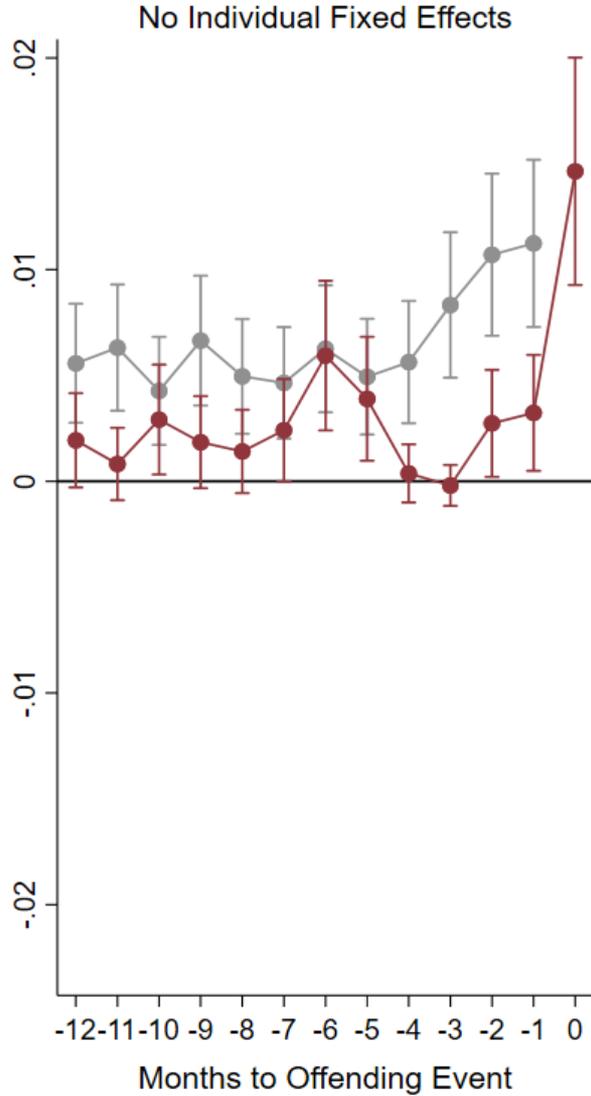
Individual Fixed Effects



Less Simultaneous V/O Incidents



Weapon Offending = $f(\text{Weapon Victimization, } \mathbf{X})$



Results Pt. 3

- The last step in our empirical analysis is estimating dynamic panel models vis-à-vis Arellano and Bond (1991)
- We present results using 1-3 lags in the dependent variable
- Due to computational limitations, this analysis is only conducted using 2019 data (system GMM estimator with 12 monthly periods)

Table 6. Dynamic panel (Arellano-Bond) estimates, 2019

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

Tests for zero autocorrelation in first-differenced errors:

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

Table 6. Dynamic panel (Arellano-Bond) estimates, 2019

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

Tests for zero autocorrelation in first-differenced errors:

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

Table 6. Dynamic panel (Arellano-Bond) estimates, 2019

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

Tests for zero autocorrelation in first-differenced errors:

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

Table 6. Dynamic panel (Arellano-Bond) estimates, 2019

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

Tests for zero autocorrelation in first-differenced errors:

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

Conclusions

- Victimization and offending are jointly determined
 - For a myriad of crime types
- Victim/offender overlap is largely driven by fixed environmental and individual characteristics
 - Also by incidents where individuals are at once classified as criminals and offenders
- Events that produce criminal/offender overlap tend to occur close together in time (i.e., usually within 2 months of each other)

Policy Implications

- Should we direct more of our criminal justice resources towards the criminal/victim overlap group?
 - A small percentage of the population
 - Resources may be better directed at prevention
- Act fast and follow-up
 - These events occur closely in time
- Acting fast may help to break the chain of recurring victimization/criminal incidents

Thank You

- Thank you for your time
- Questions?
- Contact:
 - christopher.erwin@aut.ac.nz