The Hidden Cost of Crime: Crime Victimization and Mental Health

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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.

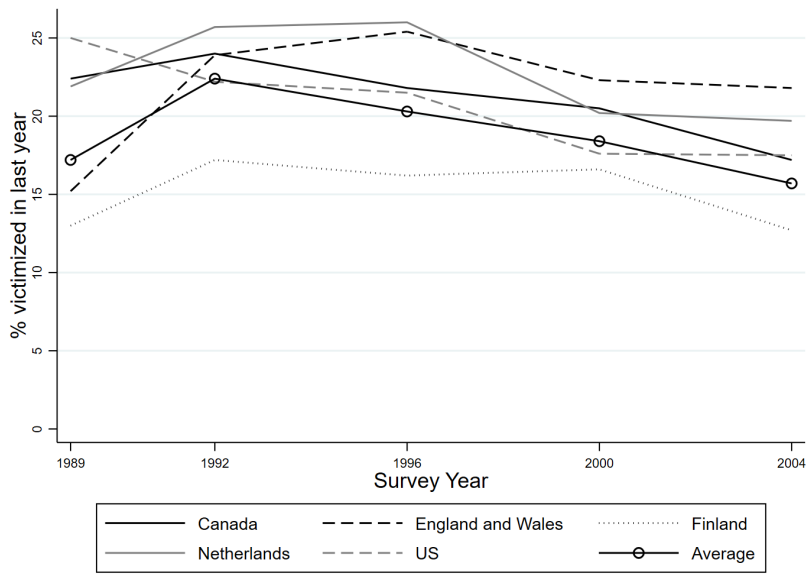
Roadmap

INTRODUCTION

Motivation: Crime Victimization

Big picture question: How does crime impact victims and society?

Many crimes are not victimless – see e.g. numbers from the *International Crime Victimization Survey*:



Source: Bindler, Ketel and Hjalmarsson (2020).

- % who report being victimized of at least 1 of 10 crimes (e.g. theft, burglary, robbery, sex offenses and assaults/threats).
- Annual avg. includes all countries reporting in a given survey year.
- In every survey round, >15% of respondents report being victimized in just the last year.

Motivation: Crime Victimization

Why do we care about victimization?

- Direct + indirect costs of crime $\sim$ 3-10% of GDP depending on definition and country (Anderson 2012; Entorf and Schulan 2018).
- Costs of crime = important ingredient for evidence-based policy-making.
- Costs of victimization = significant share of the costs of crime.

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Growing literature evaluating the impact of policies on crime, incl. criminal justice policy but also social & economic policy.

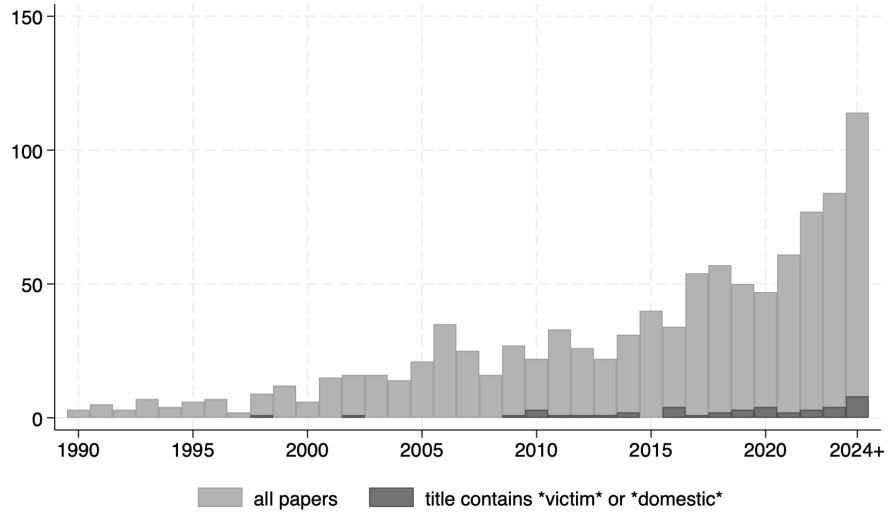
- Often of interest: cost-benefit type analyses of policies wrt crime.
- Policy cost: public spending, e.g. for police, prisons, schools, ... (+ sometimes political costs?).
- Benefits: costs of crimes prevented through respective policies.

Literature: What do we know?

Economics of crime literature (following Becker 1968):

- How does the cost of crime affect the behavior of the *offenders* (deterrence, scarring effects)? But: Scarce knowledge on the costs of crime for victims.

More recently: Young and dynamic literature on victimization and (social) costs of crime. $\rightarrow$ *Possible by access to high-quality data.*



Source: Doleac (2024). Database of crime-related papers published in Economics journals (general interest plus top field).

Literature (non-exhaustive list)

- **Physical health** (e.g., injuries, birth outcomes): Ornstein (2017), Aizer (2011), Currie et al. (2022), + public health literature.
- **Mental health and well-being:** Cornaglia et al. (2014), Dustmann and Fasani (2016), Johnston et al. (2018), Bhuller et al. (2024).
- **Economic consequences** (e.g., labour market outcomes): Velamuri and Stillman (2008), Ornstein (2017), Bindler and Ketel (2022), Bhuller et al. (2024), Adams-Prassl et al. (2024), Adams-Prassl et al. (2024).
- **Behavioural changes/precautionary behaviours** (e.g., moving, political participation, policy preferences): Dugan (1999), Braakmann (2012), Bateson (2012),Visconti (2019), Bindler et al. (2024).
- **Human capital costs of (indirect) crime exposure:** Monteiro and Rocha (2017), Foureaux-Koppensteiner and Menezes (2021), Chang and Padilla-Romo (2023), Bharadwaj et al. (2021), Cabral et al. (2020), Ang (2021).

This Paper: Crime Victimization and Mental Health

Current literature: Health and mental health show up as one potential mediator for individual (economic) costs of crime.

→ **This paper: Can we learn more?**

- Individual-level victimization data with **detailed measures of mental health** plus **victim-offender relationship** from New Zealand (*register data*).
- Trace mental health consequences and study heterogeneity by victim-offender relationship (*beyond intimate partner violence*).
- Focus on violent crimes and adult population.

Research Questions and Contribution

1. **Consequences of victimization:** What are the effects of criminal victimization on individual's mental health?

   Contribution: Replication and extention of existing findings with more **detailed high-quality data** on both crime victimization (all crime types) and mental health treatments (at monthly level),

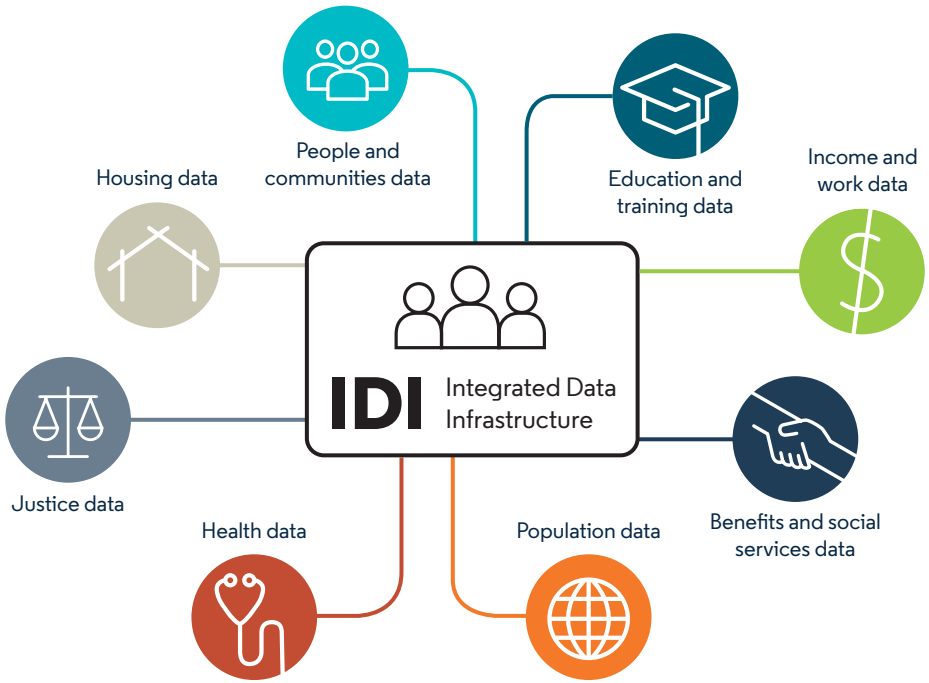
2. **Heterogeneous effects:** How does the **victim-offender relationship** (familiar/unfamiliar offender) shape mental health effects of victimization (+ downstream labor market effects)?

   Contribution: Identify relationship between victim and offender **beyond domestic violence** (in register data).

Roadmap

DATA AND DESCRIPTIVES

New Zealand (NZ) Administrative Data



- Individual-level administrative data from **StatsNZ Integrated Data Infrastructure (IDI)**.
- Research database, holding **de-identified administrative microdata about universe of people in NZ** from multiple government agencies, NGOs & surveys.

New Zealand (NZ) Administrative Data

Administrative data with (common) pros and cons.

Advantages:

- High quality data.
- Less noise/recall bias than survey data (on self-reported victimization and mental health).
- **Population-wide data**, detailed information on timing (on reported victimization, health treatments).

Disadvantages (flagged but not solved...):

- Under-reporting of victimization (based on reports to the police).
- Under-reporting of mental health problems (based on medical records).

Core Data on Crime Victimization (Treatment)

- **Spine:** Reported crime victimizations between 07/2014 and 12/2023 from **Recorded Crime Victims Statistics (RCVS)**.
- Record of all (alleged) offenses and victimizations in NZ.
- Information on:
  - Victim and offender (if known) of each (police) recorded offense,
  - type of crime,
  - exact date and time of the offense,
  - exact location of the offense,
  - police/court action taken,
  - **victim-offender relationship** (familiar versus unfamiliar offender).

Estimation Sample

Sample conditions to facilitate aggregation of raw police data to **victim-month level**.

1. Keep only most closely related offender per offense (if multiple offenders).
2. Keep only most severe offense per event (if multiple offenses).
3. Keep only the most severe event per month (if multiple events).

$\rightarrow$ **Estimation sample:** Balanced longitudinal dataset with 114 monthly observations per victim (victims-only dataset).

- Add victims' demographic information from police data (if missing: from personal details data).

Sample Restrictions

Offense-level restrictions:

- No victim-less offenses; offenses where victim = natural person.
- Keep only investigated offenses (avoid wrongful reports).
- Focus on violent crimes (ANZSOC Code 1 - 6), drop non-violent property crime from analysis (thefts and burglaries).
- Drop obs. with obvious errors (occurrence after report date).

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Victim-level restrictions:

- Drop: victims of lethal crimes (murder, manslaughter, lethal traffic off.); victims not in the estimated residential population (ERP).
- Keep: individuals with valid personal details; individuals older than 15 at time of victimization.

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Treatment-level restrictions:

- Drop: victims w/ criminal history at first victimization (charges).
- No recent victimizations in the months/years before focal victimization: Drop individuals with victimizations before 01/2016.

Victimization Sample

Sample: 28,020,600 observations for 233,505 individuals/victims.

	All		Serious Assault	Common Assault	Sexual Assault	Threat	Robbery
	Freq.	%	%	%	%	%	%
Victim-Months (row %)	352,149		52.91	34.65	6.24	1.62	4.58
Female (col %)	196,227	55.72	64.36	40.49	91.71	36.71	28.88
Familiar off. (col %)	90,192	25.61	30.74	22.43	17.03	14.83	5.84
Unfamiliar off. (col %)	261,957	74.39	69.26	77.57	82.97	85.17	94.16
Victims	233,505						
$>$1 victim-month	60,186						

Source: IDI (2022) and own calculations. *Note:* To comply with the confidentiality requirements by Statistics NZ, all counts and observation numbers presented are randomly rounded to base 3; percentages are based on rounded counts.

Number of victimizations / victim

Victimizations by Detailed Offense

	All		Female		Male	
	Freq	%	Freq	Row %	Freq	Row %
Serious Assault	**186,324**	**52.91**	**119,919**	**64.36**	**66,405**	**35.64**
Resulting in Injury	95,322	27.07	59,805	62.74	35,517	37.26
Not Resulting in Injury	91,002	25.84	60,114	66.06	30,888	33.94
Common Assault	**122,031**	**34.65**	**49,410**	**40.49**	**72,621**	**59.51**
Sex offences	**21,972**	**6.24**	**20,151**	**91.71**	**1,821**	**8.29**
Aggravated	15,447	4.39	14,202	91.94	1,245	8.06
Non-Aggravated	6,525	1.85	5,949	91.17	576	8.83
Threat	**5,688**	**1.62**	**2,088**	**36.71**	**3,600**	**63.29**
Abduction and Kidnapping	1,632	0.23	1095	67.10	537	32.90
Blackmail and Extortion	4,056	1.15	993	24.48	3,063	75.52
Robbery	**16,134**	**4.58**	**4,659**	**28.88**	**11,475**	**71.12**
Aggravated	14,841	4.21	4,281	28.85	10,560	71.15
Non-Aggravated	1,293	0.37	378	29.23	915	70.77
Total	**352,149**		**196,227**	**55.72**	**155,922**	**44.28**

Source: IDI (2022) and own calculations. *Note:* To comply with the confidentiality requirements by Statistics NZ, all counts and observation numbers presented are randomly rounded to base 3; percentages are based on rounded counts and counts below 50 are suppressed (S).

Seriousness scores

Summary Statistics

Demographics (measured in month of first victimization):

	Serious Assault		Common Assault		Sexual Offence		Threat		Robbery	
	♀	♂	♀	♂	♀	♂	♀	♂	♀	♂
Observations	91,089	43,017	22,509	38,370	8,724	738	537	831	2,007	5,172
Age (D)										
15 - 24	0.28	0.26	0.29	0.28	0.59	0.55	0.36	0.53	0.27	0.38
25 - 34	0.30	0.27	0.24	0.24	0.20	0.19	0.22	0.19	0.26	0.27
35 - 44	0.20	0.18	0.18	0.17	0.10	0.11	0.16	0.10	0.16	0.15
45 - 54	0.13	0.15	0.16	0.16	0.07	0.09	0.14	0.08	0.16	0.10
55 - 64	0.06	0.09	0.10	0.11	0.03	0.04	0.07	0.06	0.10	0.07
65+	0.03	0.04	0.04	0.06	0.01	0.01	0.05	0.04	0.06	0.04
Ethnicity (D)										
European	0.34	0.40	0.45	0.48	0.53	0.55	0.51	0.57	0.36	0.38
Maori	0.46	0.37	0.36	0.26	0.28	0.30	0.28	0.15	0.20	0.16
Pacific	0.10	0.10	0.08	0.07	0.06	0.05	0.06	0.04	0.04	0.04
Asian	0.08	0.09	0.09	0.14	0.09	0.07	0.14	0.21	0.37	0.39
Other	0.02	0.03	0.03	0.04	0.03	0.04	0.03	0.04	0.03	0.04

Source: IDI (2022) and own calculations. *Note:* To comply with the confidentiality requirements by Statistics NZ, all counts and observation numbers presented are randomly rounded to base 3; percentages are based on rounded counts and counts below 50 are suppressed (S).

Victim-Offender Relationship

Unique feature of the data: Victim-offender relationship is recorded *by the police* when known.

Gender differences in victim-offender relationship: Offender more often a familiar person when victims are female (esp. for violent crimes).

All offenses (%)	♀	♂
N	196,227	155,922
Family Member	**18.51**	**6.01**
Partner	13.19	2.11
(Grand)Parent	0.94	0.69
(Grand)Child	2.07	1.41
Sibling	1.10	0.76
Other FM	1.22	1.04
No FM	**13.80**	**11.16**
Ex-Partner	6.71	1.08
Friend, Flatmate	0.80	0.97
Other	6.29	9.12
Unknown	**67.68**	**82.83**
Stranger	6.36	18.87
No off. identified	58.94	59.69
Not stated	2.99	4.27

Source: IDI (2022) and own calculations.

By offense

Mental Health and Labor Market Data (Outcomes)

Primary outcome: Mental health (MH).

Data sources

- Challenge: Measurement of MH, even in high-quality admin data.
- Our approach: Work with *MH treatment* as a proxy.
- **Define a mental health treatment indicator:**

  Binary indicator that captures whether individual is recorded in *at least one of six* admin data sources on MH in a given month.
- *Examples for MH conditions:* anxiety, depression, emotional problems, substance abuse, psychosis, self-harm.

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Secondary outcomes: Labor market (LM) success. Benefits

- Straightforward measurement (typical admin data).
- **(Monthly) wages:** From *Inland Revenue* (NZ tax authority).
- **(Monthly) social benefits:** Based on *benefit dynamics data* from Ministry of Social Development.

Summary Statistics

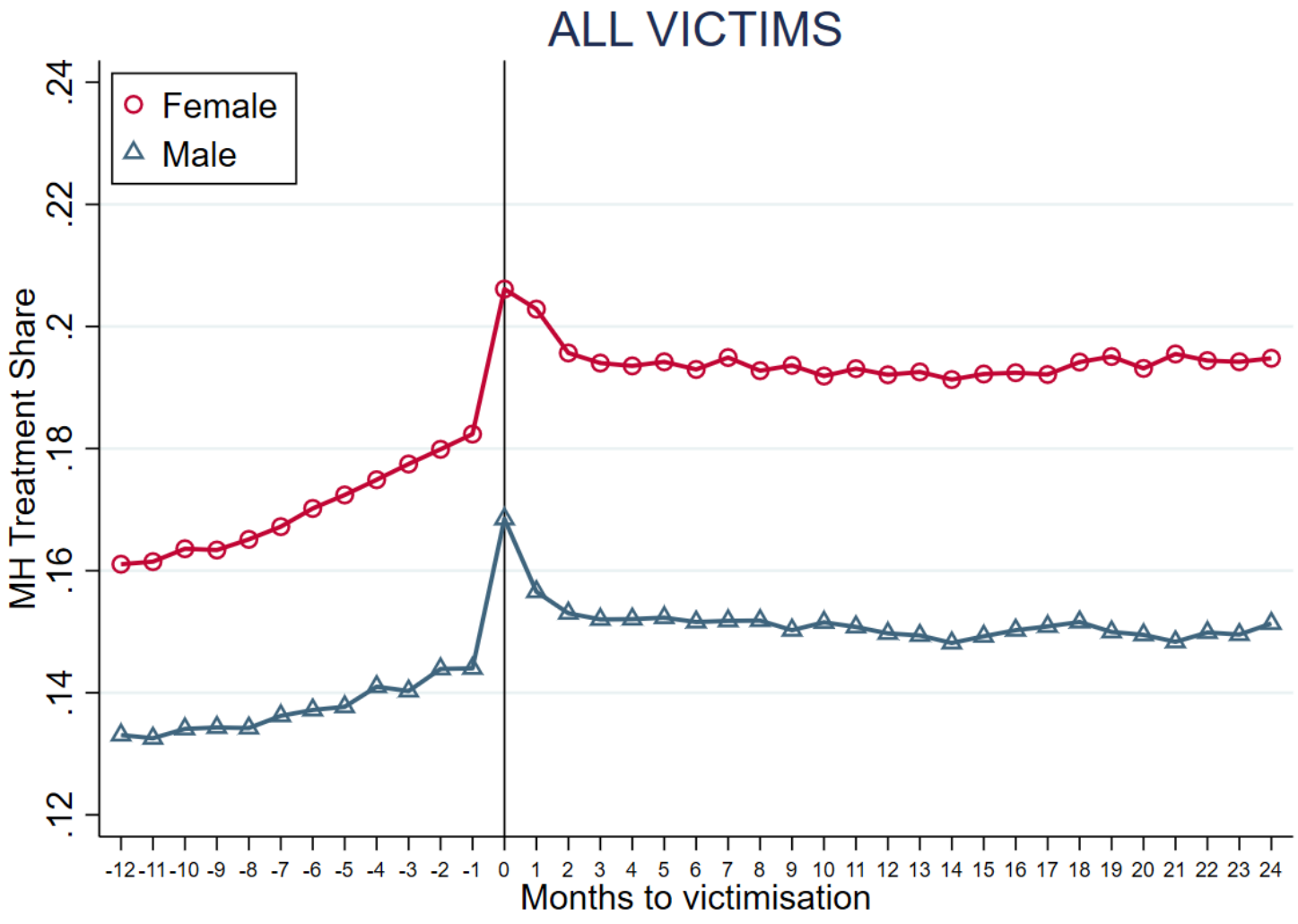
Outcomes (measured in snapshot month):

	Serious Assault		Common Assault		Sexual Offence		Threat		Robbery	
	♀	♂	♀	♂	♀	♂	♀	♂	♀	♂
Observations	91,089	43,017	22,509	38,370	8,724	738	537	831	2,007	5,172
LM Outcomes (in month of first victimization):										
Positive Wage (D)	0.44	0.54	0.51	0.55	0.48	0.37	0.49	0.63	0.55	0.54
Wage in $1000	3.73	5.11	3.83	4.72	2.98	3.45	4.16	4.58	3.63	3.80
Positive Benefits (D)	0.45	0.26	0.33	0.21	0.24	0.26	0.26	0.11	0.19	0.18
Benefits in $1000	1.51	1.30	1.38	1.19	1.34	1.22	1.47	1.33	1.37	1.18
MH Outcomes (in month before first victimization):										
MH treatment (D)	17.29	14.12	18.97	15.22	23.85	26.72	15.52	9.92	9.48	9.20

Source: IDI (2022) and own calculations. *Note:* To comply with the confidentiality requirements by Statistics NZ, all counts and observation numbers presented are randomly rounded to base 3; percentages are based on rounded counts and counts below 50 are suppressed (S).

CRIME VICTIMIZATION AND MENTAL HEALTH

Mental Health Treatment over Time (Raw Data)



Source: IDI (2022), own calculations.

Challenges for Identification

1. **Selection on unobservables:** Individuals who become a victim of crime may differ in (common) unobservable characteristics.

   $\rightarrow$ Use a victim-only sample (**change of counterfactual**).

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   $\rightarrow$ **Individual, time and age-group FE.**

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3. **Reversed causality:** MH affects victimization risk (directly or indirectly) while victimization affects MH.

   $\rightarrow$ **Event-study design:** Trace out MH responses to victimization *by month*; focus on changes at event and pay attention to pre-trends.

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3. **Reversed causality:** MH affects victimization risk (directly or indirectly) while victimization affects MH.

   $\rightarrow$ **Event-study design.**

4. **Measurement problems:** Underreporting of victimization and undertreatment of MH.

   $\rightarrow$ Descriptive analysis using **survey data** (work in progress).

Econometric Model and Estimation (I)

Event-study based on TWFE model (as in Bindler and Ketel 2022).

$$MH_{it} = \sum_{j=-5}^{12} \beta_j V_{i,t+j} + \delta_i + \delta_t + \delta_{ag} + \epsilon_{it}$$

- MH_{it}: Indicator (1/0) for mental health treatment of individual i at time t (= calendar month).
- $V_{i,t+j}$: Indicator (1/0) for 1st victimization event j periods from t.

  Omitted period: $j = -1$. V_{it}^{j} is binned at the endpoints: $j \in [\underline{j} = -5, \bar{j} = 12]$) (Schmiedheiny and Siegloch 2023).
- FEs: δ_i (individual), δ_t (time, monthly level), δ_{ag} (age-group).
- Inference: Standard errors clustered by individual.

Econometric Model and Estimation (II)

Timing of treatment:

- We do *not* assume that victimization is random.
- But: Context with no exogenous variation in victimization.
- Implication: We have to assume that *timing* of victimization is (conditionally) as good as random.

Econometric Model and Estimation (II)

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- But: Context with no exogenous variation in victimization.
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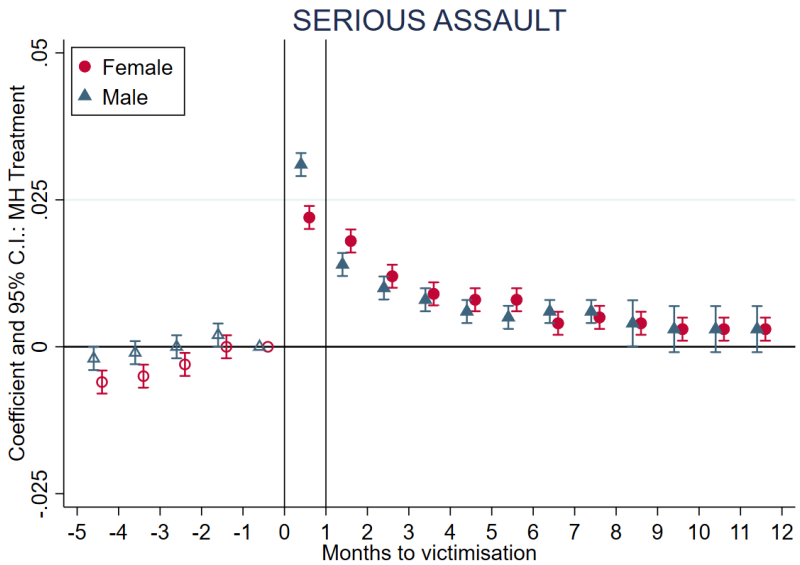
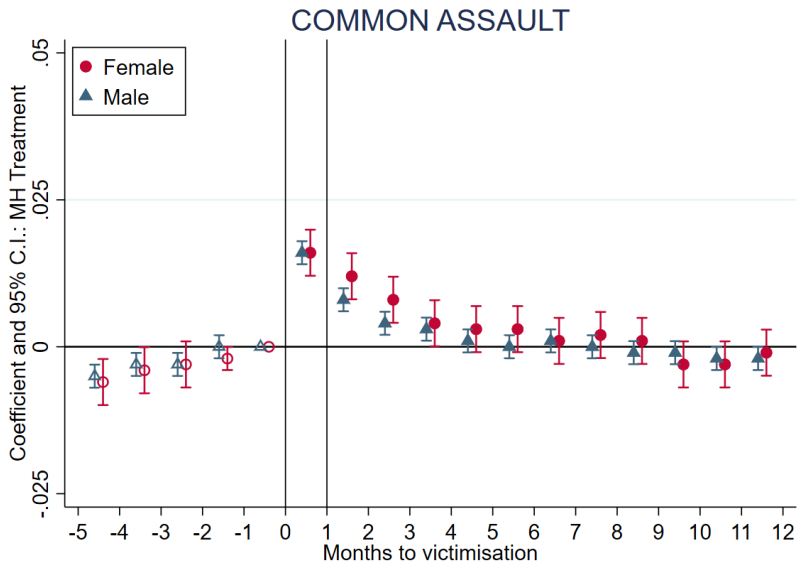
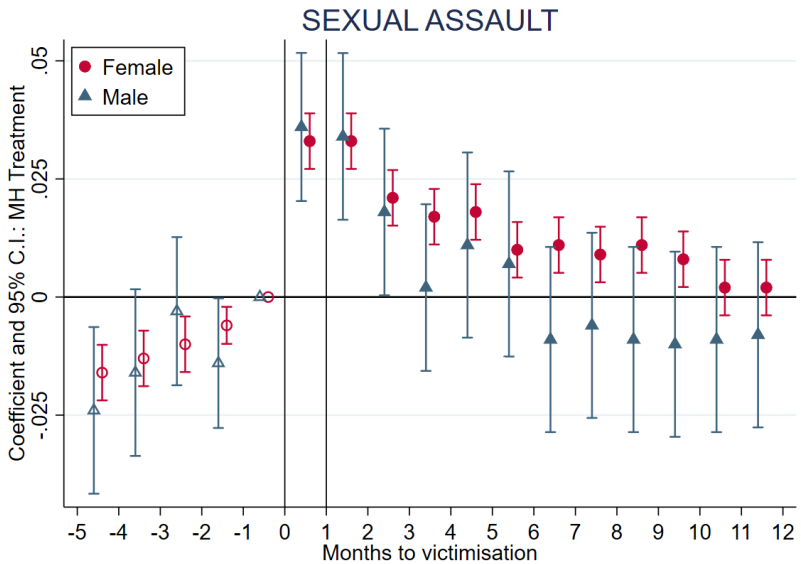
Heterogeneous treatment effects:

- Heterogeneity in the treatment:
  $\rightarrow$ Estimation on subsamples by offense and gender.
- Heterogeneity across (treatment) groups:
  $\rightarrow$ Event-study instead of TWFE-DiD.
- Heterogeneity over time (within groups):
  $\rightarrow$ Reweighting estimator (Callaway Sant'Anna 2021; in progress).

Results: Mental Health after Victimization







Robbery Threat

Source: IDI (2022), own calculations.

Econometric Model and Estimation (III)

Heterogeneity by offender:

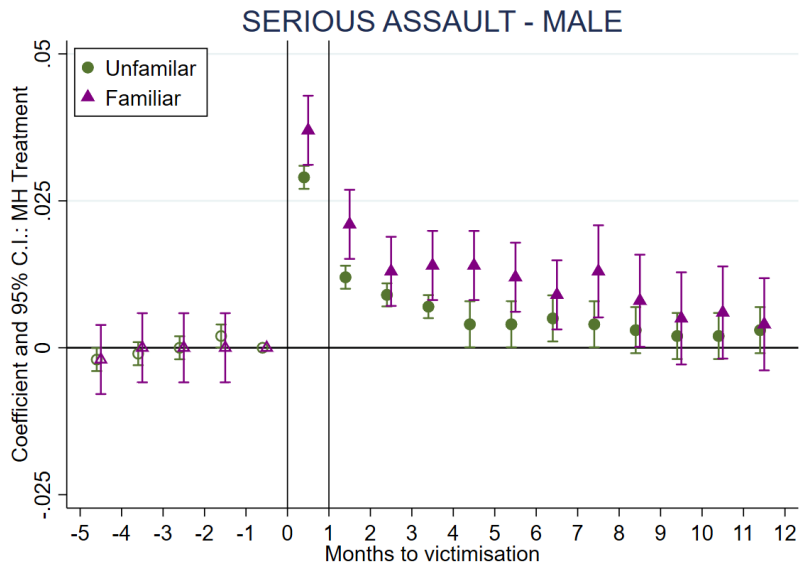
- Start by pooling all cases (results just shown).
- Our next question: Does the victim-offender relationship (VOR) matter?

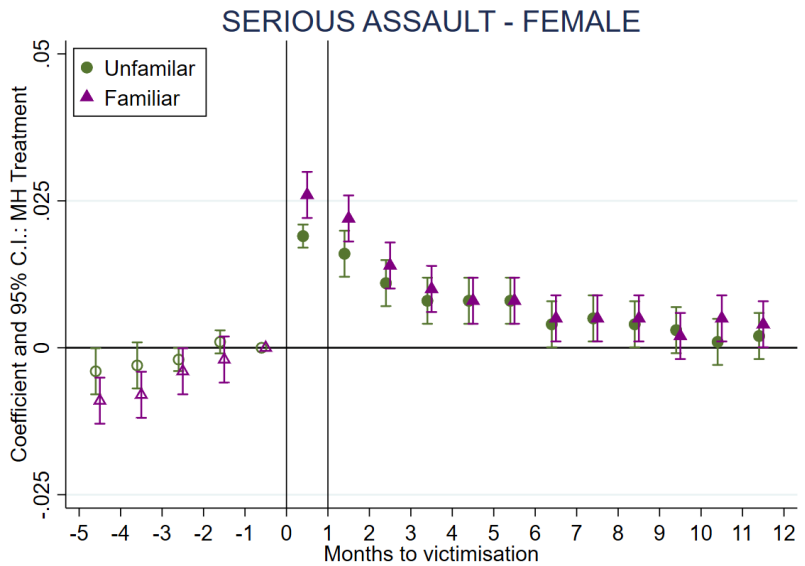
$$MH_{it} = \sum_{j=-5}^{12} \theta_j V_{i,t+j}^{VOR} + \delta_i + \delta_t + \delta_{ag} + \nu_{it}$$

- Focus on 2 cases: VOR = Familiar vs. unfamiliar offender.

Results: Mental Health and Knowing the Offender (I)

Serious Assault:

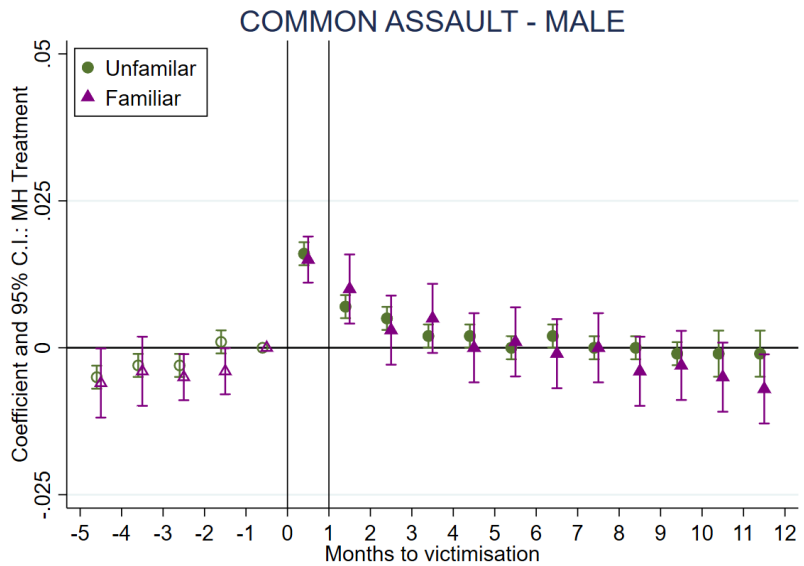


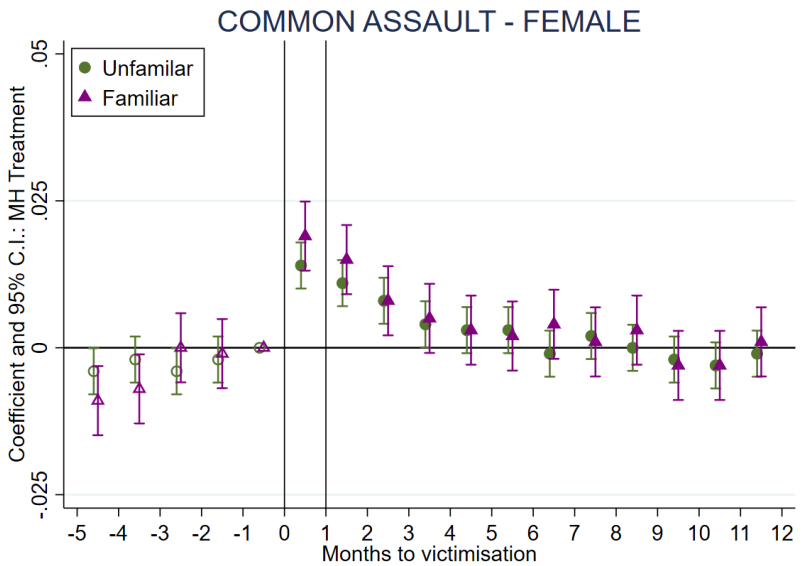


Source: IDI (2022), own calculations.

Results: Mental Health and Knowing the Offender (II)

Common Assault:





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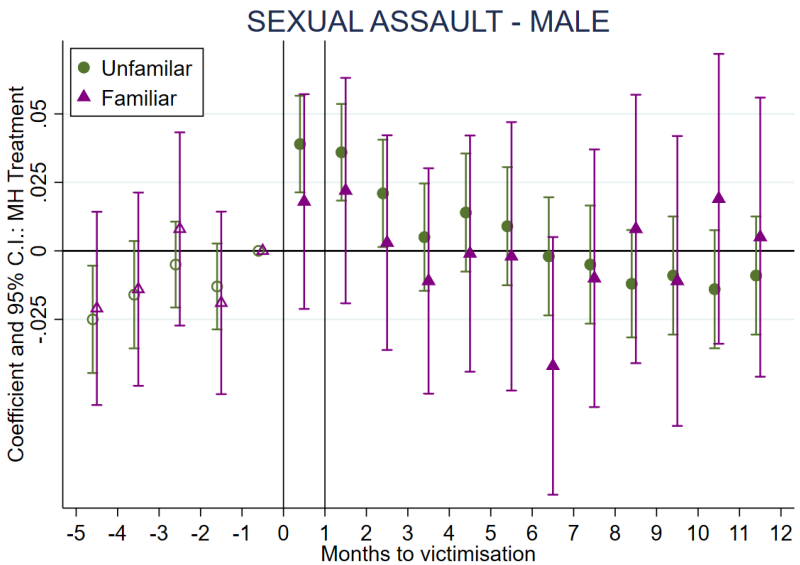
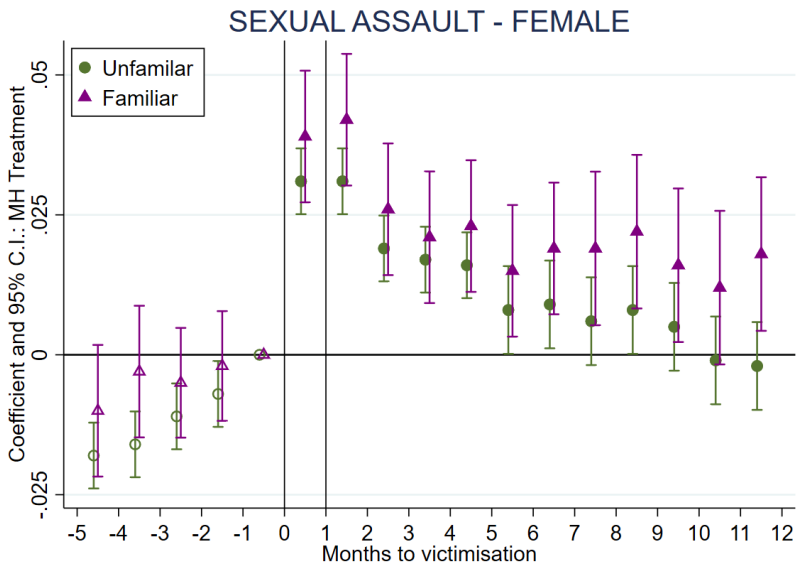
Results: Mental Health and Knowing the Offender (III)

Sexual Assault:





Source: IDI (2022), own calculations.

Mental Health and Victimization

Taking stock:

- Short-run increase in MH treatment in response to violent crime victimization. *In the short-run:* Likely means deterioation in mental health. *In the longer run:* Treatment versus prevalence.
- Supports existing findings in the literature (e.g. Bindler and Ketel 2022; Bhuller et al. 2024).
- Monthly data highlights dynamics within the first year after victimization.
- Not much heterogeneity in terms of familiar vs. unfamiliar offender (if anything, only for serious assault in the short-run).

Next step: Impacts on labor market outcomes (where MH might be one mediator)?

CRIME VICTIMIZATION AND LABOR MARKET OUTCOMES

Econometric Model and Estimation (IV)

Baseline as before – but with labor market relevant outcomes.

$$Y_{it} = \sum_{j=-5}^{12} \beta_j V_{i,t+j} + \delta_i + \delta_t + \delta_{ag} + \epsilon_{it}$$

where Y denotes **monthly wages** (in \$1000) or **benefits** (in \$1000).

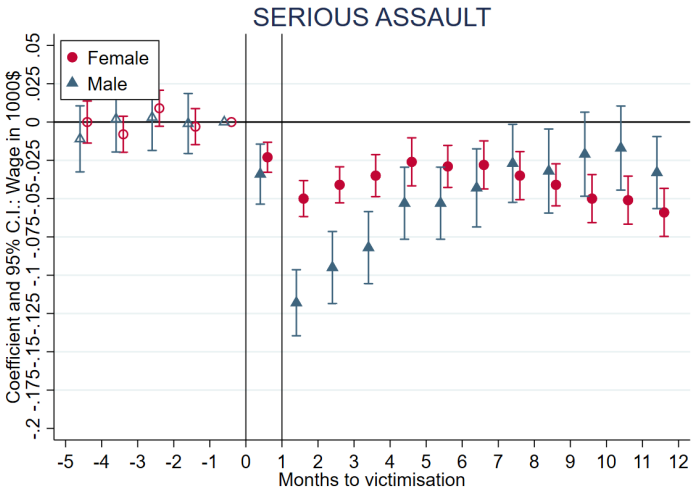
Plus again: Heterogeneity by victim-offender relationship.

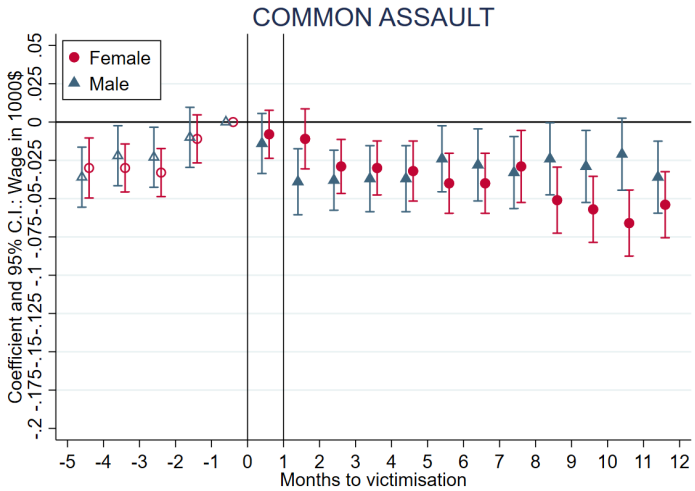
$$Y_{it} = \sum_{j=-5}^{12} \theta_j V_{i,t+j}^{VOR} + \delta_i + \delta_t + \delta_{ag} + \nu_{it}$$

Results: Labor Market Outcomes after Victimization

Wages in $1000

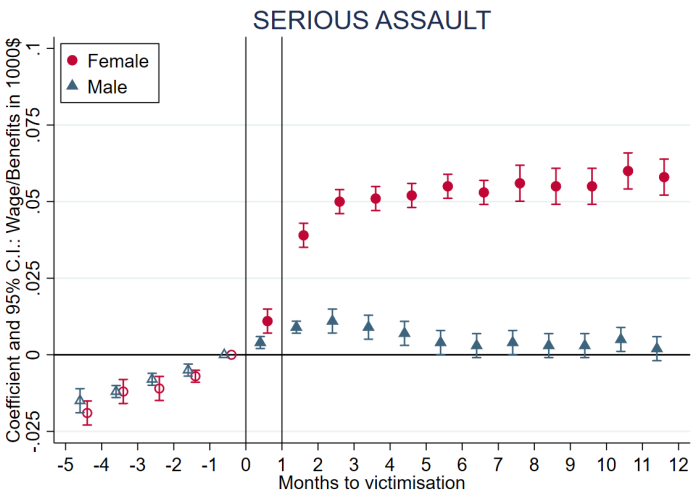
Sexual Assault | Robbery | Threat

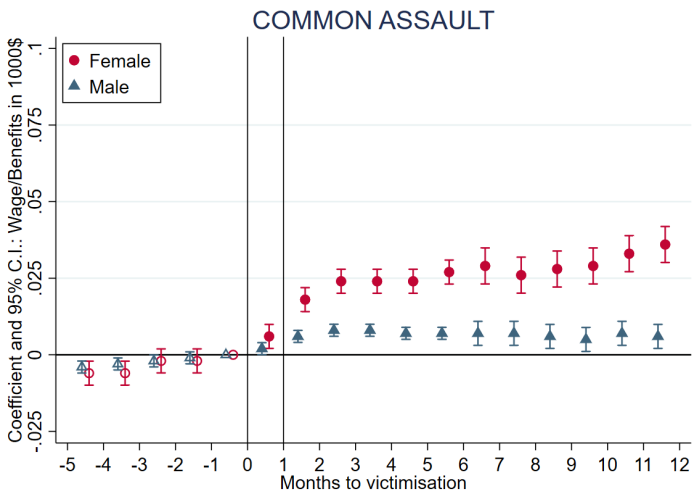




Benefits in $1000

Sexual Assault | Robbery | Threat



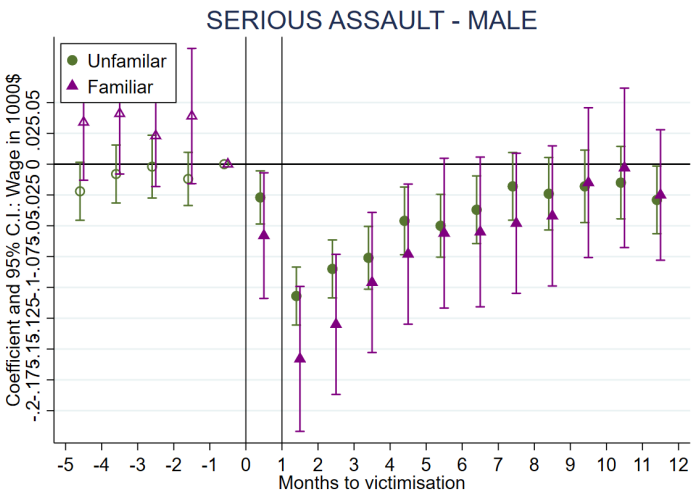


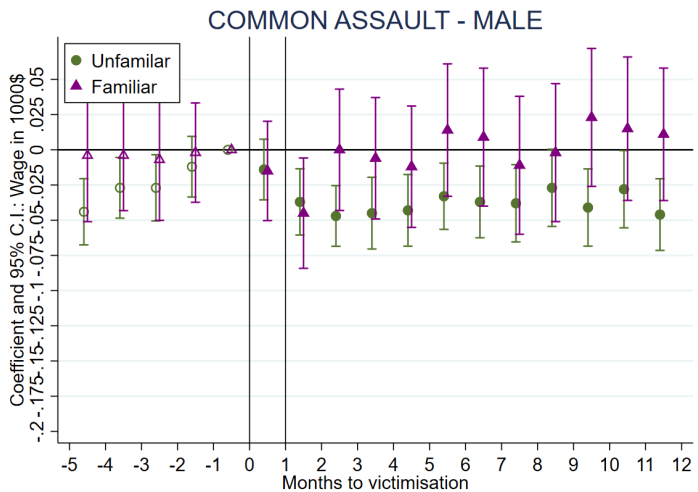
Source: IDI (2022) and own calculations.

Results: Wages and Knowing the Offender

Males

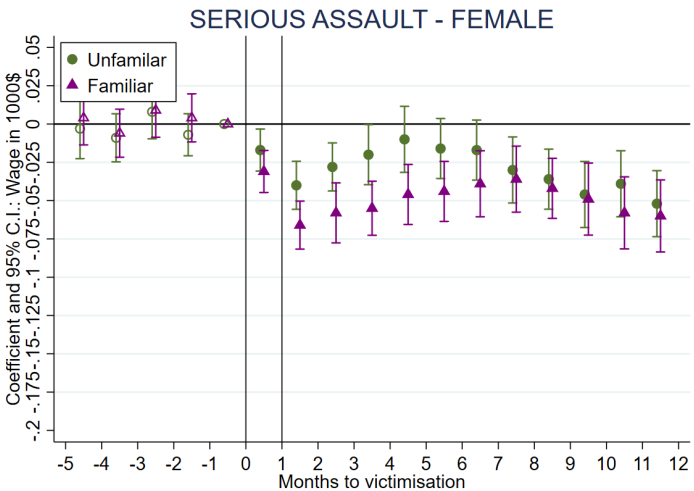
Sexual Assault

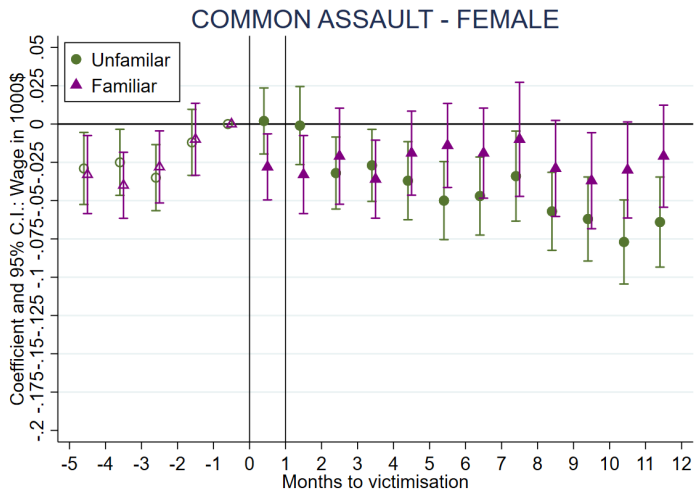




Females

Sexual Assault



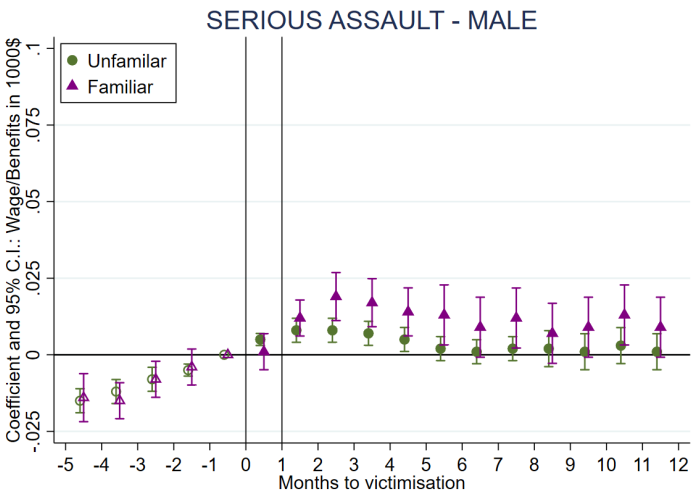


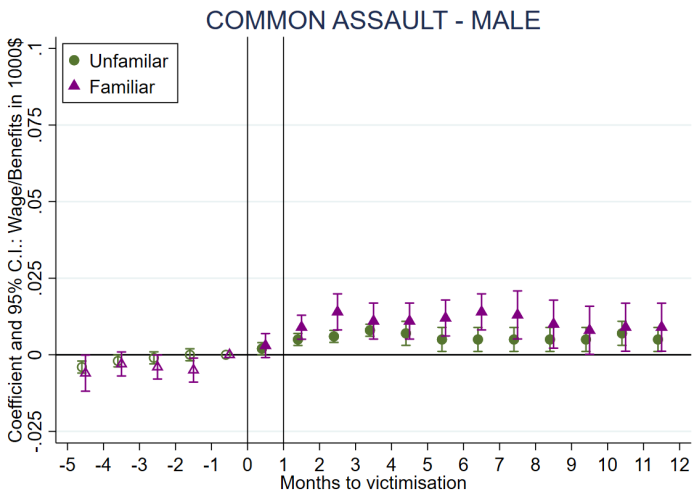
Source: IDI (2022) and own calculations.

Results: Benefits and Knowing the Offender

Males

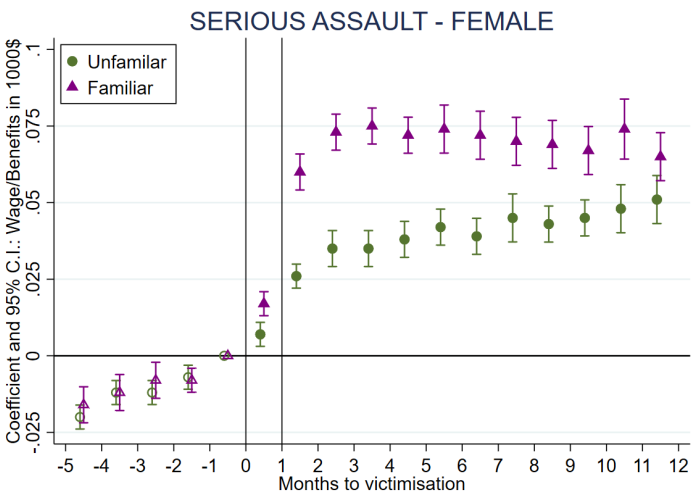
Sexual Assault

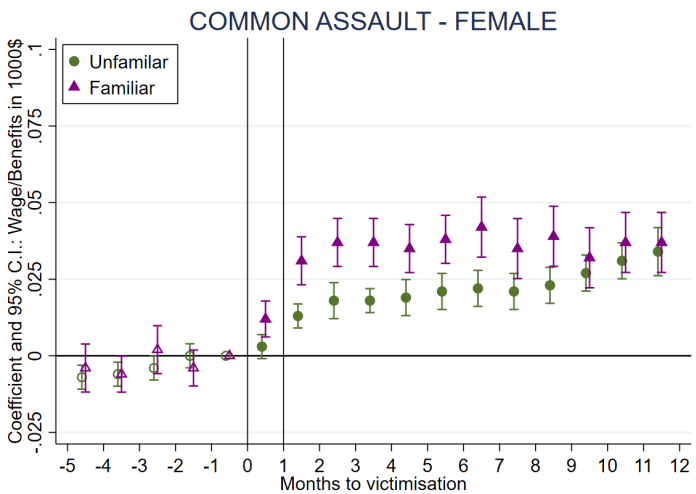




Females

Sexual Assault





Source: IDI (2022) and own calculations.

Labor Market Outcomes and Victimization

Taking stock:

- Decreases in wage income and increases in benefit income linked to violent crime victimization. Supports existing findings in the literature (e.g. Bindler and Ketel 2022; Bhuller et al. 2024).
- Impacts higher for more severe assaults.
- Wage effects larger for males, but reversing sooner than for females (persistent over 12 months). Benefit impacts much larger for females and persistent over 12 months.
- Heterogeneity in terms of familiar vs. unfamiliar offender mostly for females receiving benefits.
  (Driven by domestic violence cases and household dissolution – given not much heterogeneity in MH?)

Roadmap

DISCUSSION AND CONCLUSION

Findings

Short summary of findings:

- **Short-run $\uparrow$ in MH treatment** in first year after victimization.
- Results highlight dynamics *within first year* after victimization.
- $\downarrow$ **in wage income and** $\uparrow$ **in benefit income** in response to victimization with heterogenous patterns by gender.
- **Not much heterogeneity by victim-offender relationship** (exception: benefits/females).

Implications

- Supports the implications of young literature on economics of victimization: **Social cost of crime** is substantial and includes intangible costs ($\rightarrow$ mental health).
- Highlights importance of mental health support after (violent crime) victimization plus role of **victim support** more generally.

Implications

- Supports the implications of young literature on economics of victimization: **Social cost of crime** is substantial and includes intangible costs ($\rightarrow$ mental health).
- Highlights importance of mental health support after (violent crime) victimization plus role of **victim support** more generally.

- Lack of heterogeneity contrasts literature that finds substantially larger social costs of **domestic compared to non-domestic violence**.
- **Our results:** *Suggestive* that this is not due to knowing the offender, but might be linked to other factors (e.g., being in an economic union as a household).

Work in Progress

This is work in progress, more on our to-do-list:

- Details on mental health outcomes: Look at MH treatment separated by source (outpatient, drugs, inpatient, ...)
- Robustness tests: Longer pre-treatment period, stronger restriction on “no previous victimization” period, heterogenous treatment effects (Callaway SantAnna 2021), ...
- Measurement: Survey data to understand unreported victimization and untreated MH issues.

Thank you!

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APPENDIX

Number of Victimizations per Individual

Number of victimizations (per victim)	**Freq.**	**%**
1	173,319	74.22
2	34,509	14.78
3	12,360	5.29
4	5,757	2.47
5	3,069	1.31
6	1,725	0.74
7	1,107	0.47
8 or more	1,659	0.71
Total	233,505	100.00

Source: IDI (2022) and own calculations. *Note:* To comply with the confidentiality requirements by Statistics NZ, all counts and observation numbers presented are randomly rounded to base 3; percentages are based on rounded counts and counts below 50 are suppressed (S).

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Seriousness Score by Offense

	Average seriousness score	
	Female	**Male**
Serious Assault	**165.57**	**320.49**
Resulting in Injury	214.58	445.73
Not Resulting in Injury	96.96	125.68
Common Assault	**14.78**	**16.91**
Sex offences	**2269.64**	**2288.36**
Aggravated	3034.75	2951.35
Non-Aggravated	442.34	856.50
Threat	**1069.61**	**890.24**
Abduction and Kidnapping	1350.00	1386.79
Blackmail and Extortion	759.83	803.40
Robbery	**875.11**	**883.33**
Aggravated	901.91	909.90
Non-Aggravated	570.71	576.65

Source: IDI (2022) and own calculations. *Note:* To comply with the confidentiality requirements by Statistics NZ, all counts and observation numbers presented are randomly rounded to base 3; percentages are based on rounded counts and counts below 50 are suppressed (S).

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Victim-Offender Relationship by Offense

	Serious Assault (%)		Common Assault (%)		Sexual Offense (%)		Threat (%)		Robbery (%)	
	♀	♂	♀	♂	♀	♂	♀	♂	♀	♂
Observations	119,925	66,402	49,416	72,618	20,145	1,821	2,085	3,600	4,656	11,481
Family Member	**24.14**	**7.08**	**12.40**	**6.30**	**4.66**	**2.31**	**11.94**	S	**1.16**	**0.34**
Partner	18.57	2.08	5.99	2.60	2.01	S	10.79	S	0.52	S
(Grand)Parent	0.93	0.83	1.05	0.69	1.01	S	S	S	S	S
(Grand)Child	2.23	1.95	2.73	1.22	S	S	S	S	S	S
Sibling	1.26	0.90	1.21	0.80	S	S	S	S	S	S
Other FM	1.16	1.32	1.43	0.97	1.38	S	S	S	S	S
No FM	**14.13**	**10.06**	**14.15**	**13.33**	**12.73**	**10.71**	**16.69**	**6.58**	**5.15**	**5.30**
Ex-Partner	9.23	1.26	2.65	1.12	2.58	S	11.37	S	S	S
Friend, Flatmate	0.70	0.85	1.05	1.19	0.95	S	S	S	S	S
Other	4.20	7.95	10.45	11.02	9.20	9.72	S	5.58	4.38	4.86
Unknown	**61.73**	**82.85**	**73.45**	**80.38**	**82.61**	**86.99**	**71.37**	**93.17**	**93.69**	**94.36**
Stranger	4.70	23.04	7.18	14.24	7.39	6.26	8.20	7.67	35.37	29.55
No Off.Identified	55.14	55.48	63.00	61.84	72.60	77.76	60.72	83.92	53.80	59.99
Not Stated	1.89	4.33	3.27	4.30	2.62	2.97	2.45	1.58	4.51	4.81

Source: IDI (2022) and own calculations. *Note:* To comply with the confidentiality requirements by Statistics NZ, all counts and obs. numbers presented are randomly rounded to base 3; % are based on rounded counts, counts below 50 are suppressed (S).

Example: *Serious assault*. Female vs. male victims – **38% vs. 17%** of cases with offender known (by the victim).

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Mental Health Treatment: Six Admin Data Sources

1. **Program for the Integration of MH Data (PRIMHD) from MoH:** Referral level information on secondary inpatient, residential, outpatient and community services provided by DHBs and NGOs.
2. **Pharmaceutical data from Ministry of Health (MoH):** Pharmaceuticals subsidized dispensing data related to mental health/addiction meds (based on chemical codes).
3. **Publicly funded hospital discharge data from MoH:** Events related to mental health.
4. **National Needs Assessment and Service Coordination Information (SOCRATES) by MoH:** Individuals who are eligible for Disability Support Services (DSS) for mental health reasons.
5. **Benefit dynamics data from Ministry of Social Development (MSD):** Individuals who receive the MSD incapacity benefit for mental health reasons.
6. **Injury claims data from Accident Compensation Corporation (ACC):** Claims made related to self-harm event

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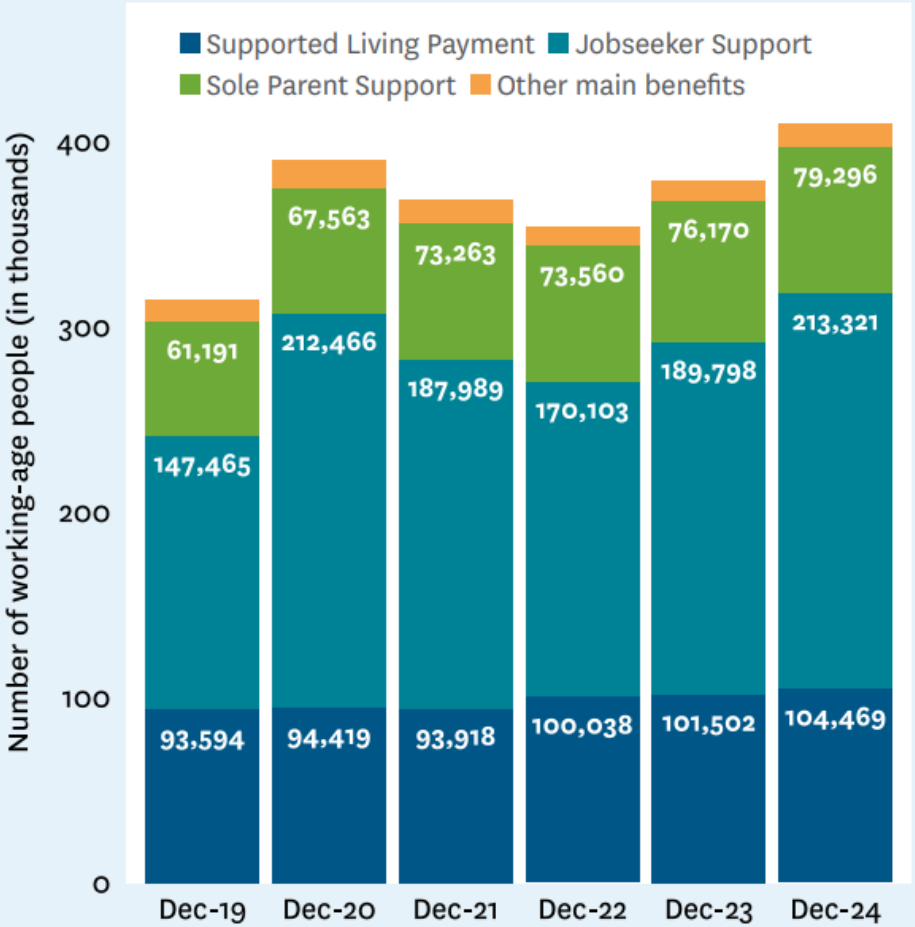
Social Benefits: Details

Figure 1b: Number of people receiving a main benefit by benefit type at the end of the last six December quarters.



In Figure 1b, other main benefits include:

- Youth Payment and Young Parent Payment
- Emergency Benefit
- Emergency Maintenance Allowance
- Jobseeker Support Student Hardship

Source: Ministry of Social Development, Benefit Fact Sheets - Snapshots (December 2024).

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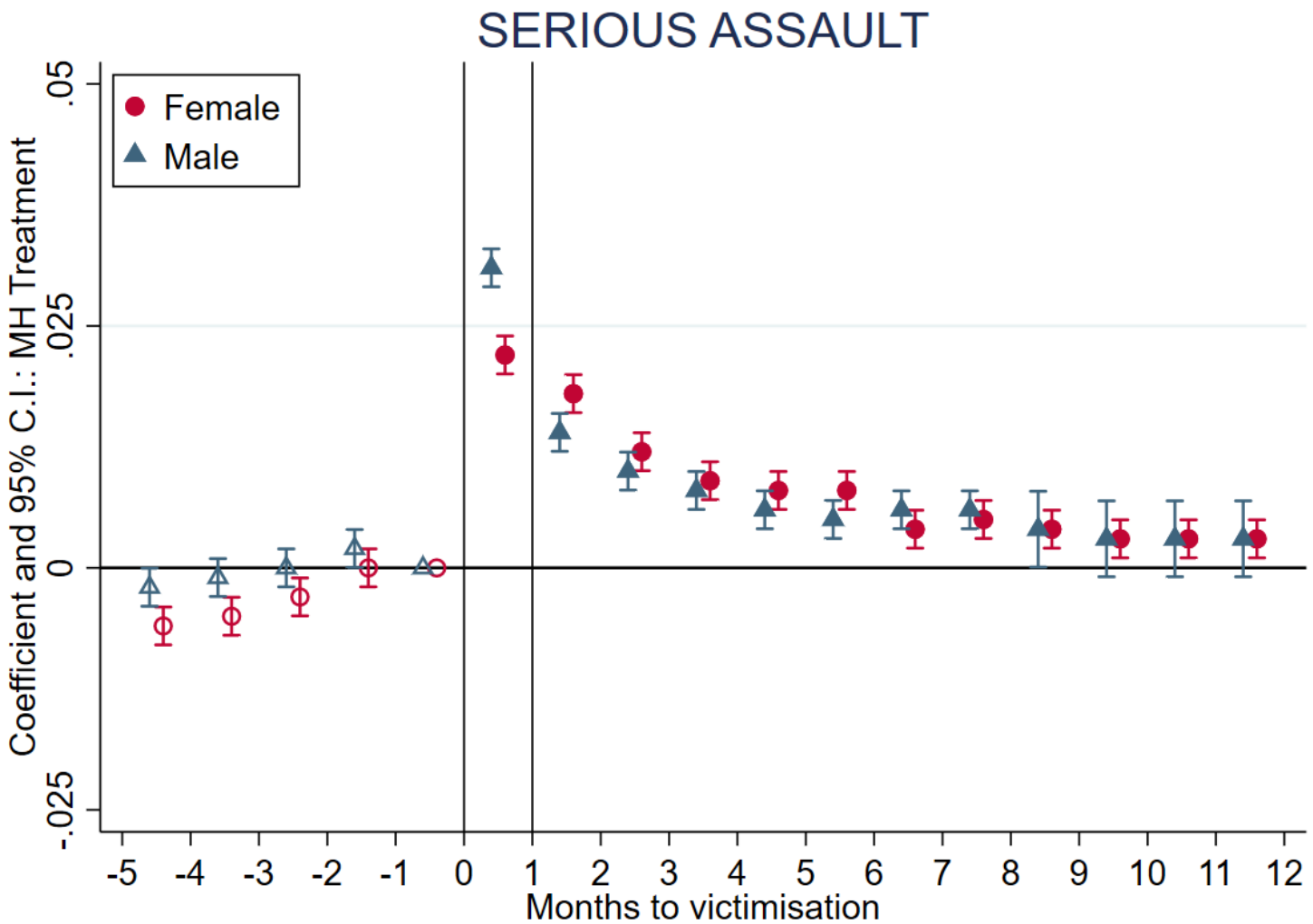
Serious Assault and MH



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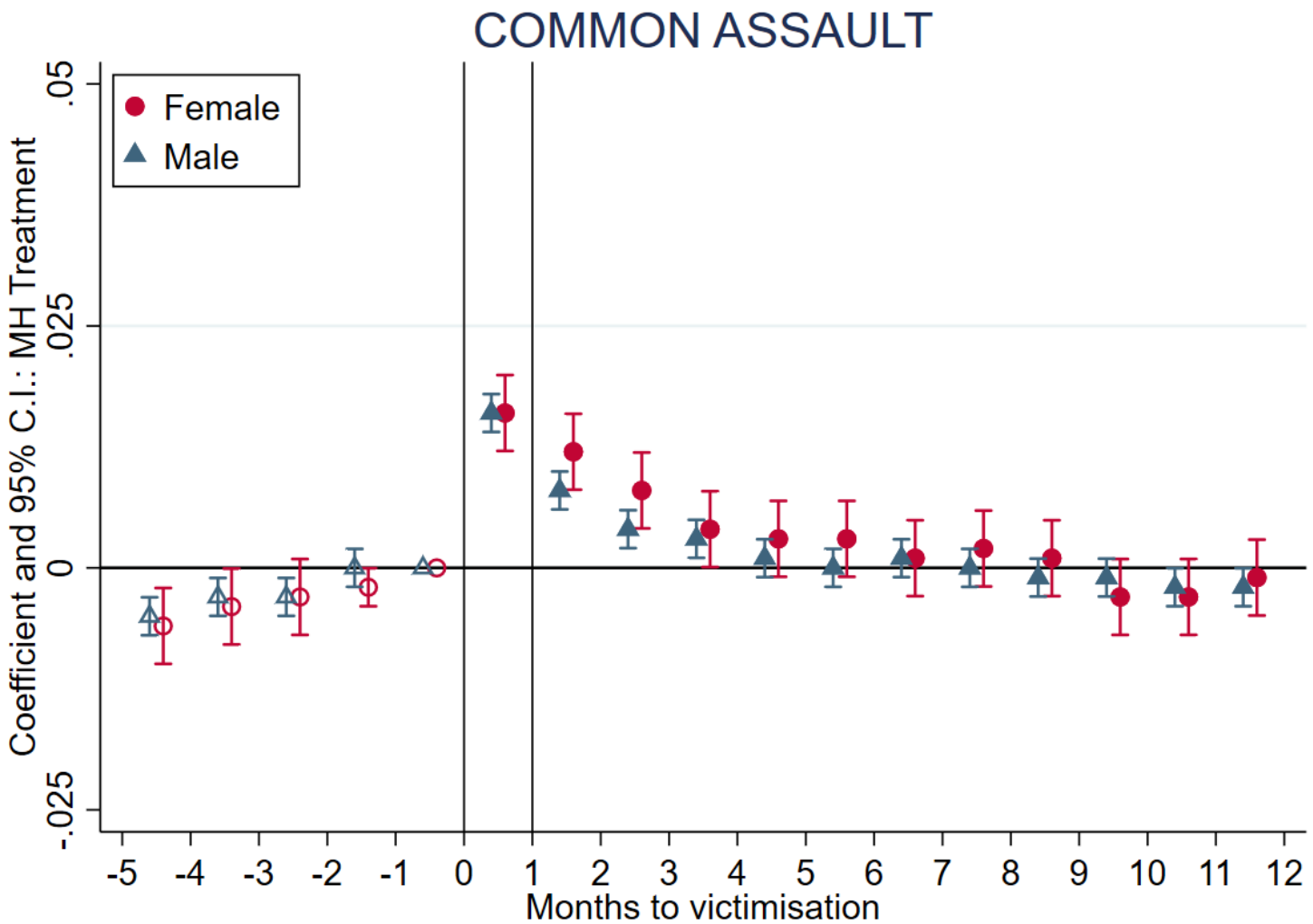
Common Assault and MH



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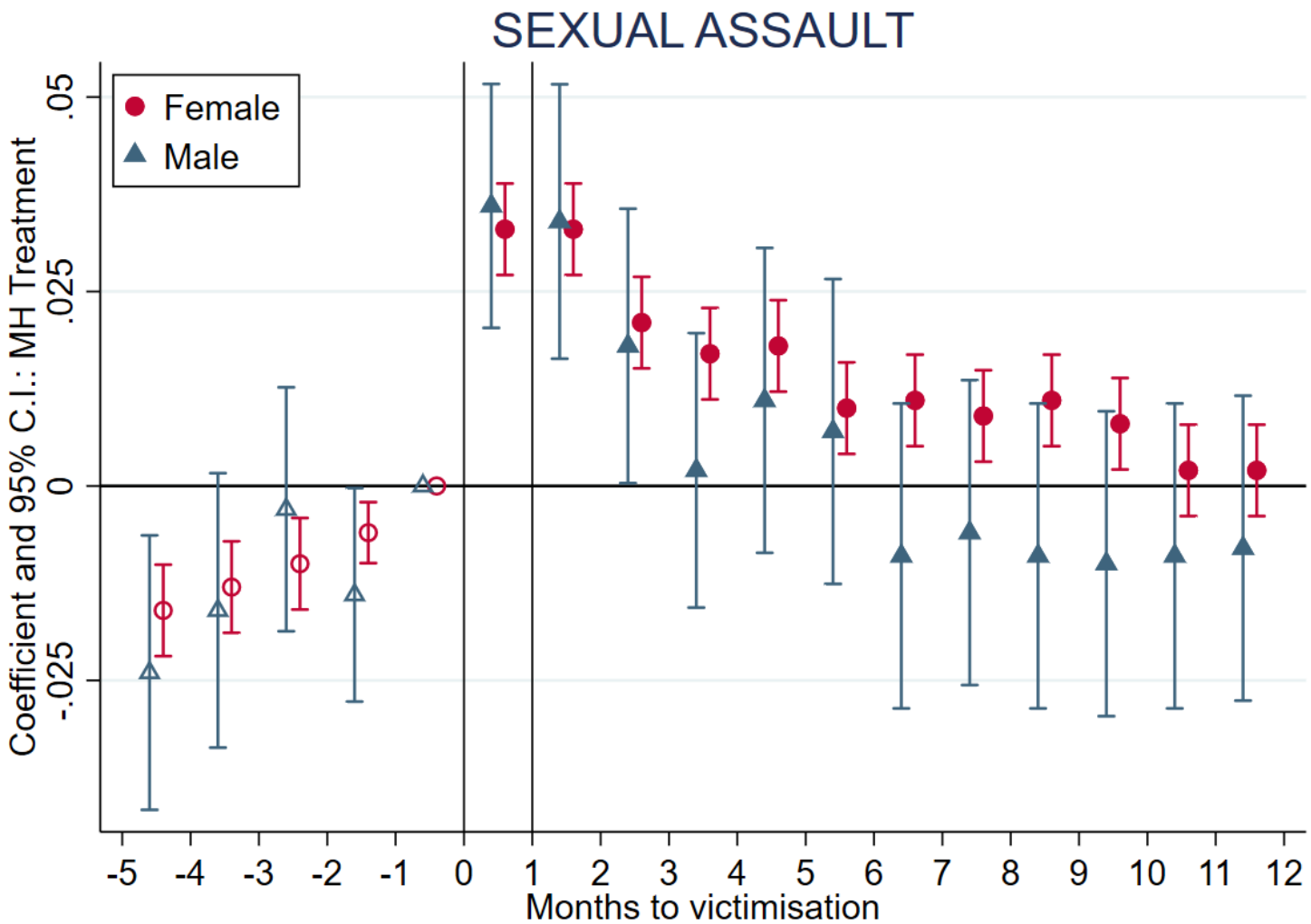
Sexual Assault and MH



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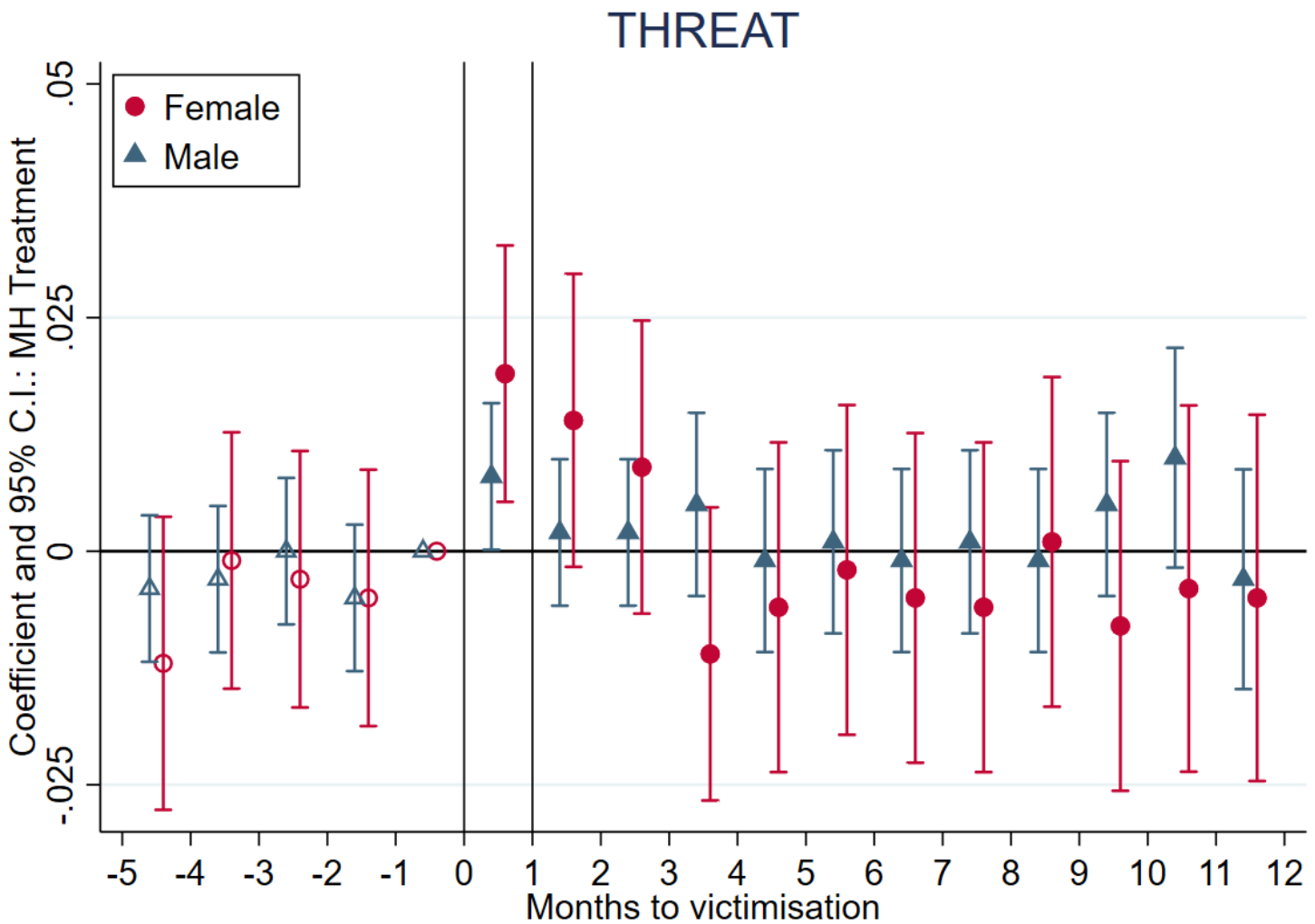
Threat and MH



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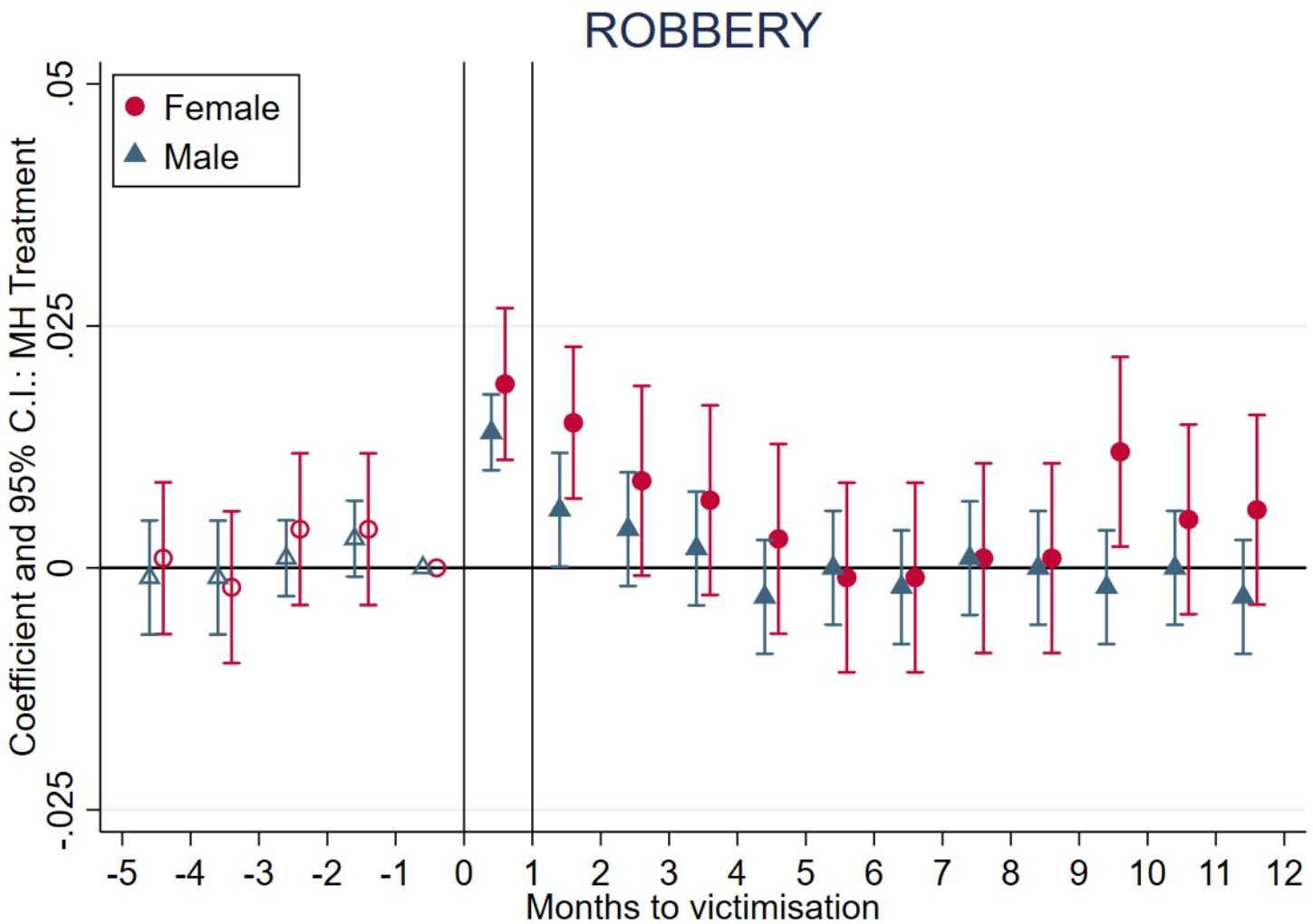
Robbery and MH



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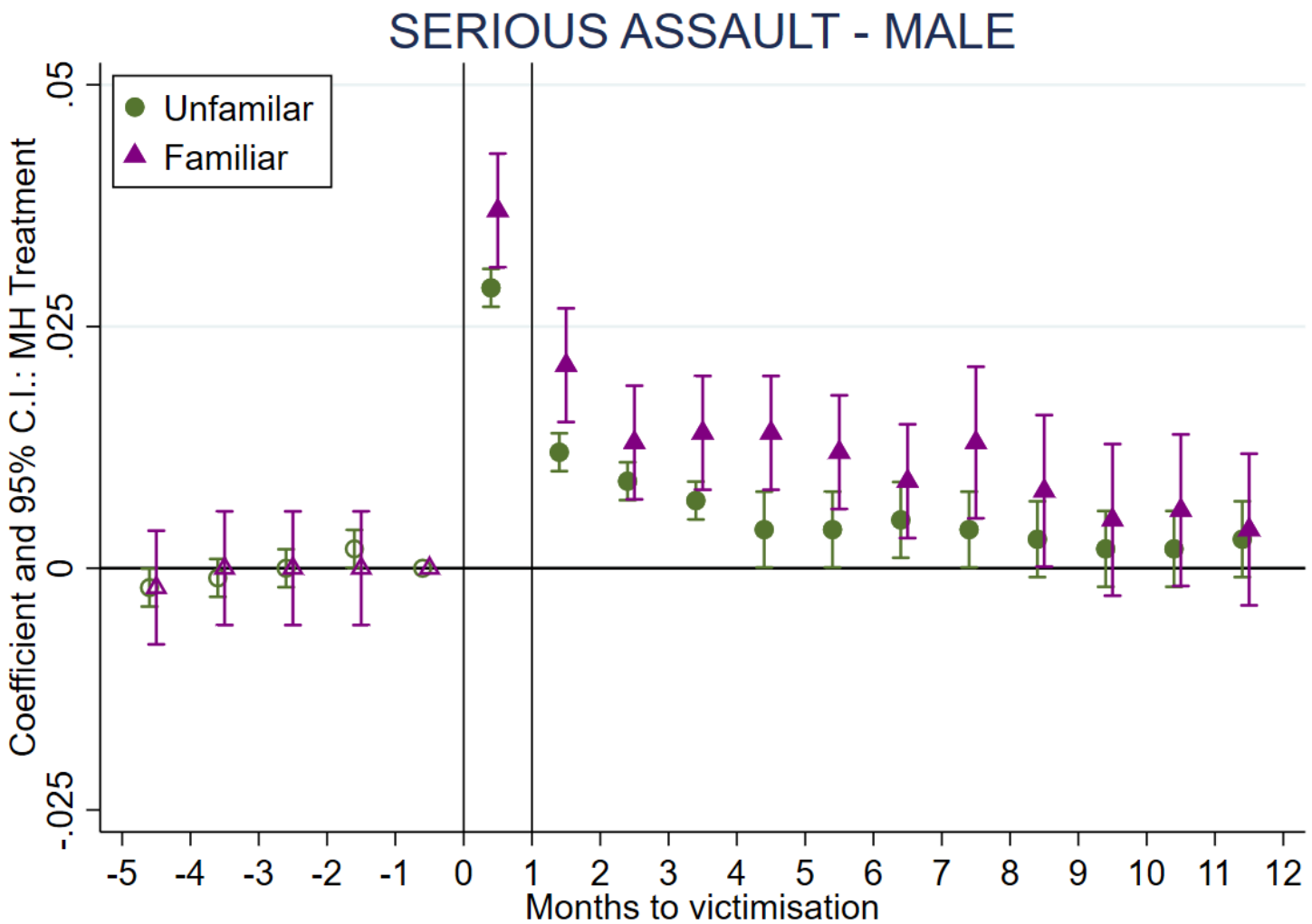
Serious Assault: Males



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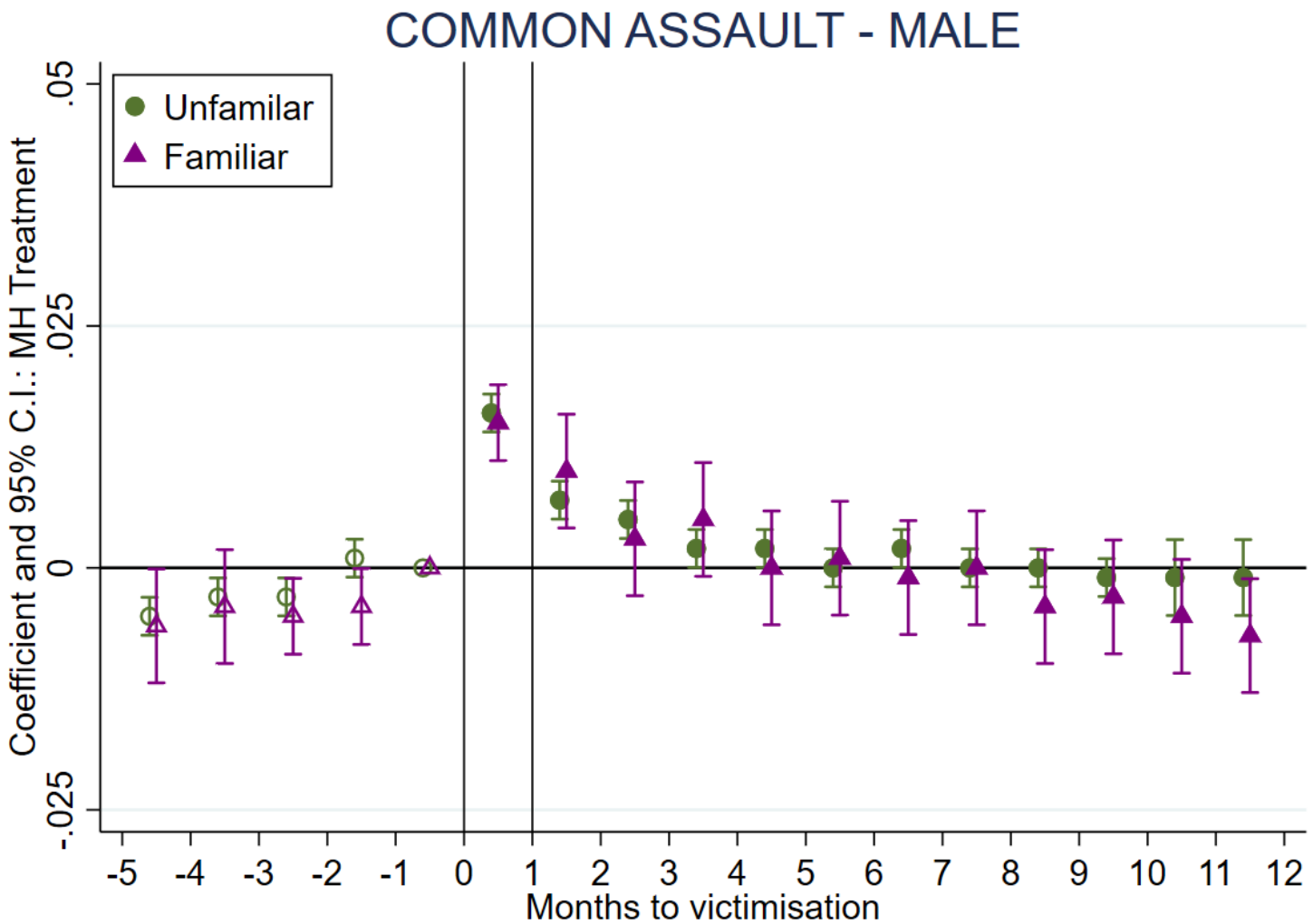
Common Assault: Males



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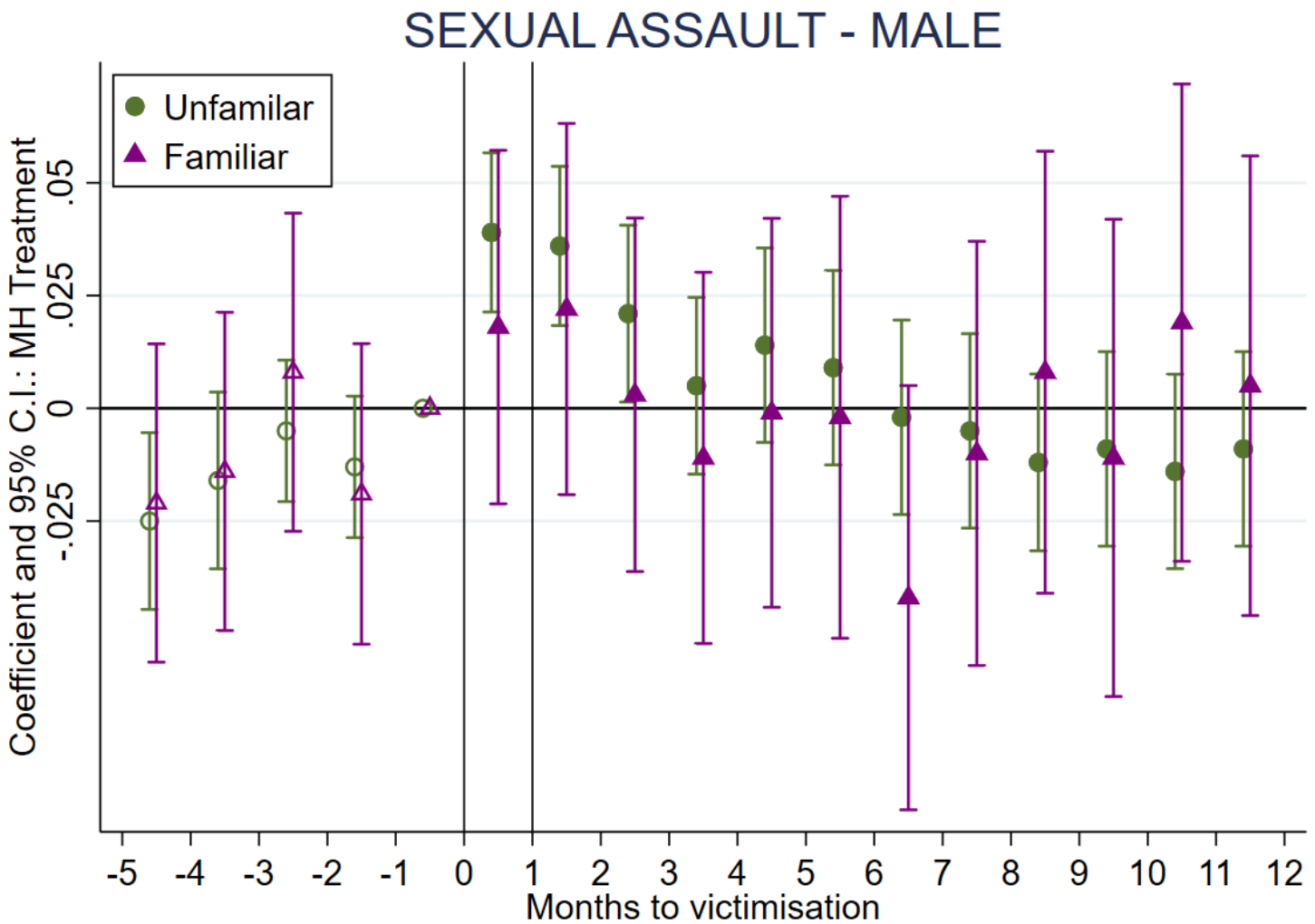
Sexual Assault: Males



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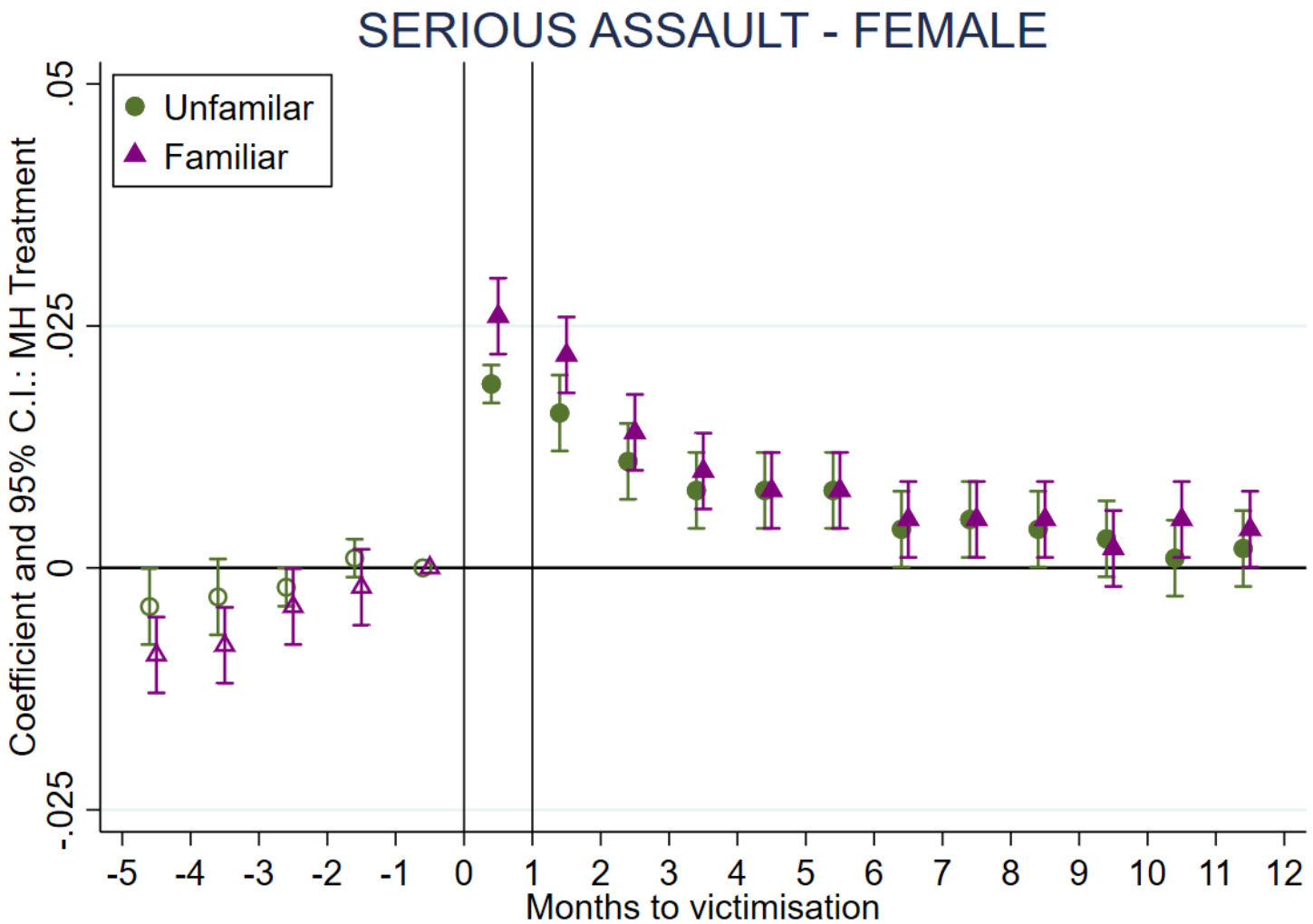

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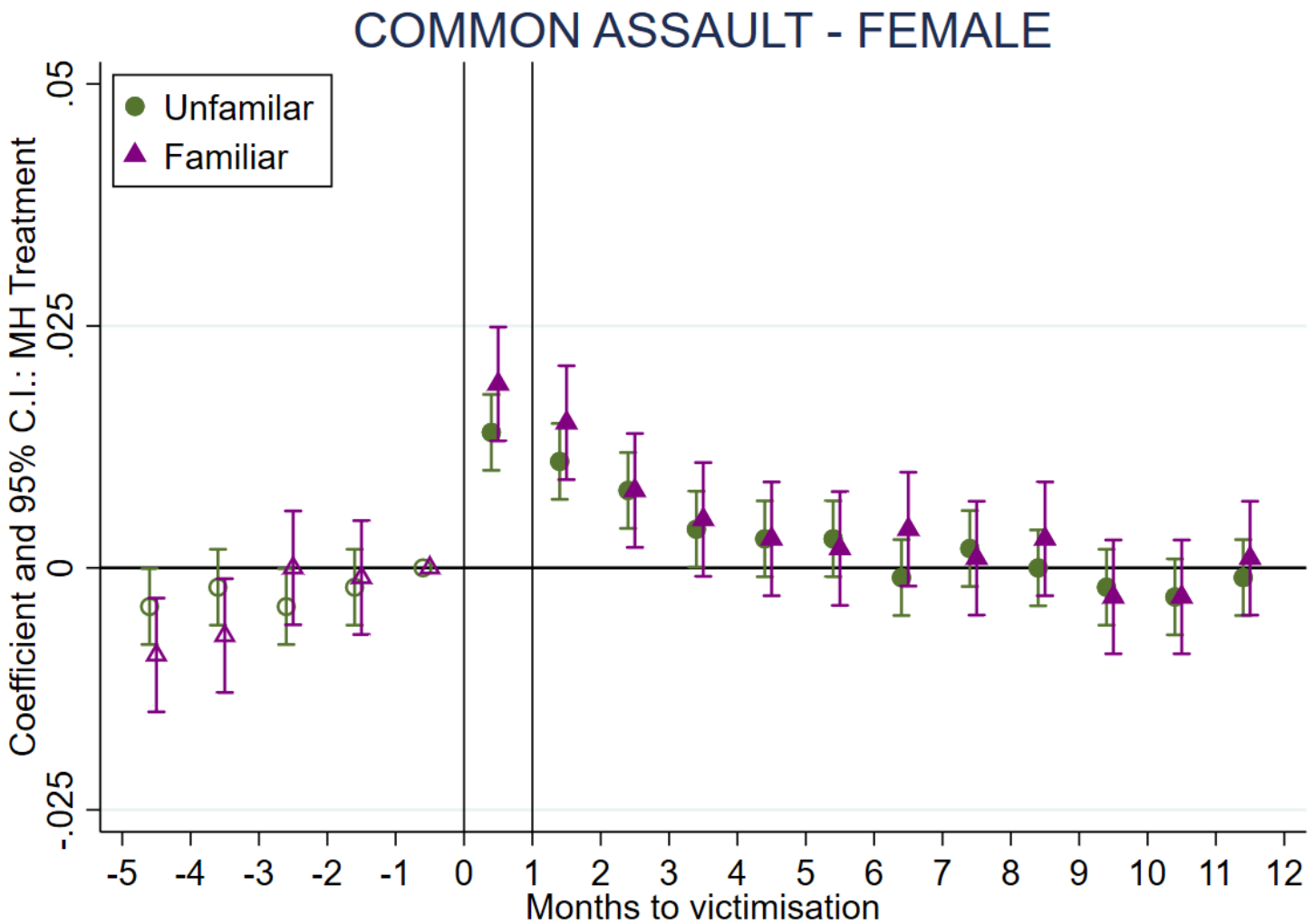

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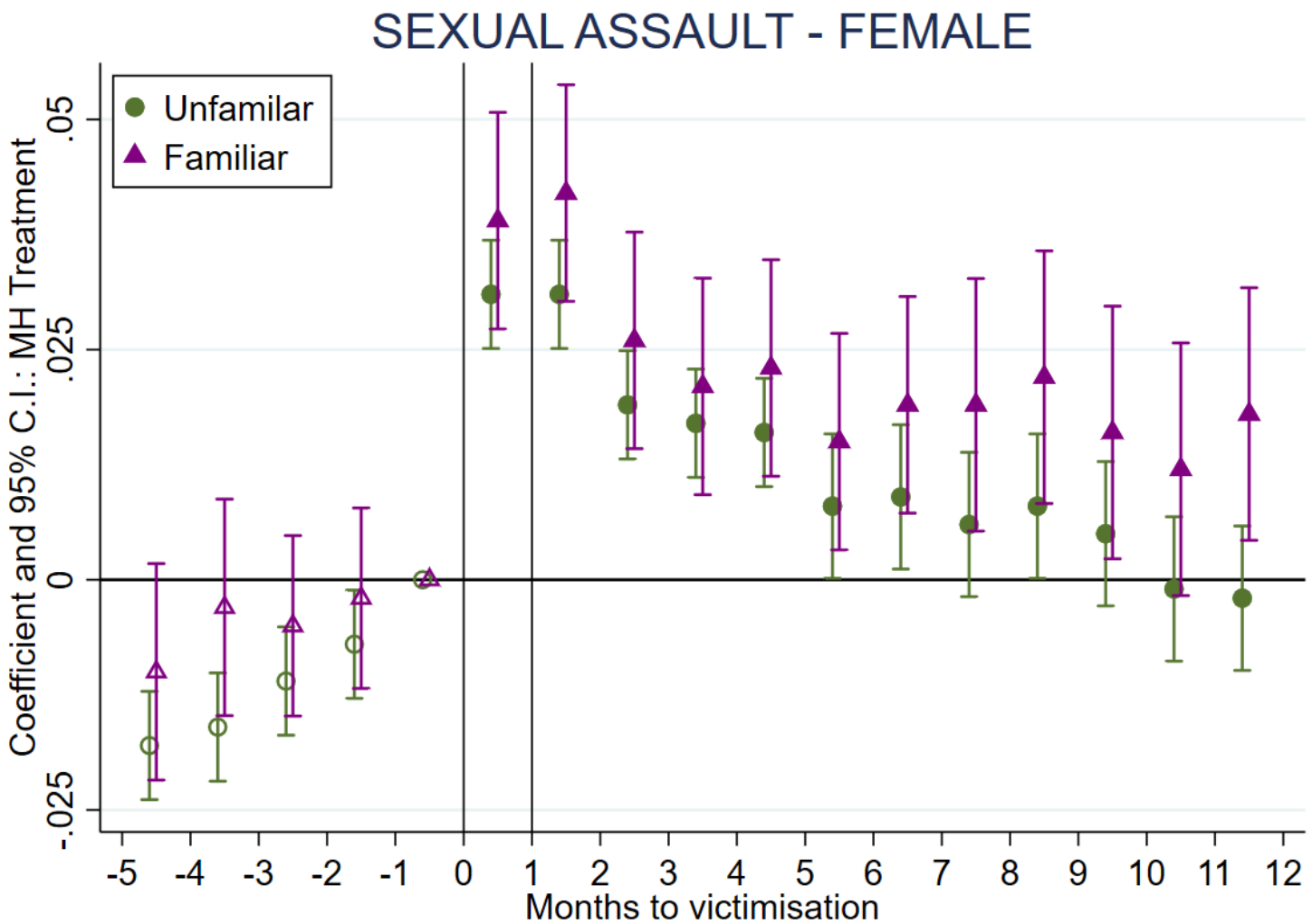

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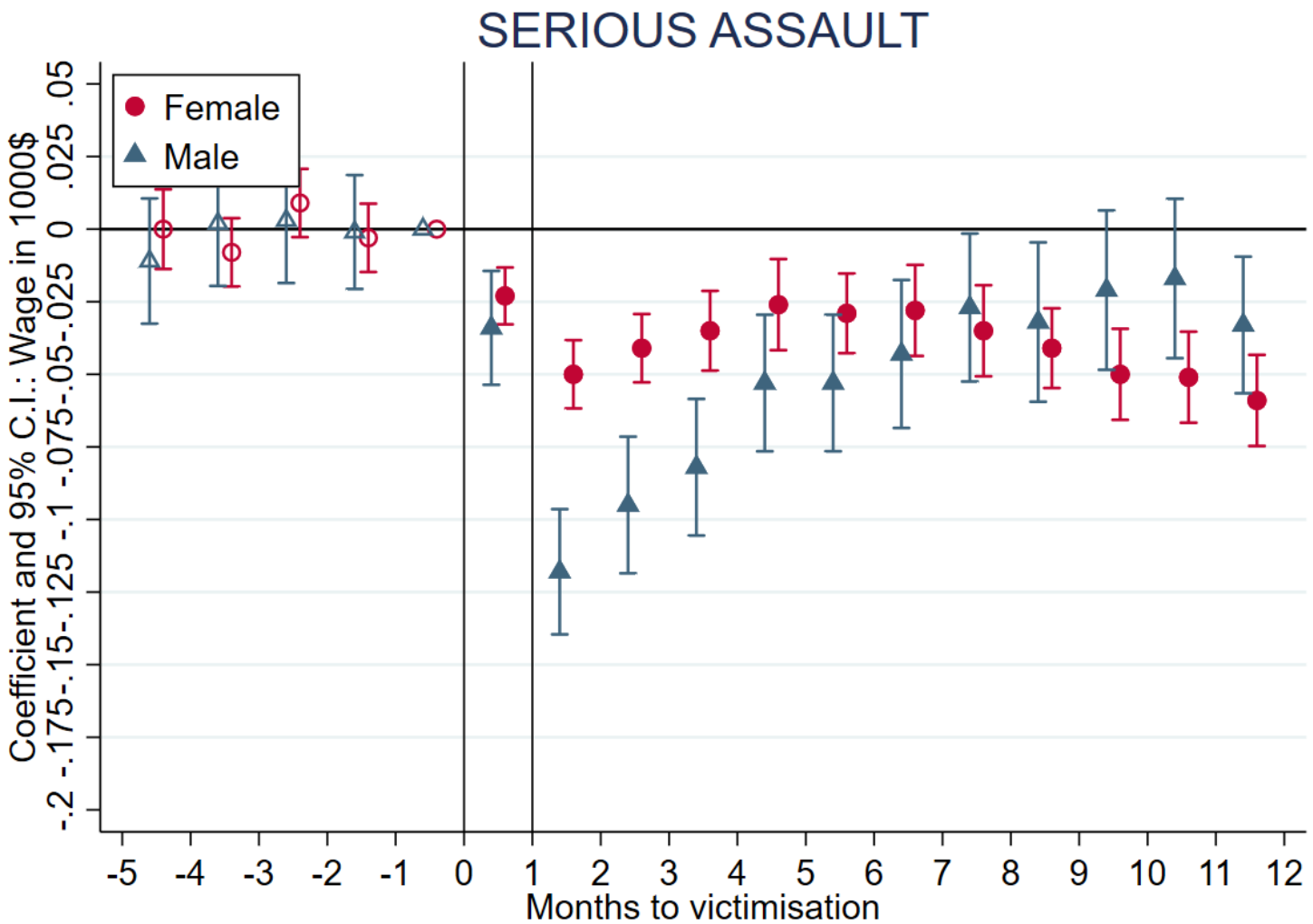
Serious Assault and Wages



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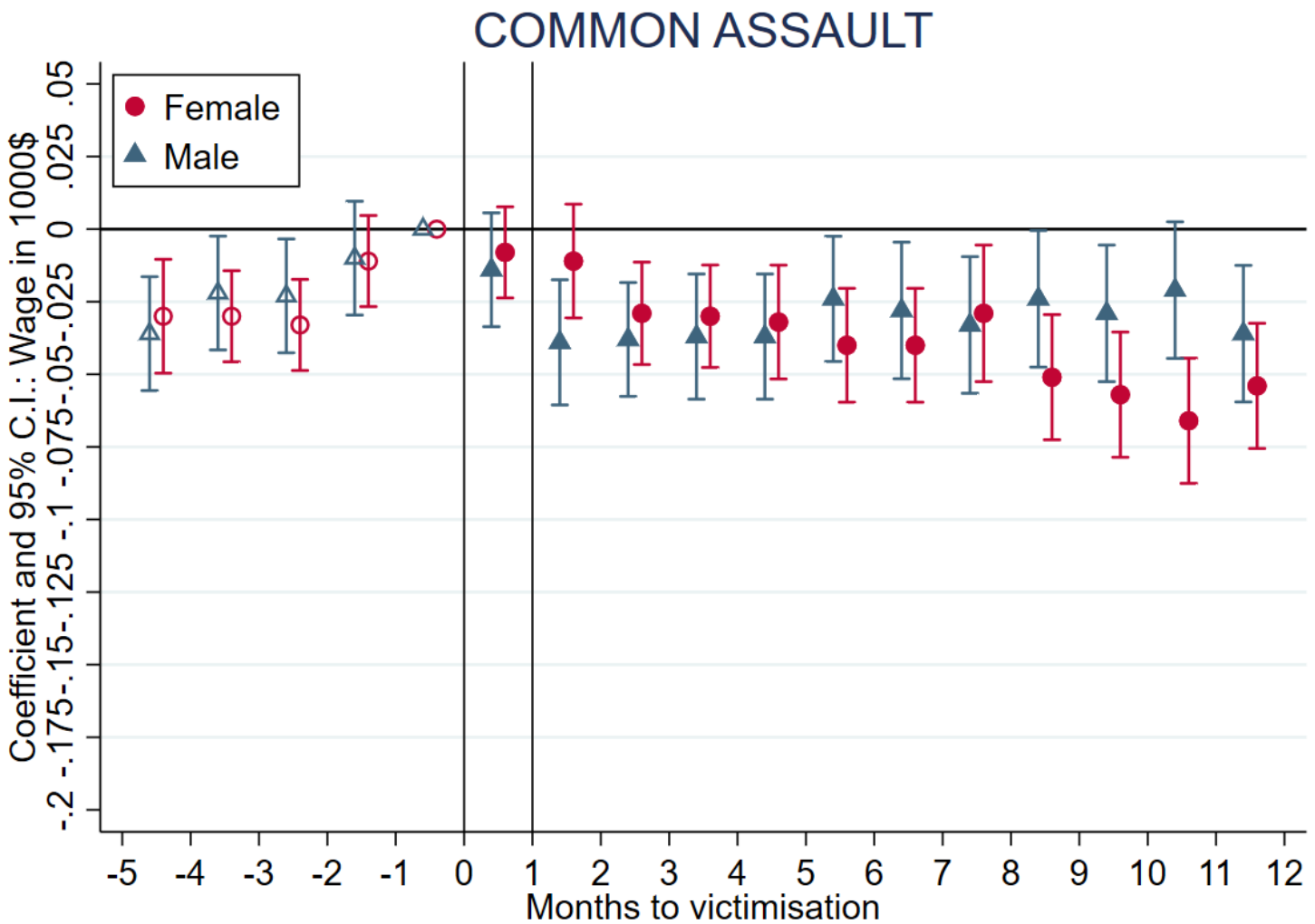

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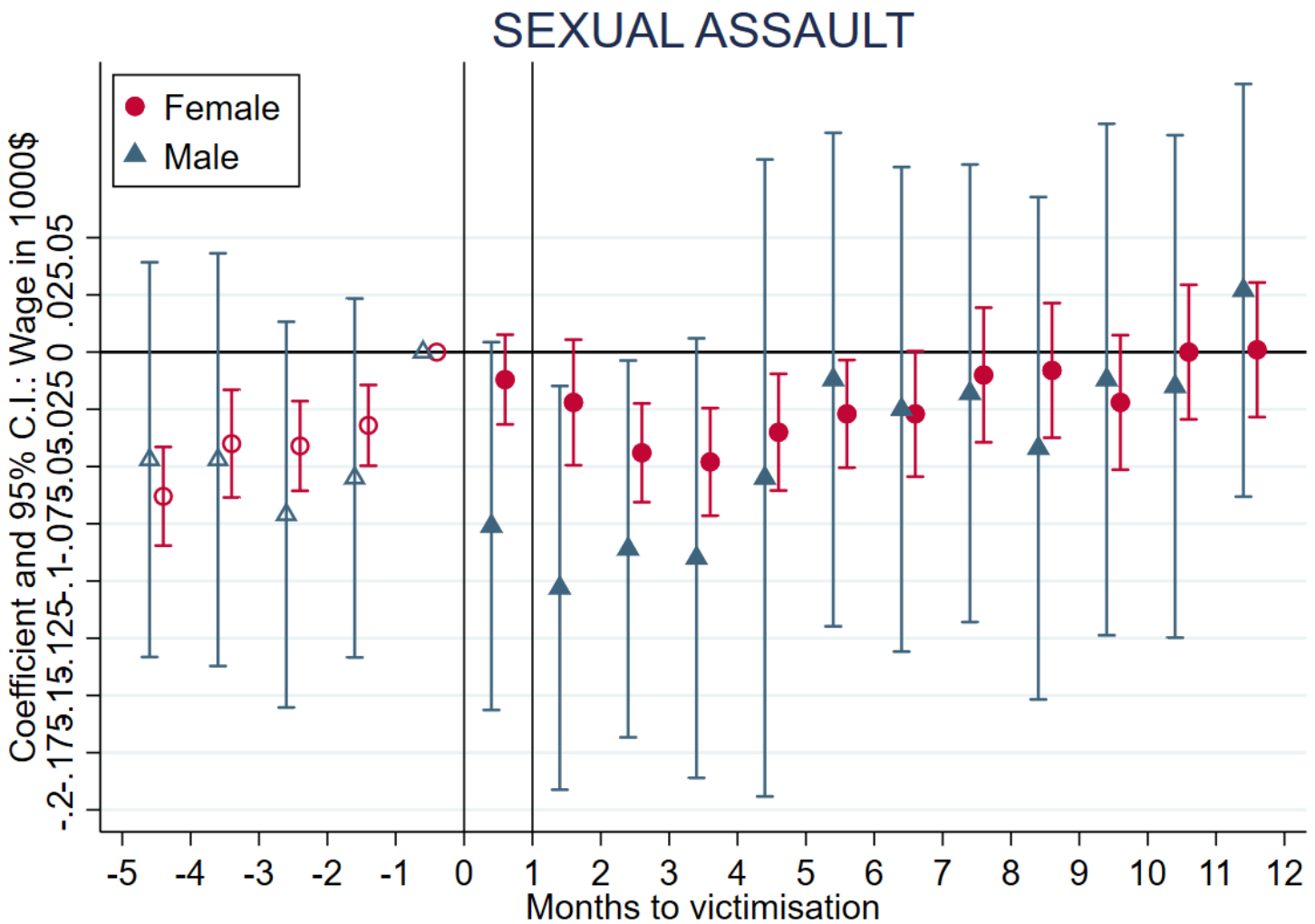
Sexual Assault and Wages



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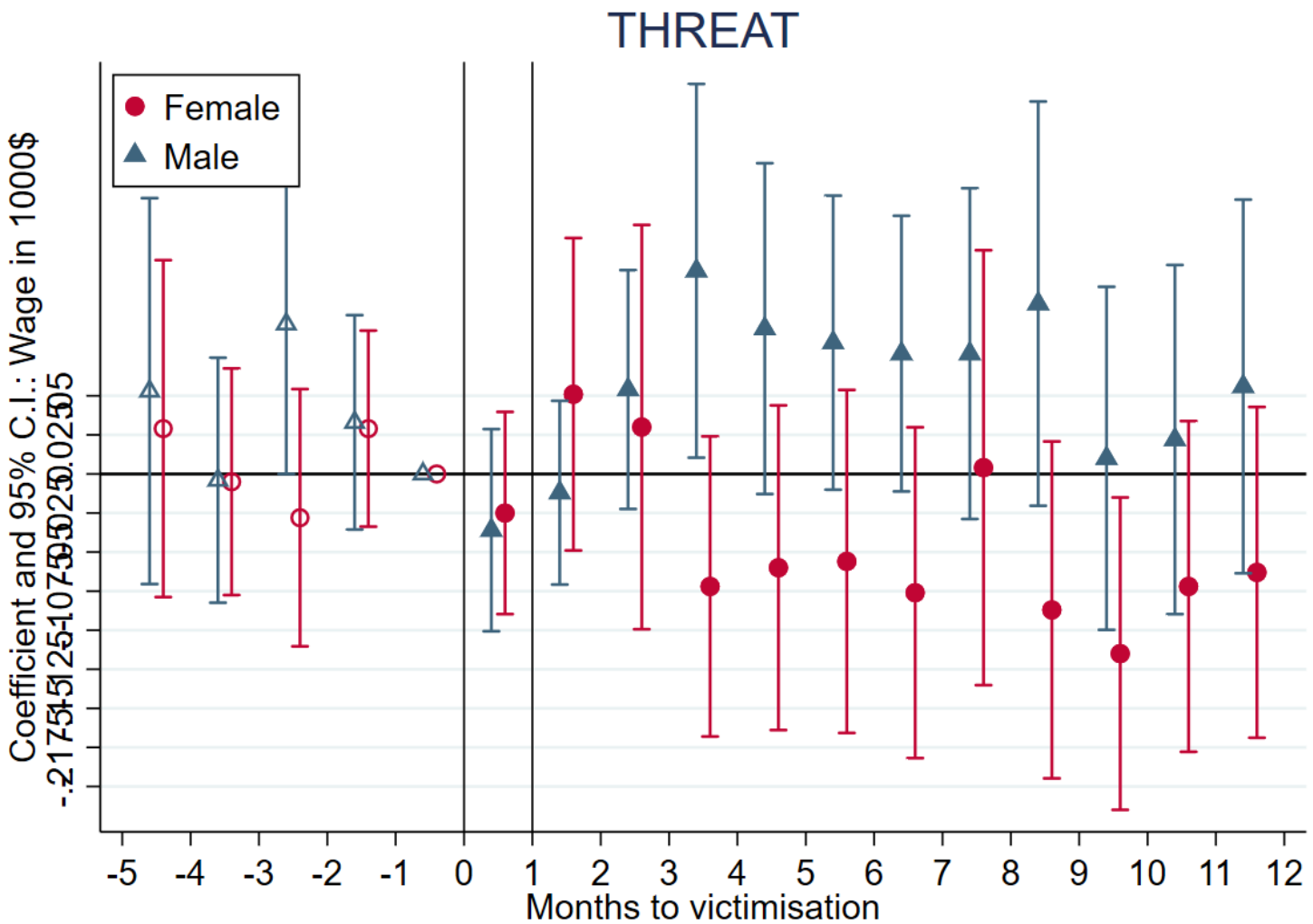
Threat and Wages



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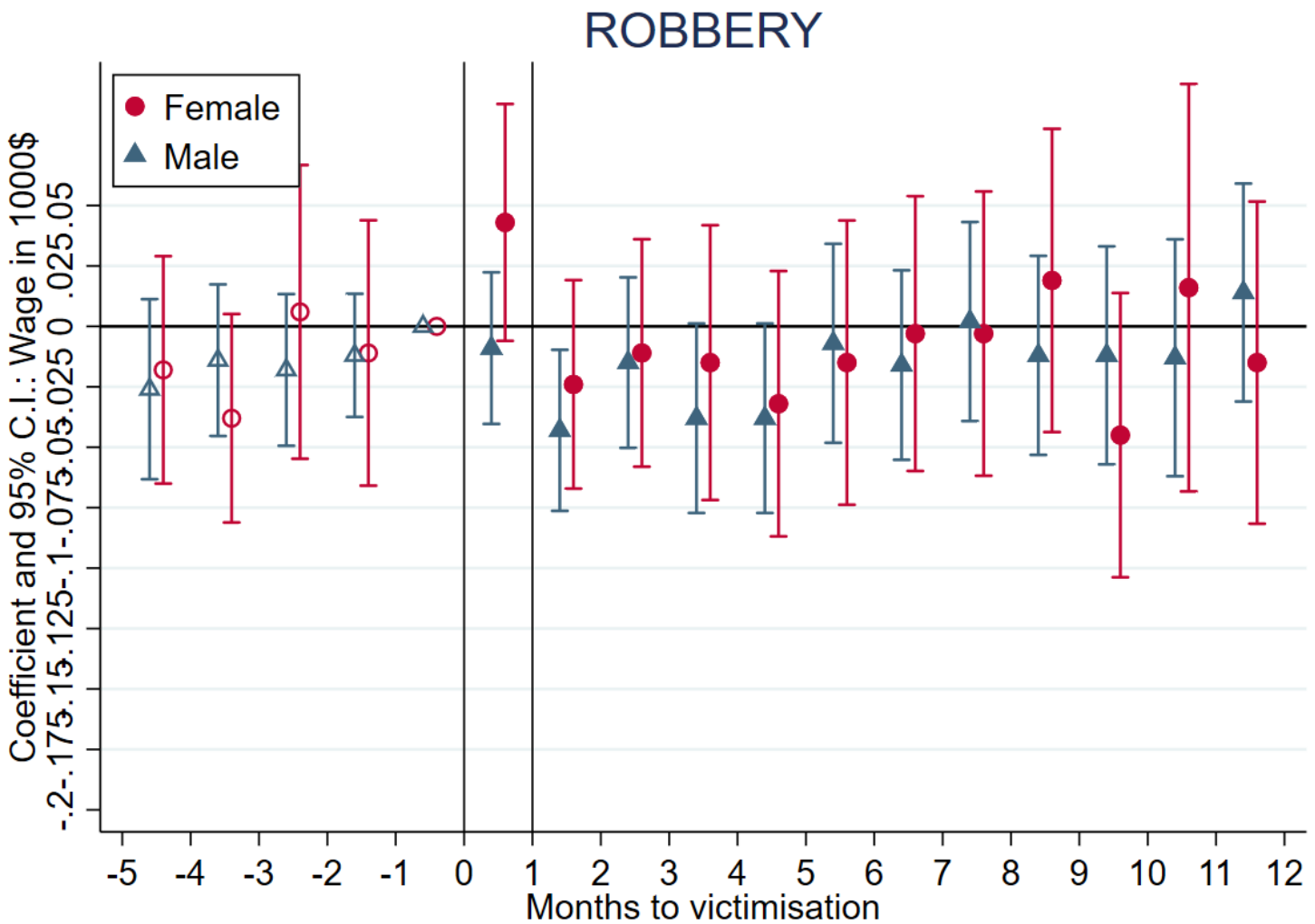
Robbery and Wages



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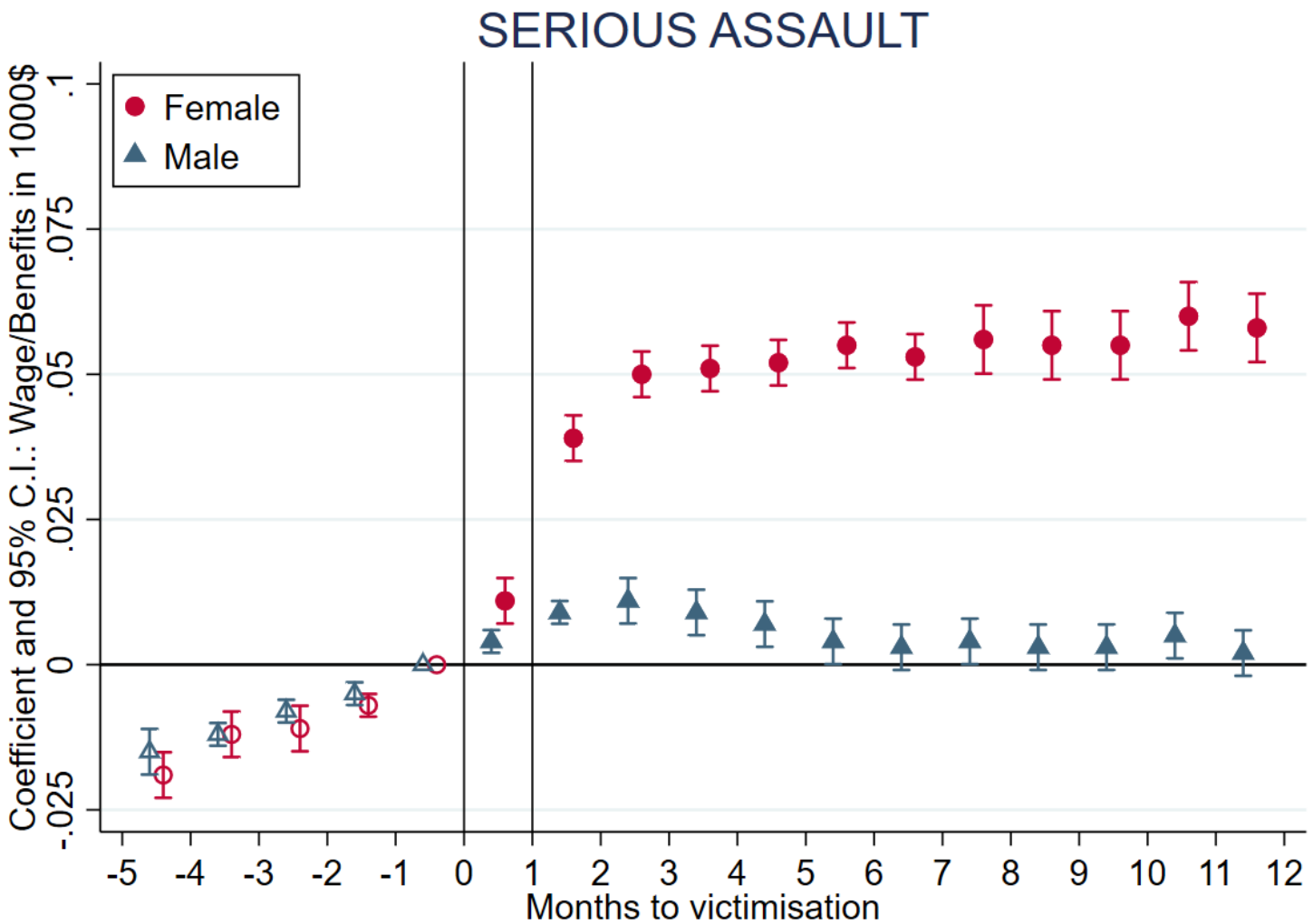
Serious Assault and Benefits



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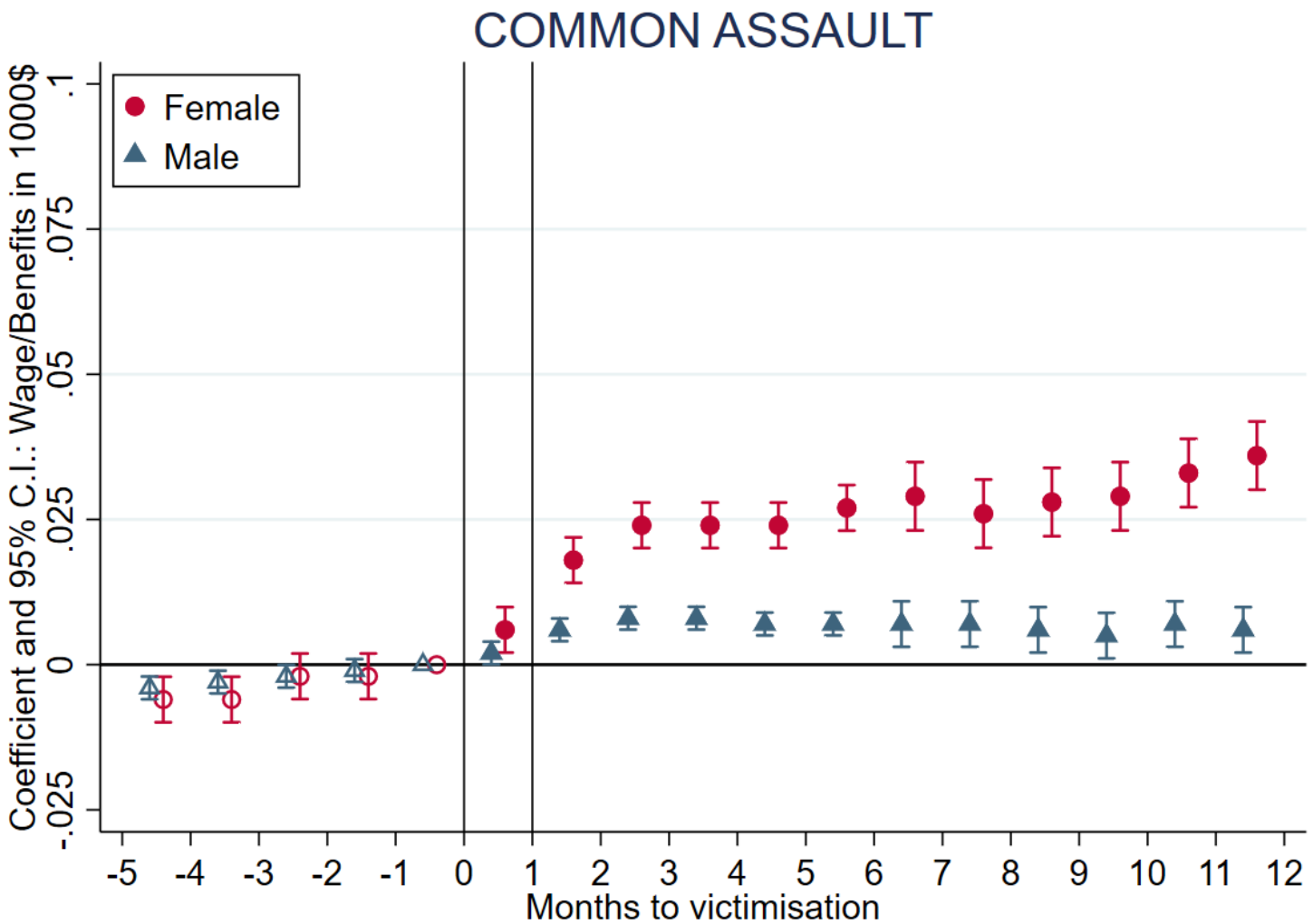

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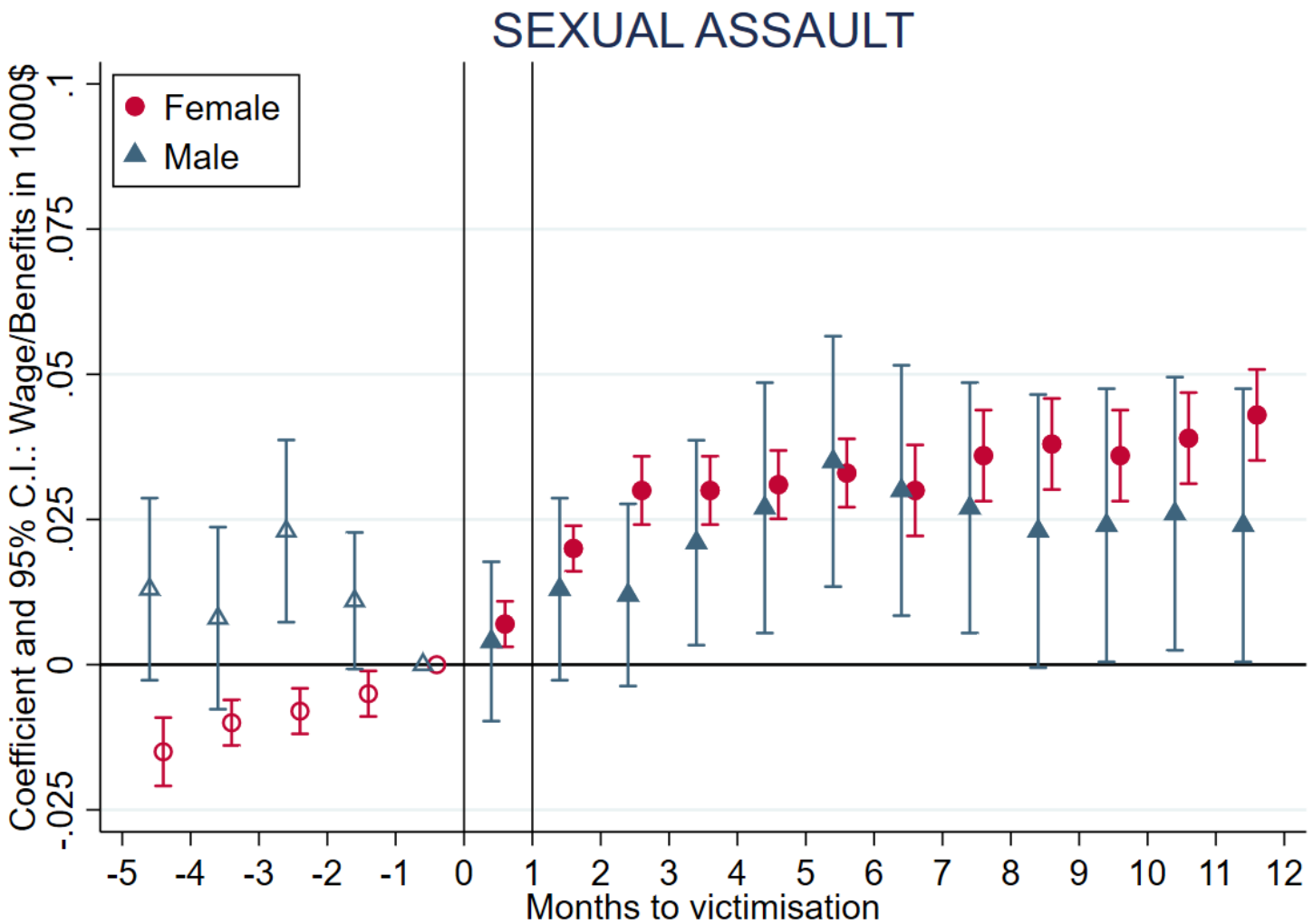

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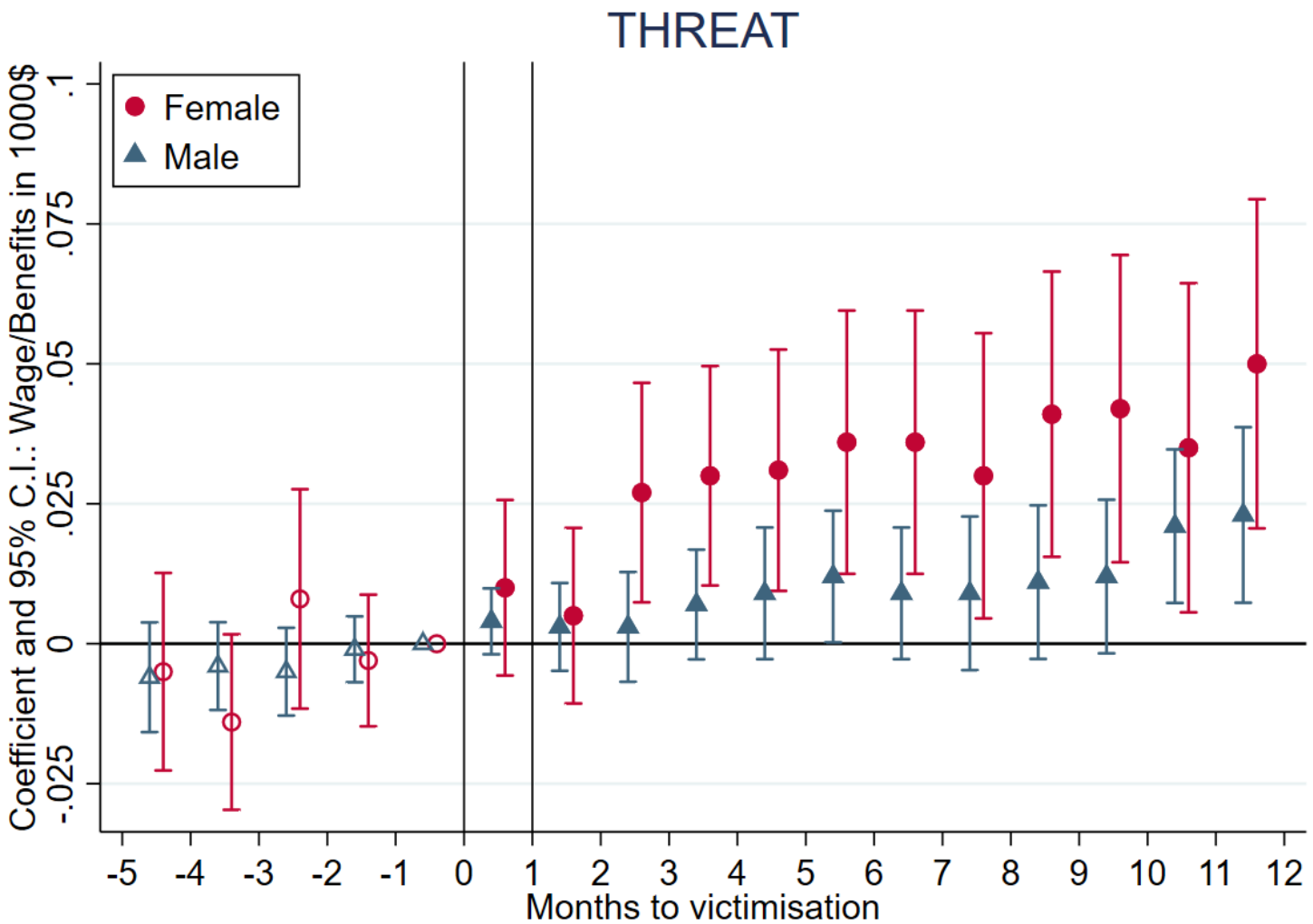

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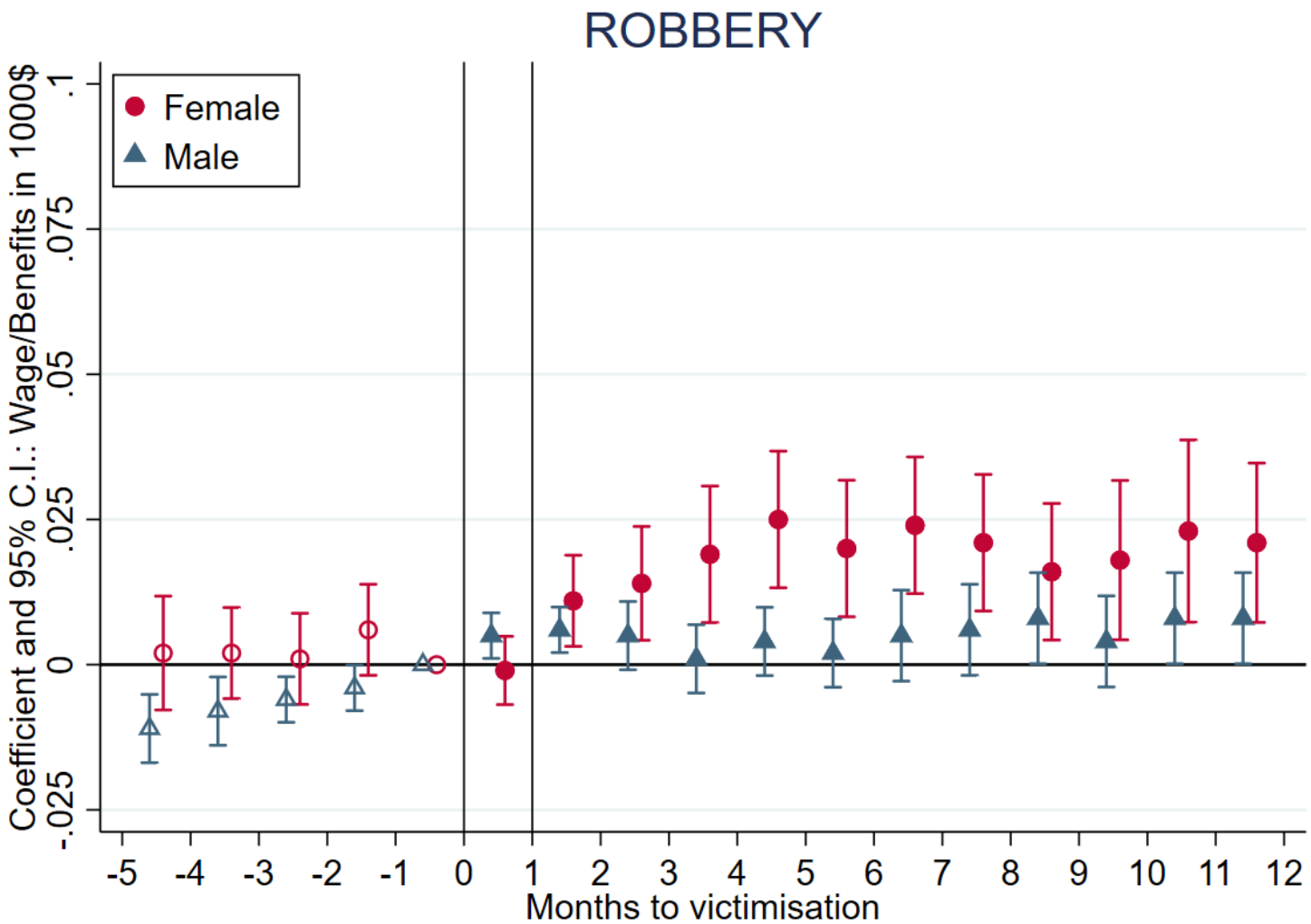
Robbery and Benefits



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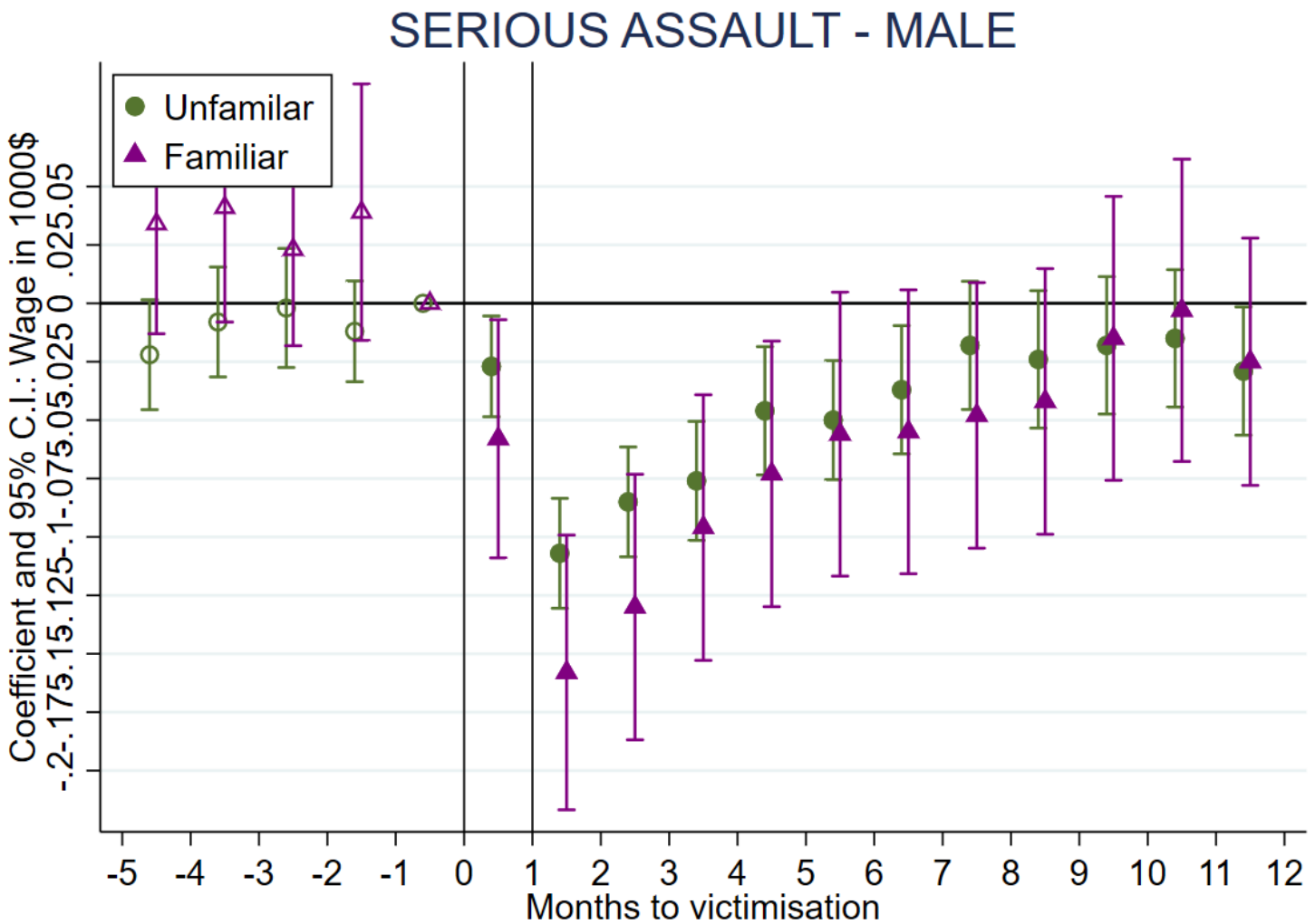

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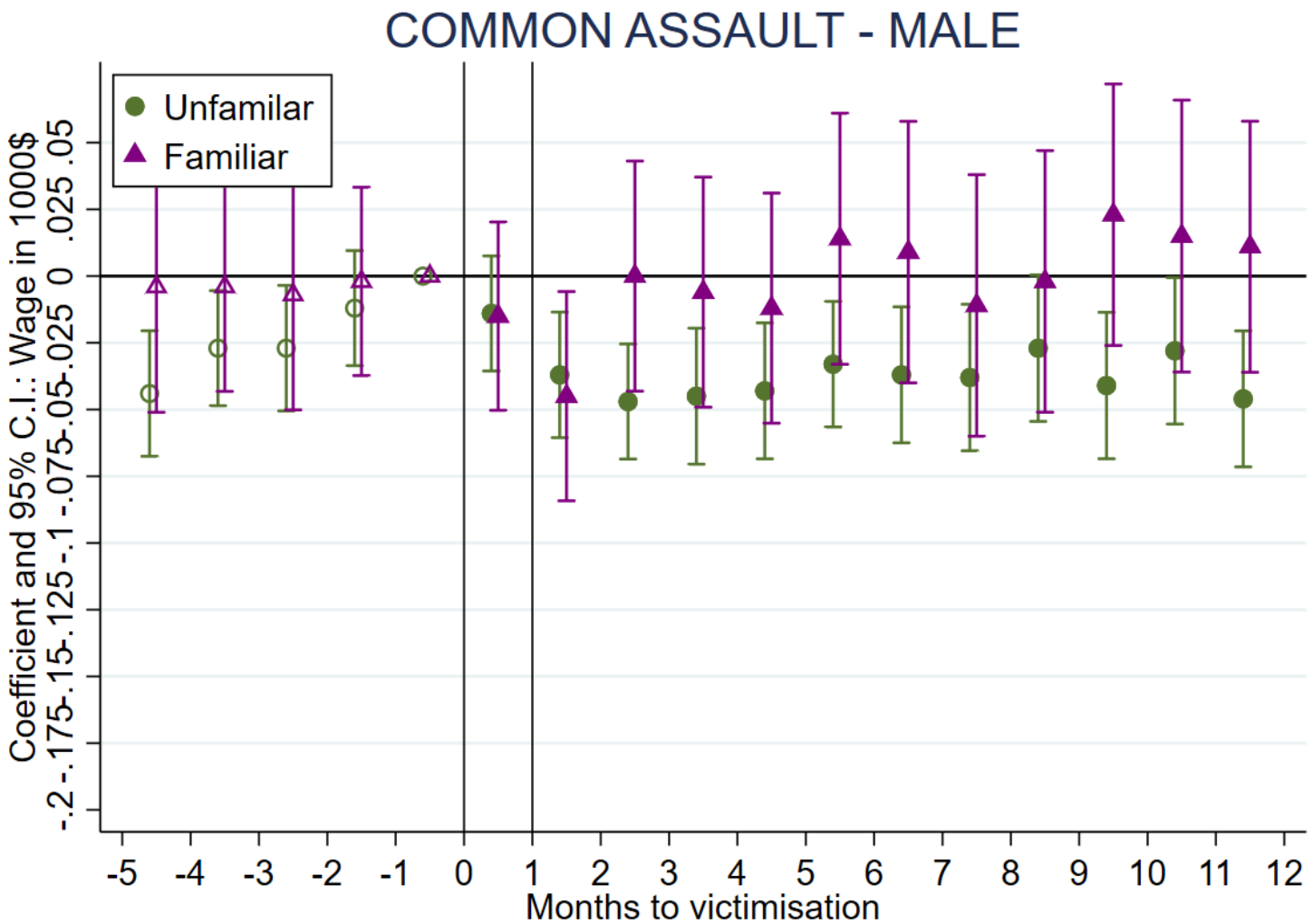
Common Assault and Wages: Males



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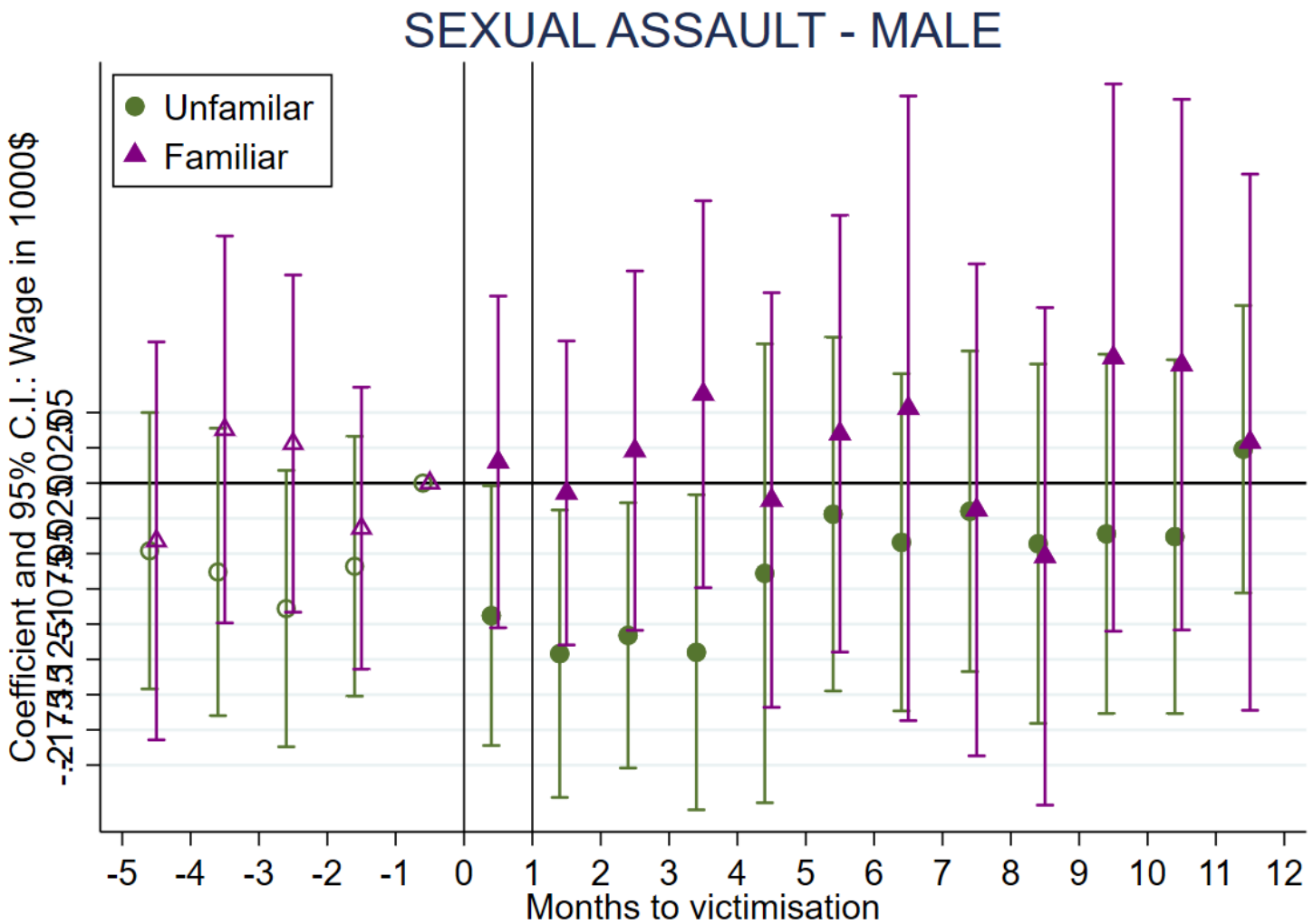

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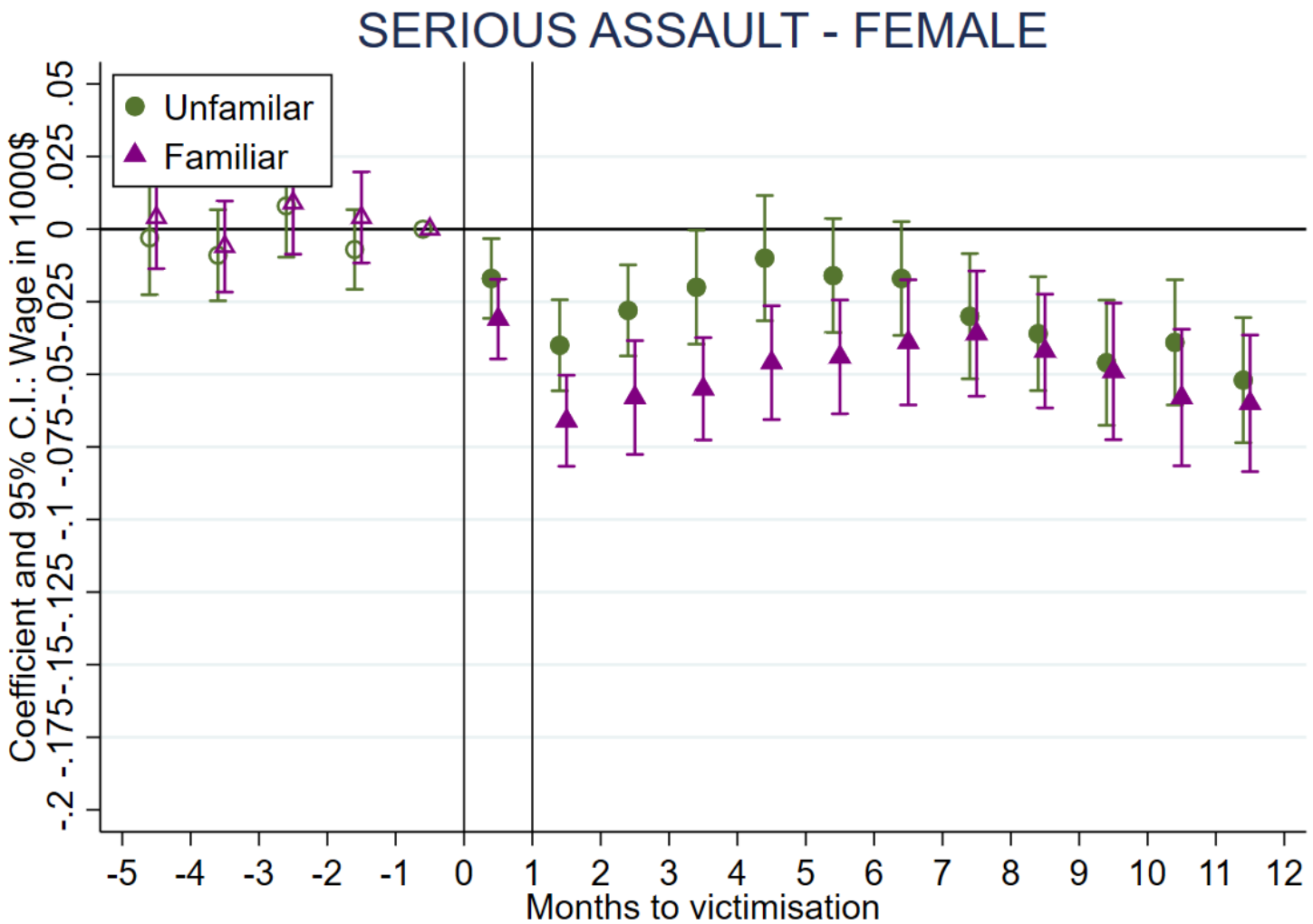

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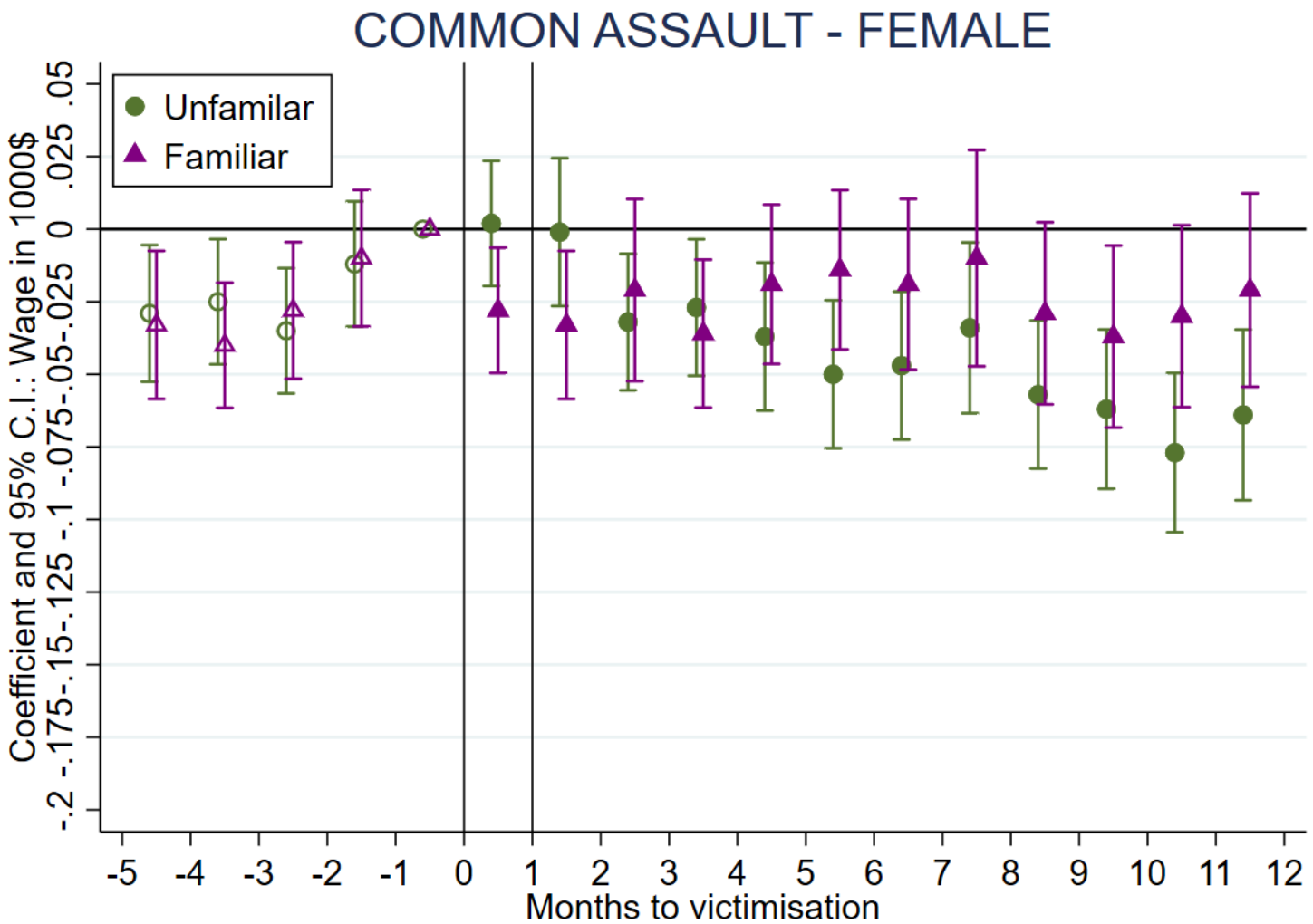

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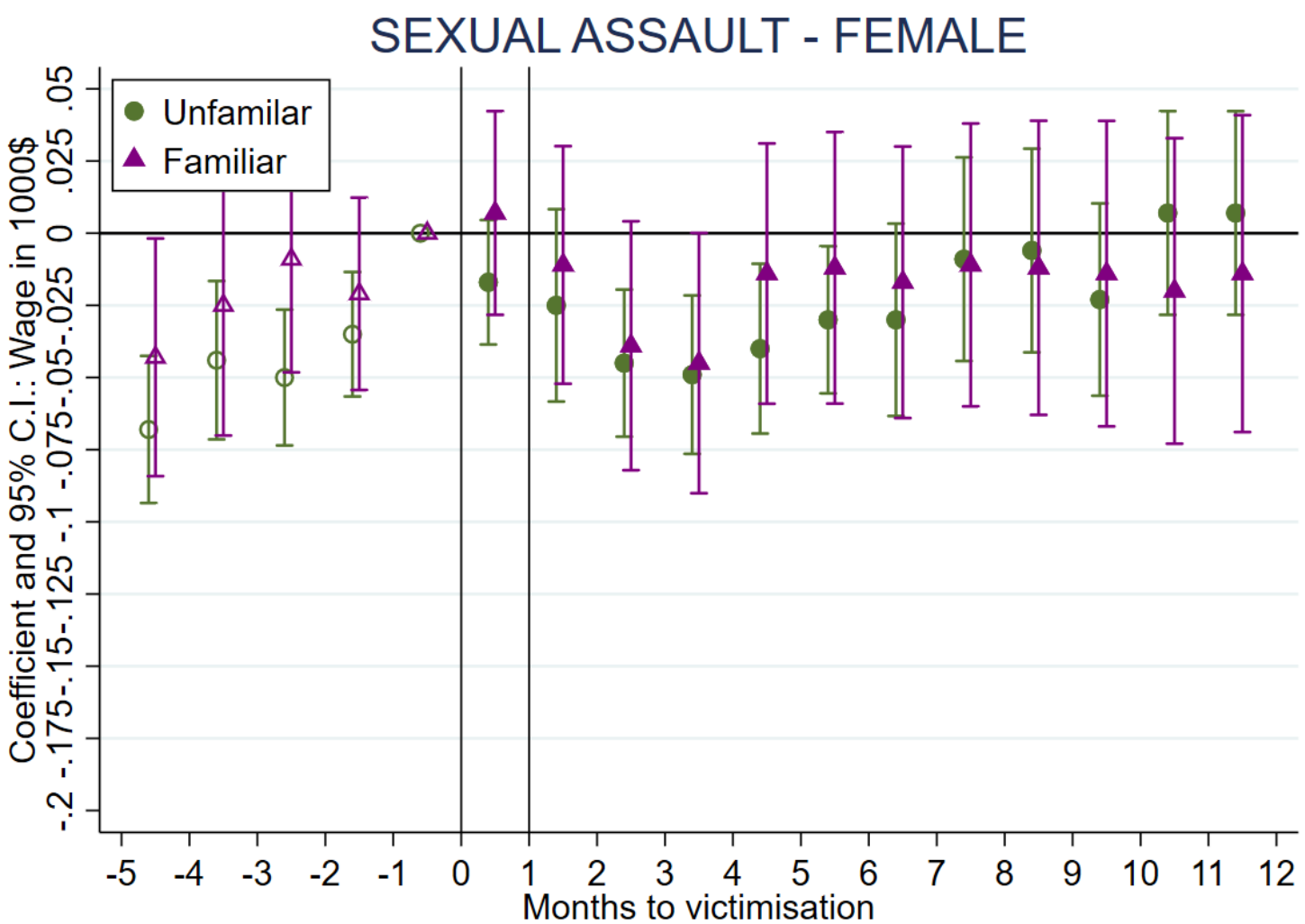

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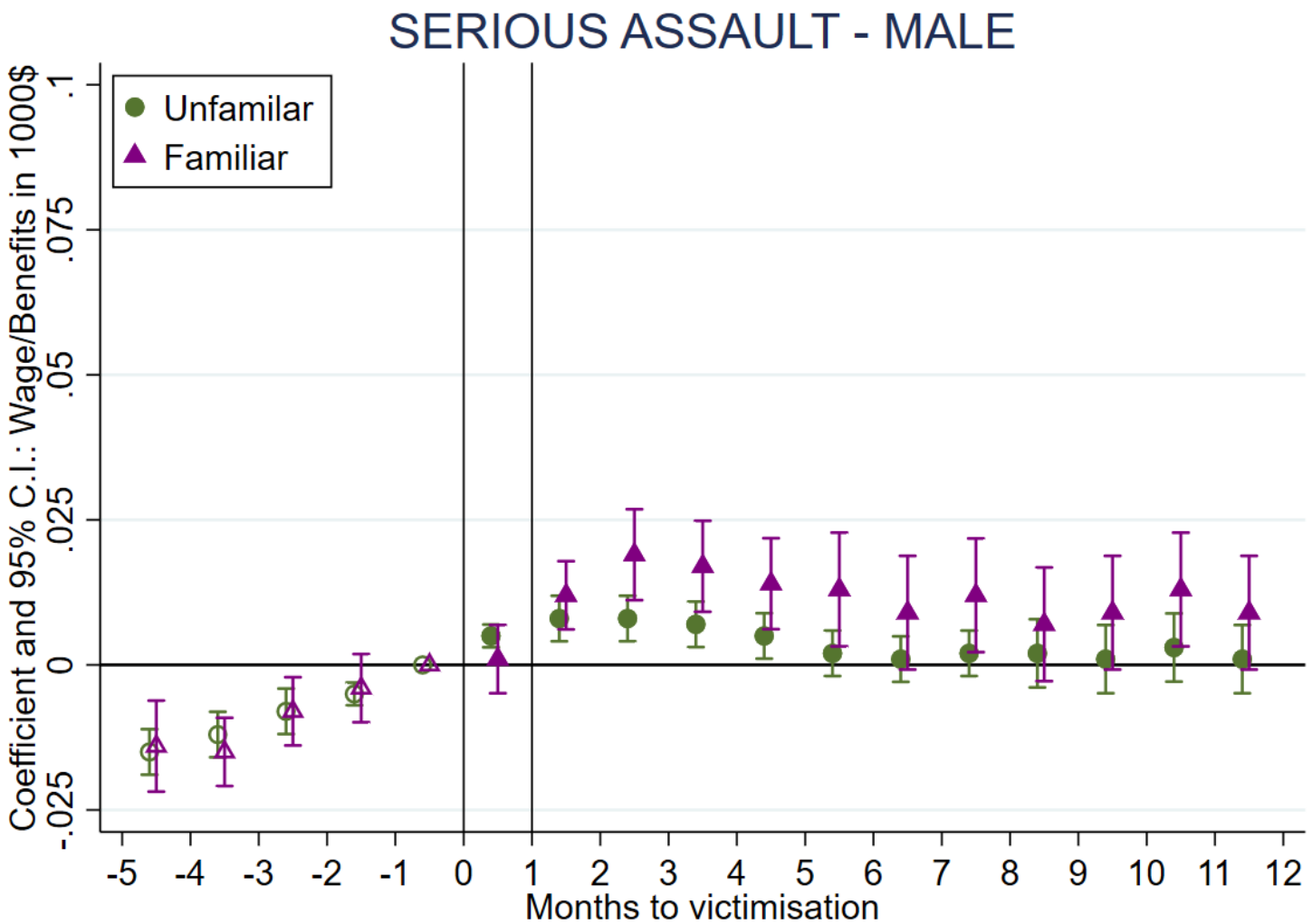

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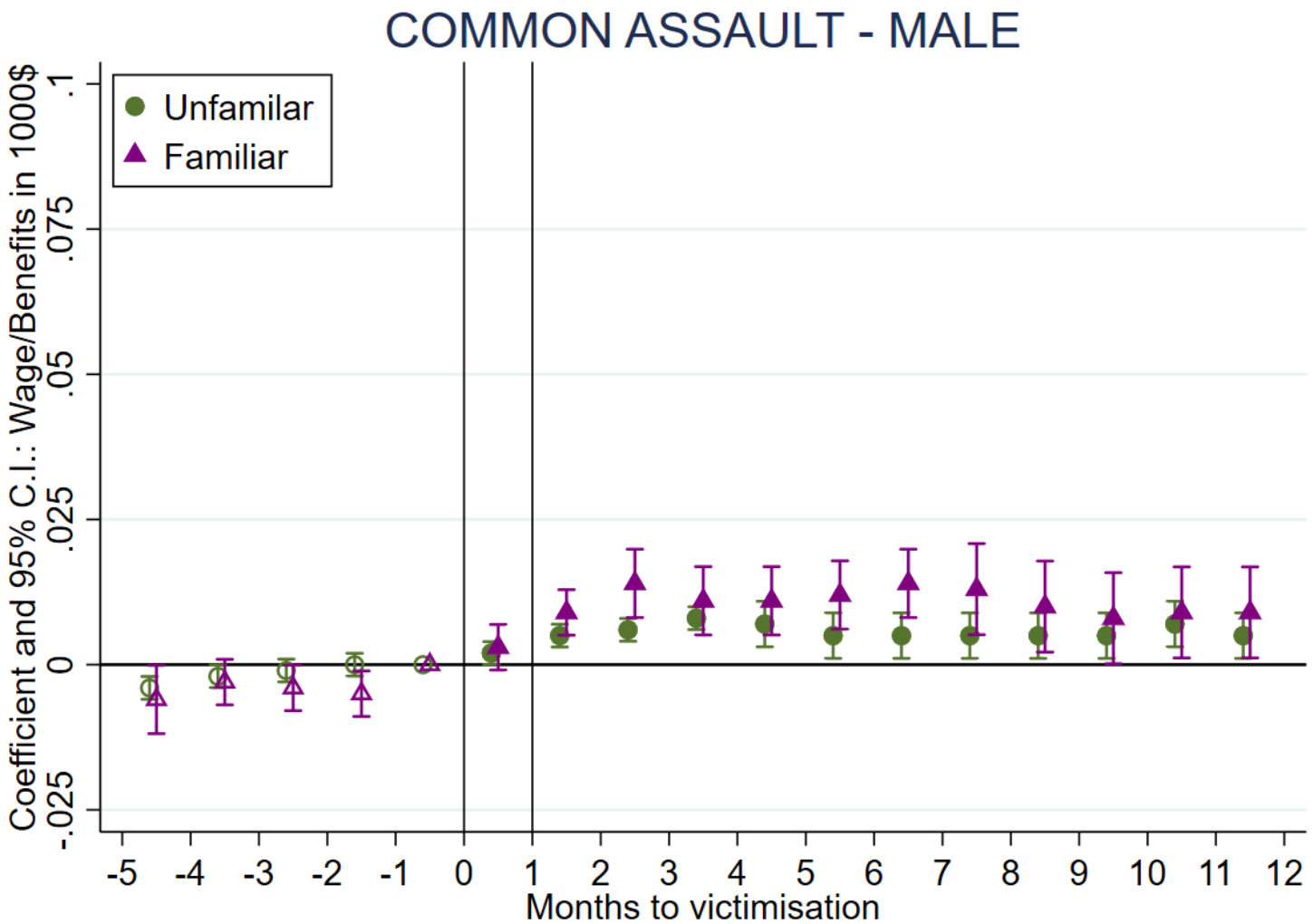

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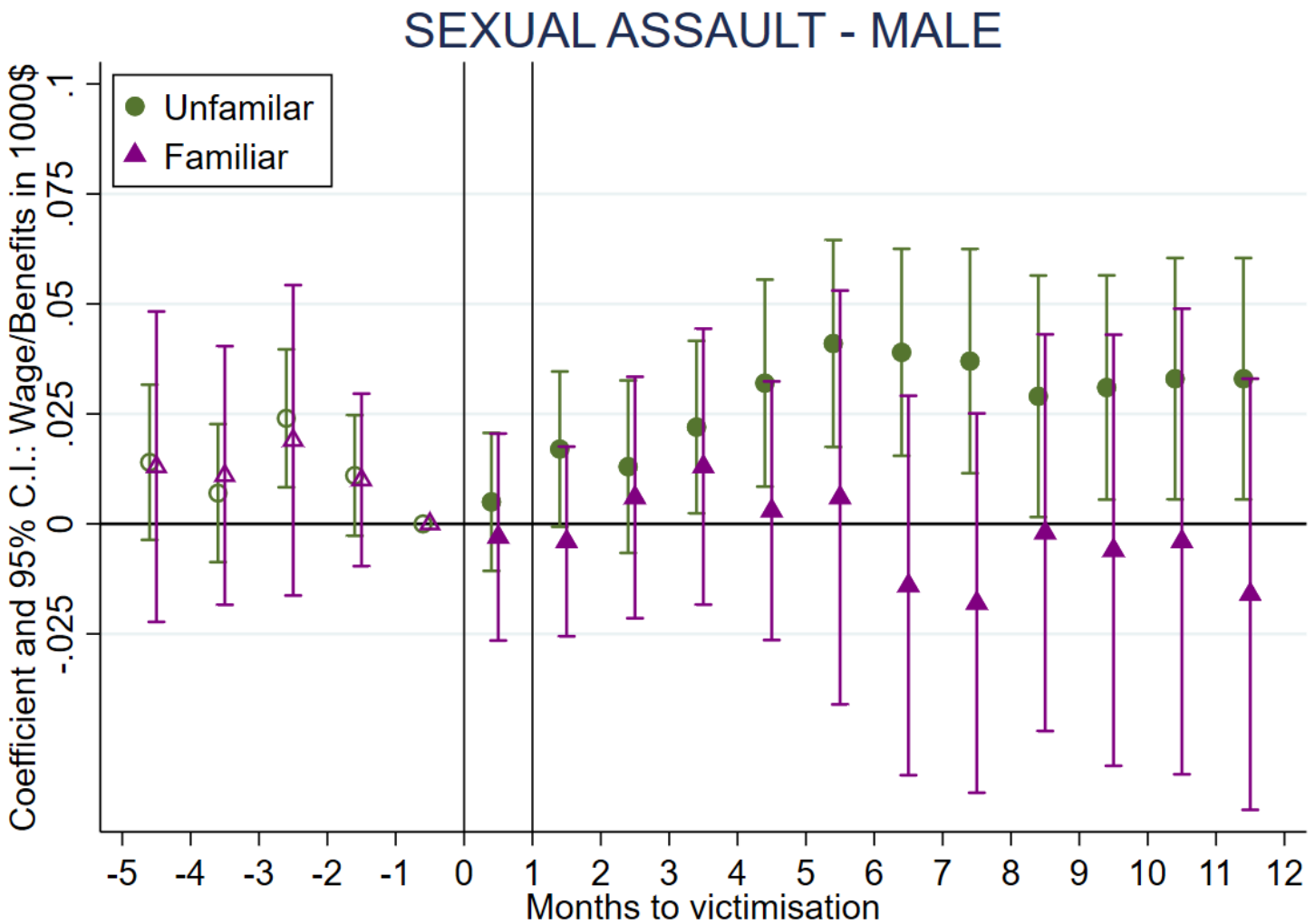
Sexual Assault and Benefits: Males



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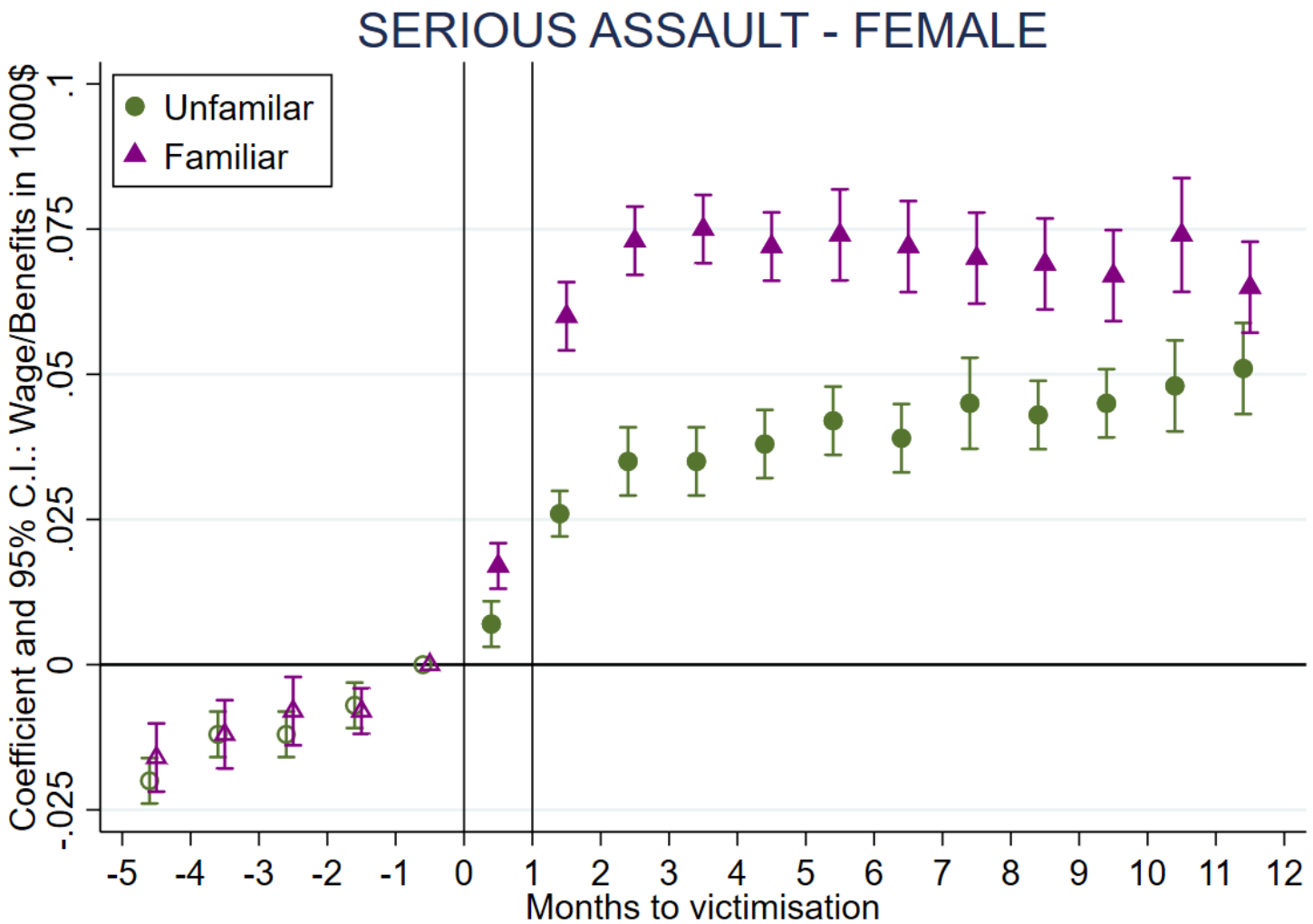
Serious Assault and Benefits: Females



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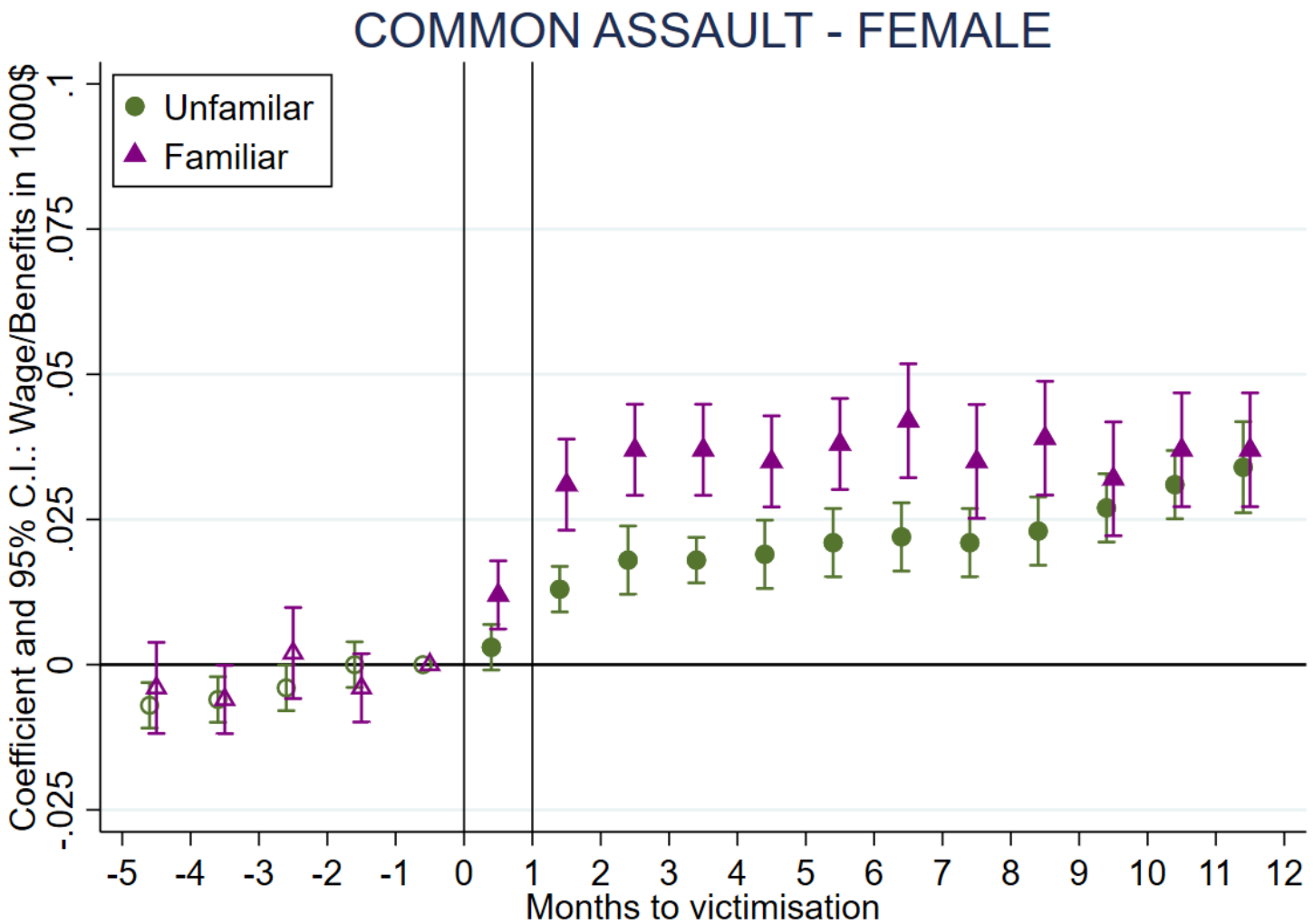
Common Assault and Benefits: Females



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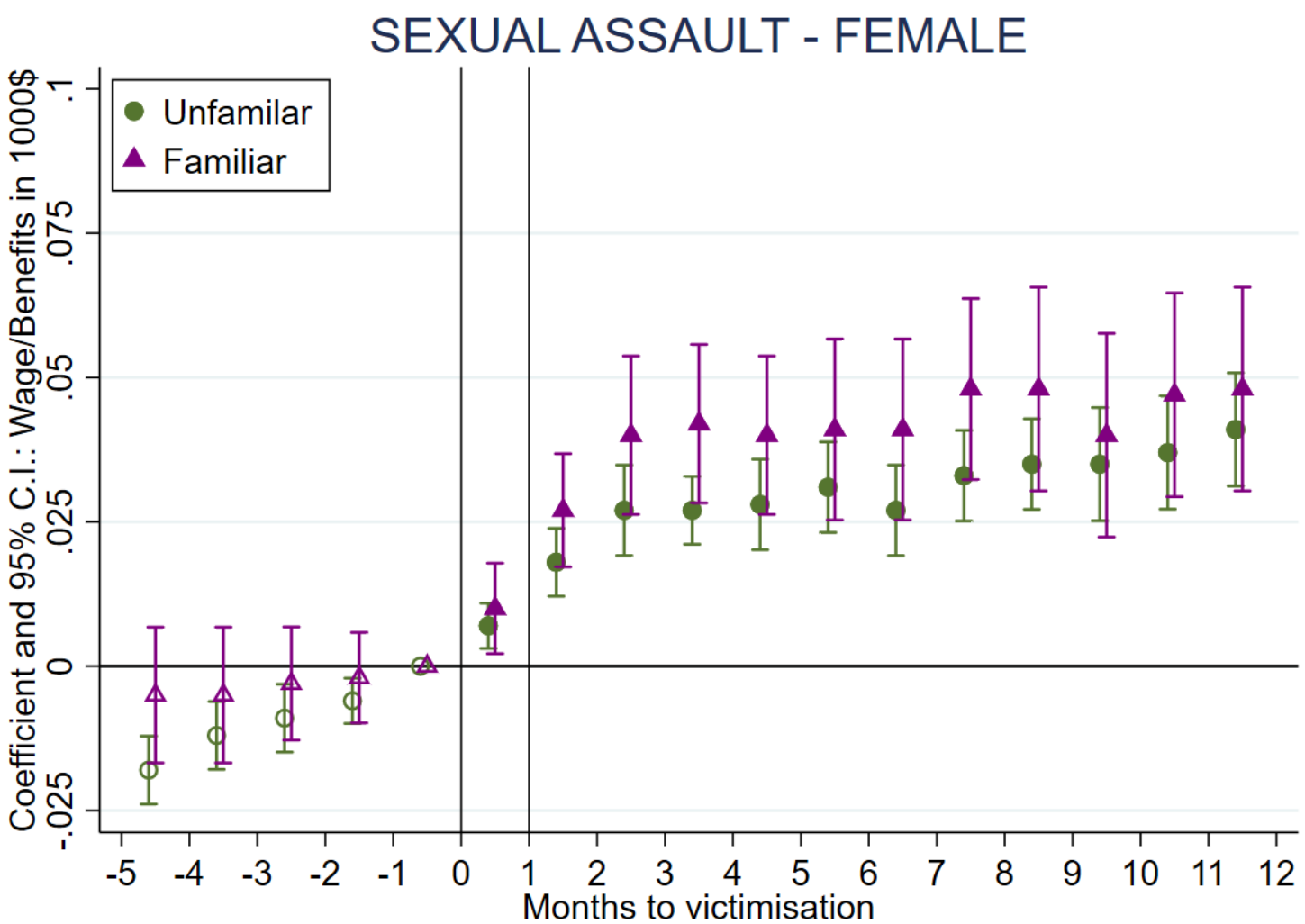
Sexual Assault and Benefits: Females



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