Offender specialization among z-proso participants

5th z-proso International Research Network (zIReN) Meeting

14th – 16th September 2023
Max Plank Institute for the Study of Crime, Security and Law, Freiburg i. Br.

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Offending specialization

Introduction

- Specialization reflects systematic differences in the type of offenses committed by individuals.

(Osgood & Schreck, 2007)

- "Should criminological theories assume that all types of offending reflect the same underlying theoretical construct (e.g. an antisocial personality) or should they assume that violent offending reflects an underlying violent potential, that theft reflects an underlying thieving potential, etc?"

(Farrington, 2023, p. 125)

- Evidence of specialized offenders has been elusive.
  - Early studies strongly supported offending versatility.

(Schreck, 2014)

DOVE

OFFENDING SPECIALIZATION

METHODS

- Limitations in the availability of statistical methods.
  - Recent studies increasingly find more indications of specialization.

- Most frequently used methods:
  - **Forward Specialization Coefficient (FSC)** - Single value summary based on transition matrices.
  - **Diversity index (D index) –** Individual-level value summary of specialization.
  - **Latent class analysis (LCA) -** Provides a sense of the nature of offending patterns.

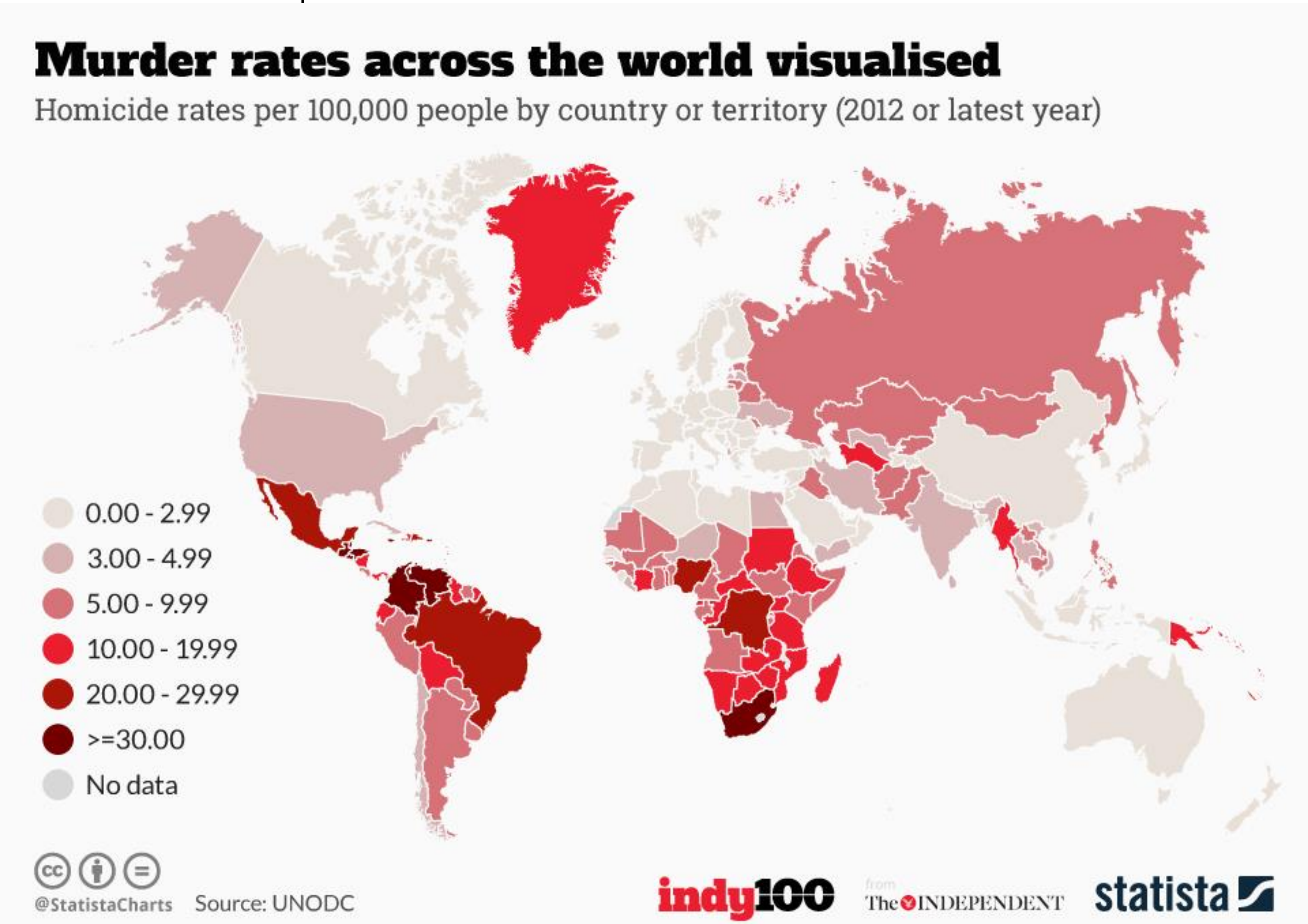
Offending specialization - LCA

Study	Country	Sample (N)	Methods	Key findings
Sullivan et al. (2009)	USA	1,308 juvenile inmates incarcerated in three California Youth Authority (CYA)	LCA (prevalence) K = 16	3 classes 1. Violent and sex crimes 2. Property and less violent offenses 3. Diverse offenses
Besemer (2012)	UK	CSDD (fathers)	LCA (Prevalence of convictions) K = 10	2 classes 1. Violent/other 2. Property
Francis et al. (2004)	USA	The Home Office Offenders Index birth cohort for 1953 provided official conviction histories up to 1993 (age 40) Separately for males and females.	LCA (Prevalence) K = 71 for males K = 29 for females	Male offending - 9 classes Female offending - 3 classes

Current study

Main research question

- Is there evidence of specialized offenders in the Pelotas cohort?



Pelotas

Population 340,000

Relatively Poor City in South Brazil

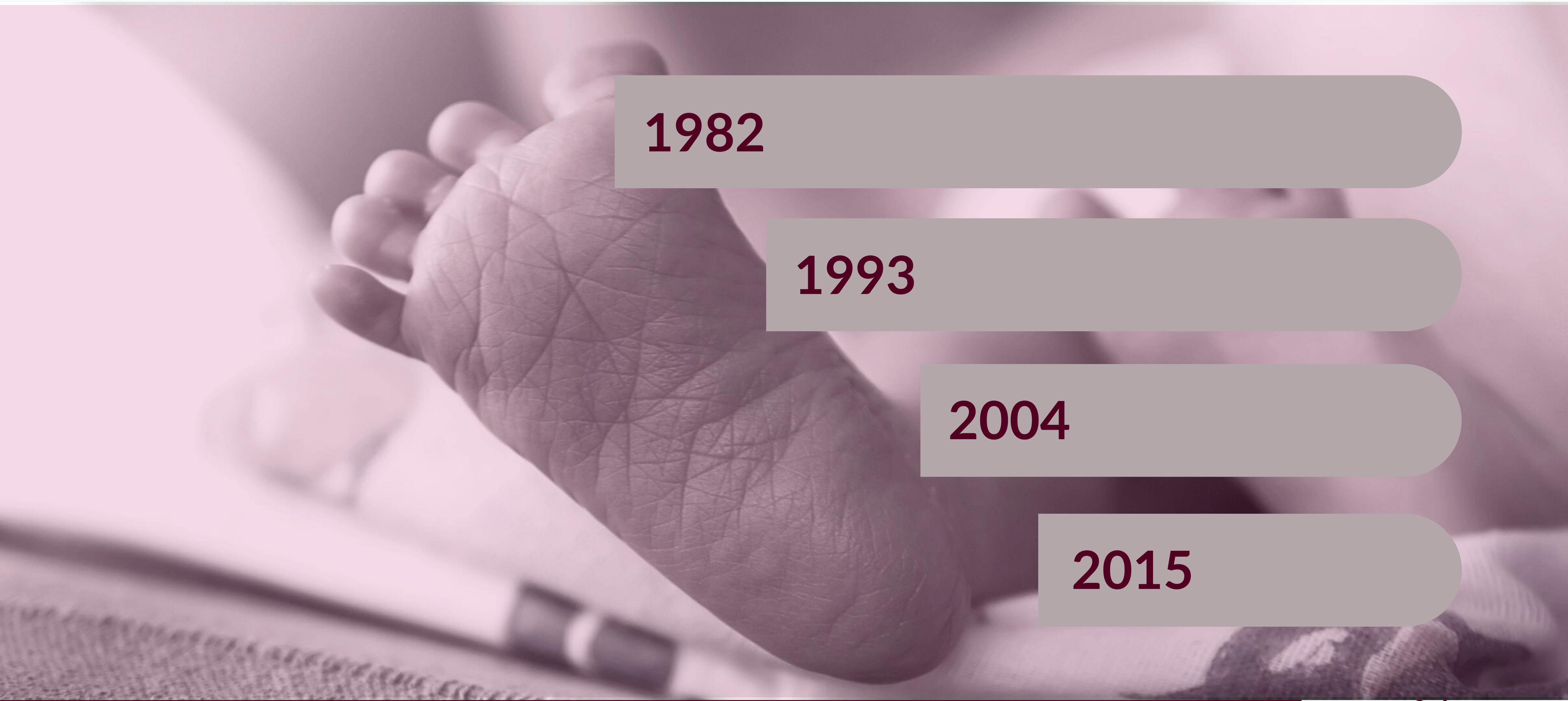
PELOTAS, RIO GRANDE DO SUL, BRAZIL






Pelotas Birth Cohort Studies

20,000 Families



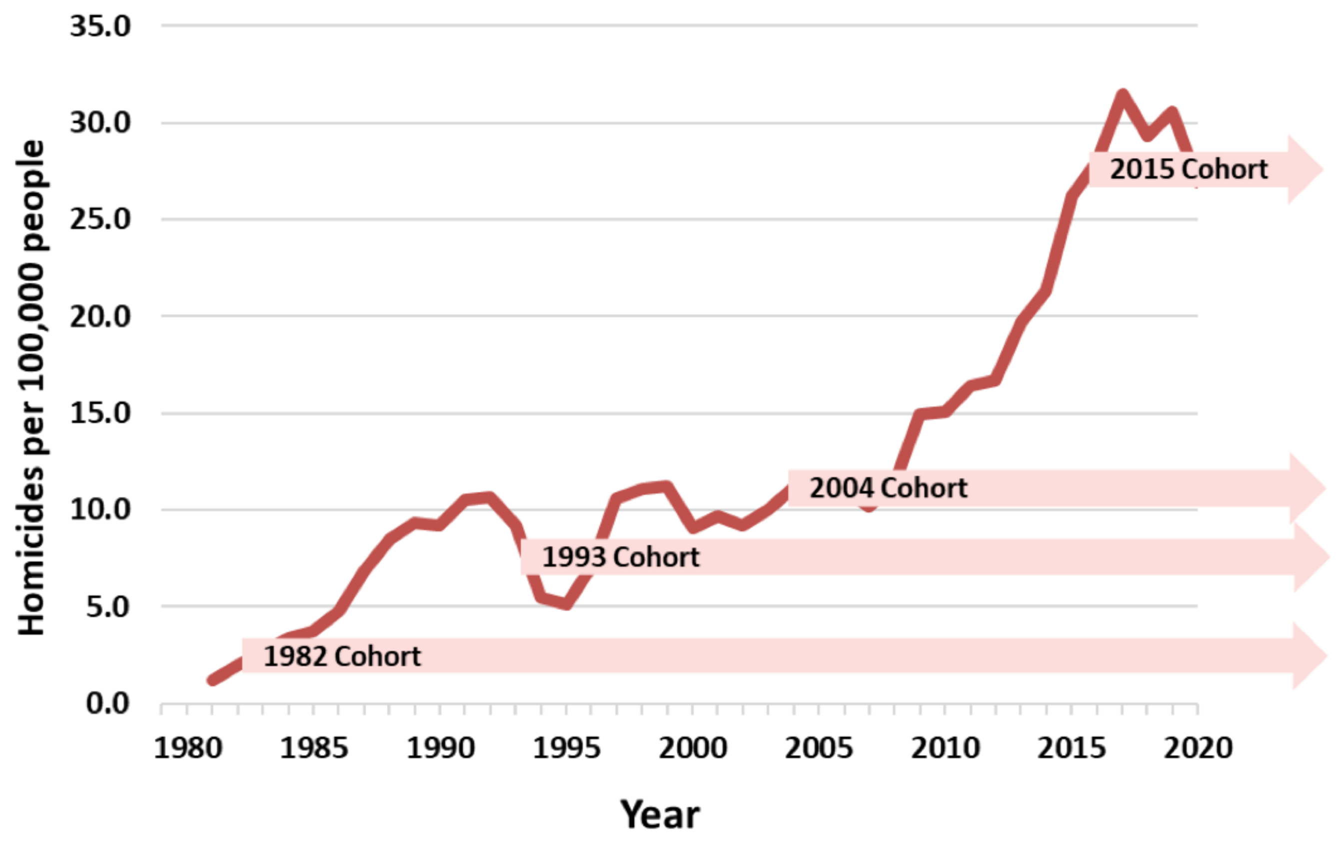
1982

1993

2004

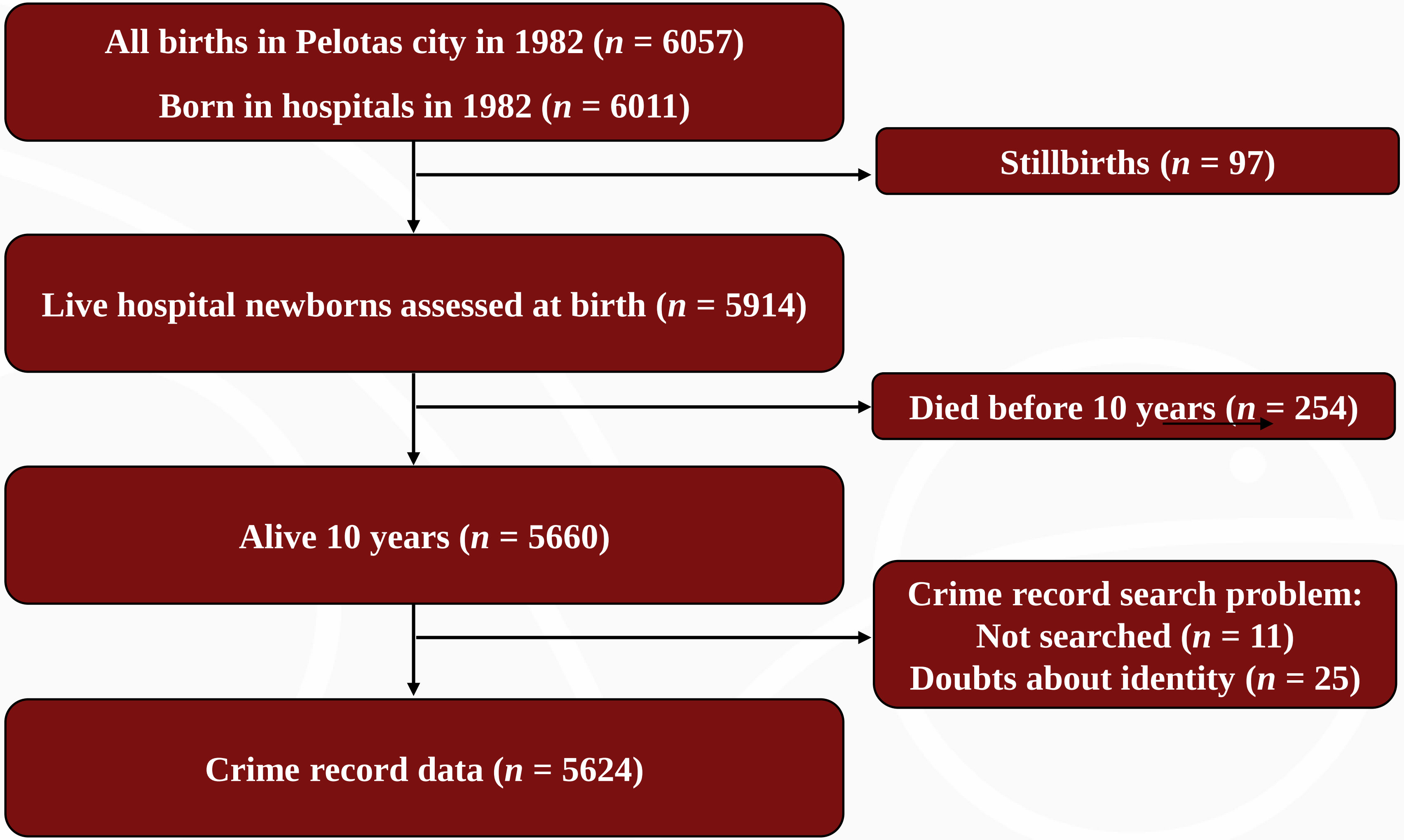
2015

Homicide Trends in Pelotas
During the Pelotas Birth Cohort Studies



Current Study

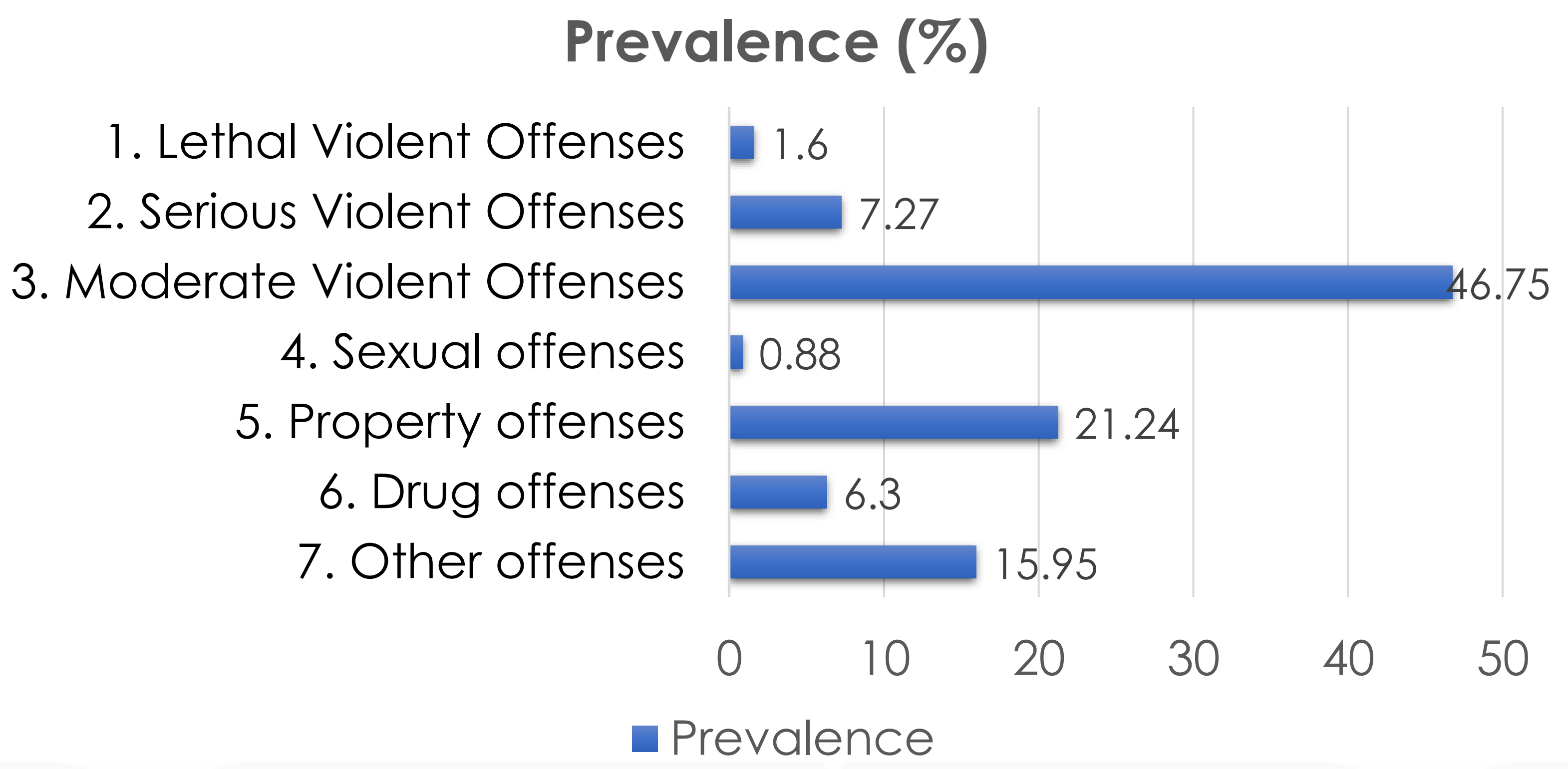
Participants



Results

Specialization

- Offenses were classified into 7 different categories:



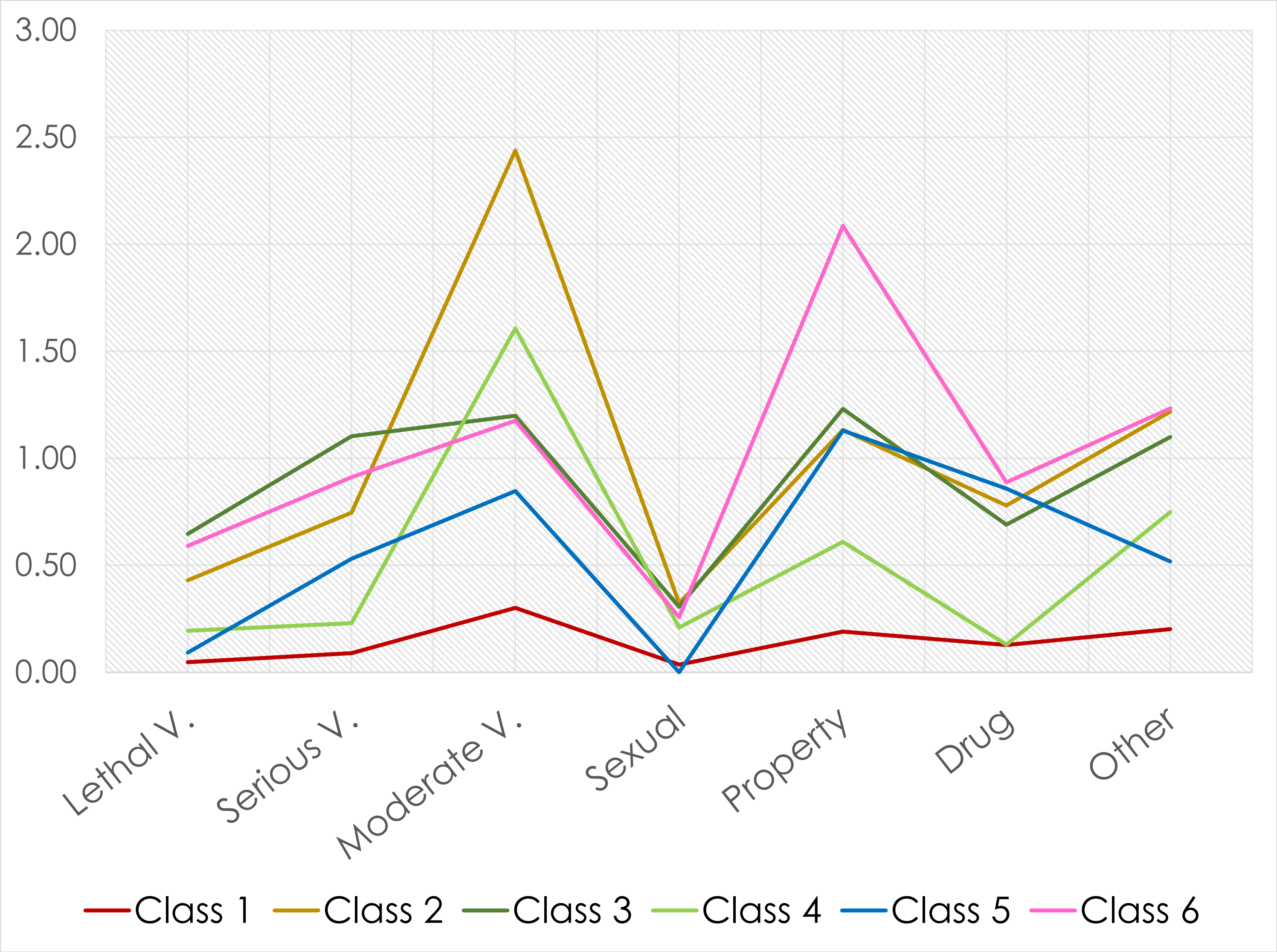
Results: Specialization

Latent Class Analysis (LCA) – for MALES

- Based on Bayesian Information Criterion (BIC = 14322), the 6-class model seems to best fit our data

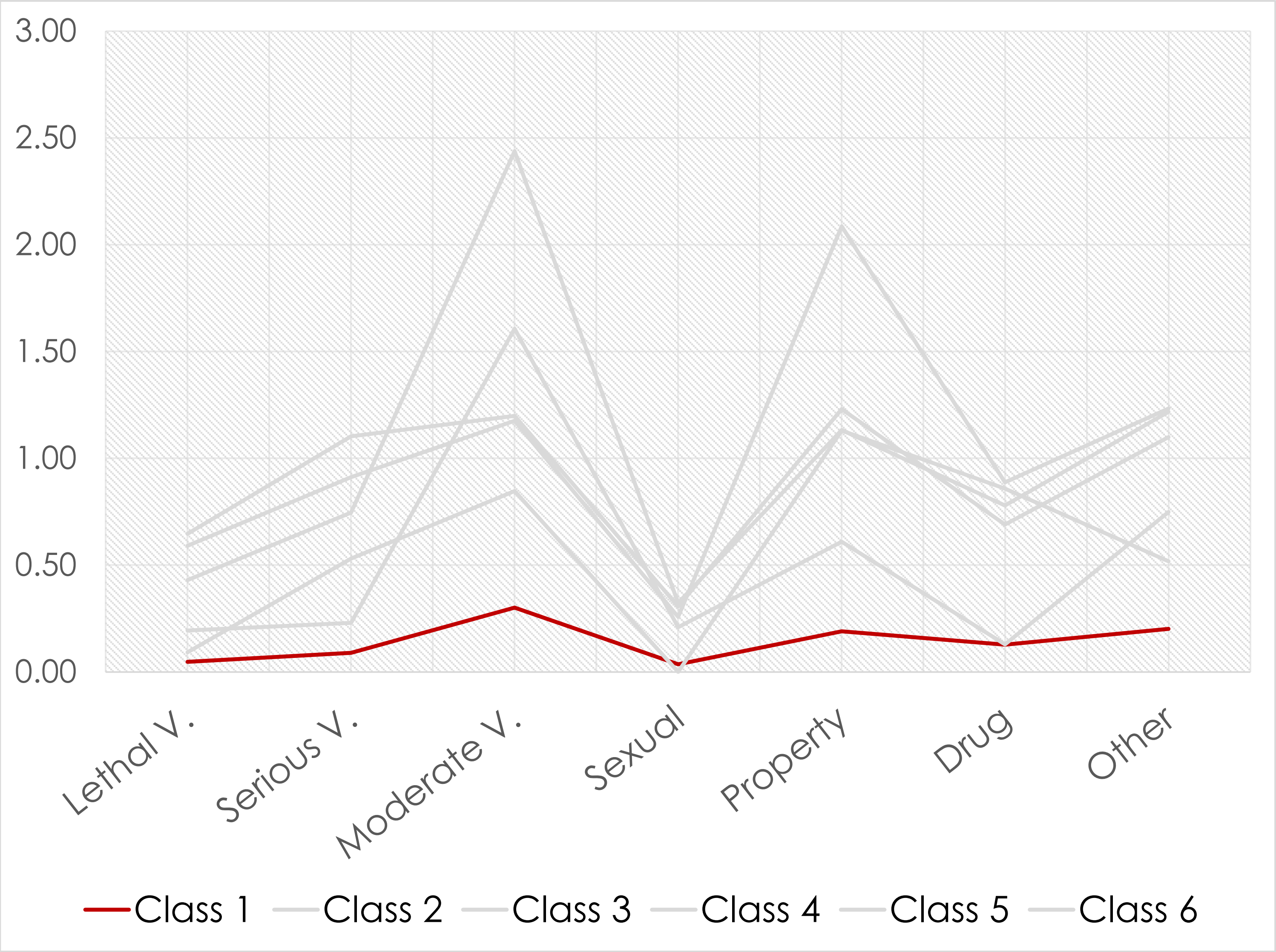
Offending categories	Log(Intercepts)					
	Class 1 (75.99%)	Class 2 (2.11%)	Class 3 (1.48%)	Class 4 (15.31%)	Class 5 (4.59%)	Class 6 (0.53%)
1. Lethal Violent Offenses	-6.14	-1.67	-0.62	-3.41	-3.99	-0.09
2. Serious Violent Offenses	-4.75	-0.79	0.98	-3.09	-1.36	1.90
3. Moderate Violent Offenses	-2.59	1.94	0.29	0.55	-0.31	1.38
4. Sexual Offenses	-7.00	-2.15	-1.97	-3.20	-73.46	-2.72
5. Property Offenses	-3.28	0.60	0.92	-1.26	0.28	2.67
6. Drug Offenses	-4.09	-0.32	-0.61	-3.82	-0.07	0.50
7. Other Offenses	-3.24	0.51	0.50	-0.79	-1.10	1.05

RESULTS: SPECIALIZATION



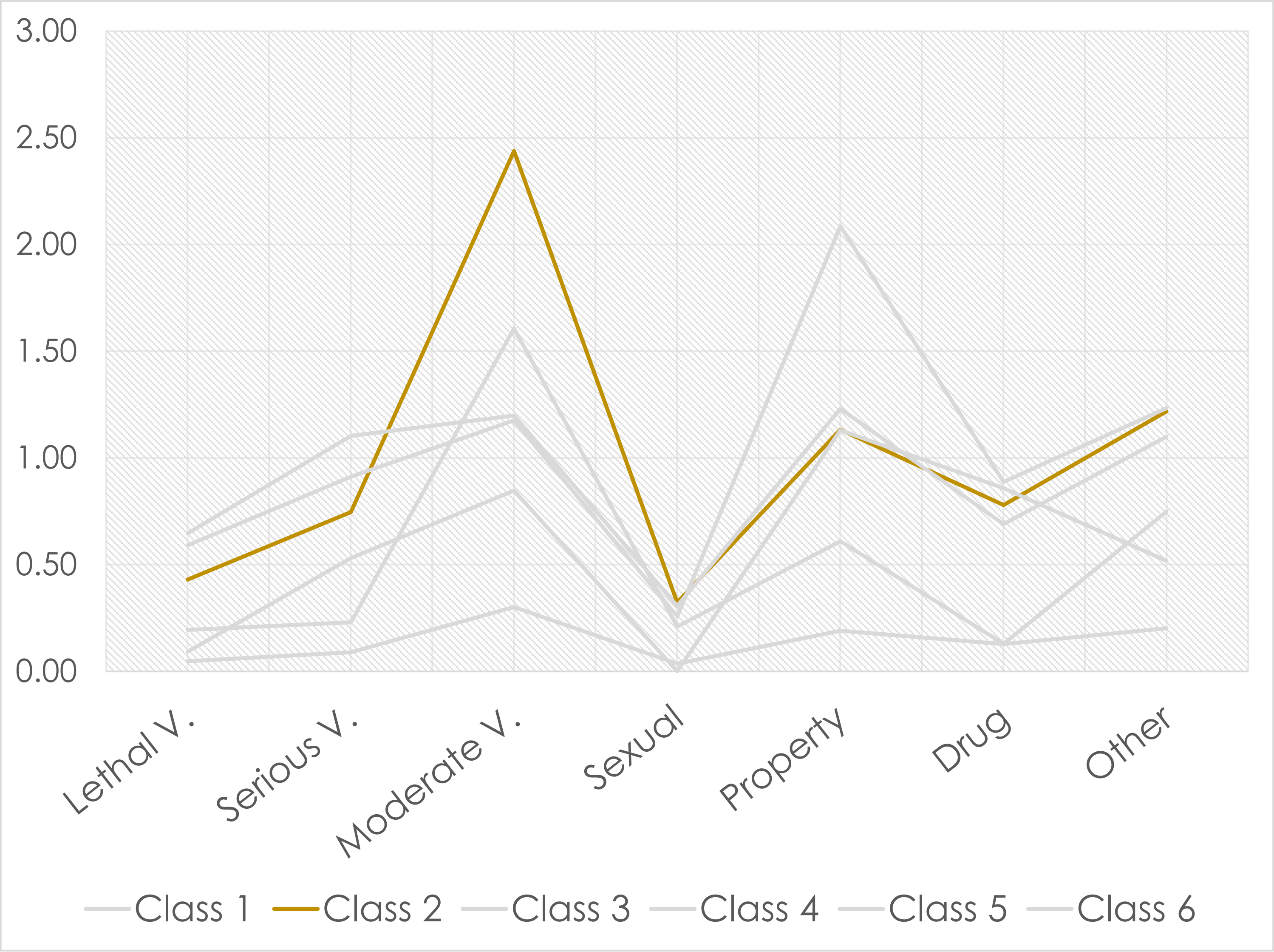
Results: Specialization

- **Class 1 (75.99%)** – Non-offenders



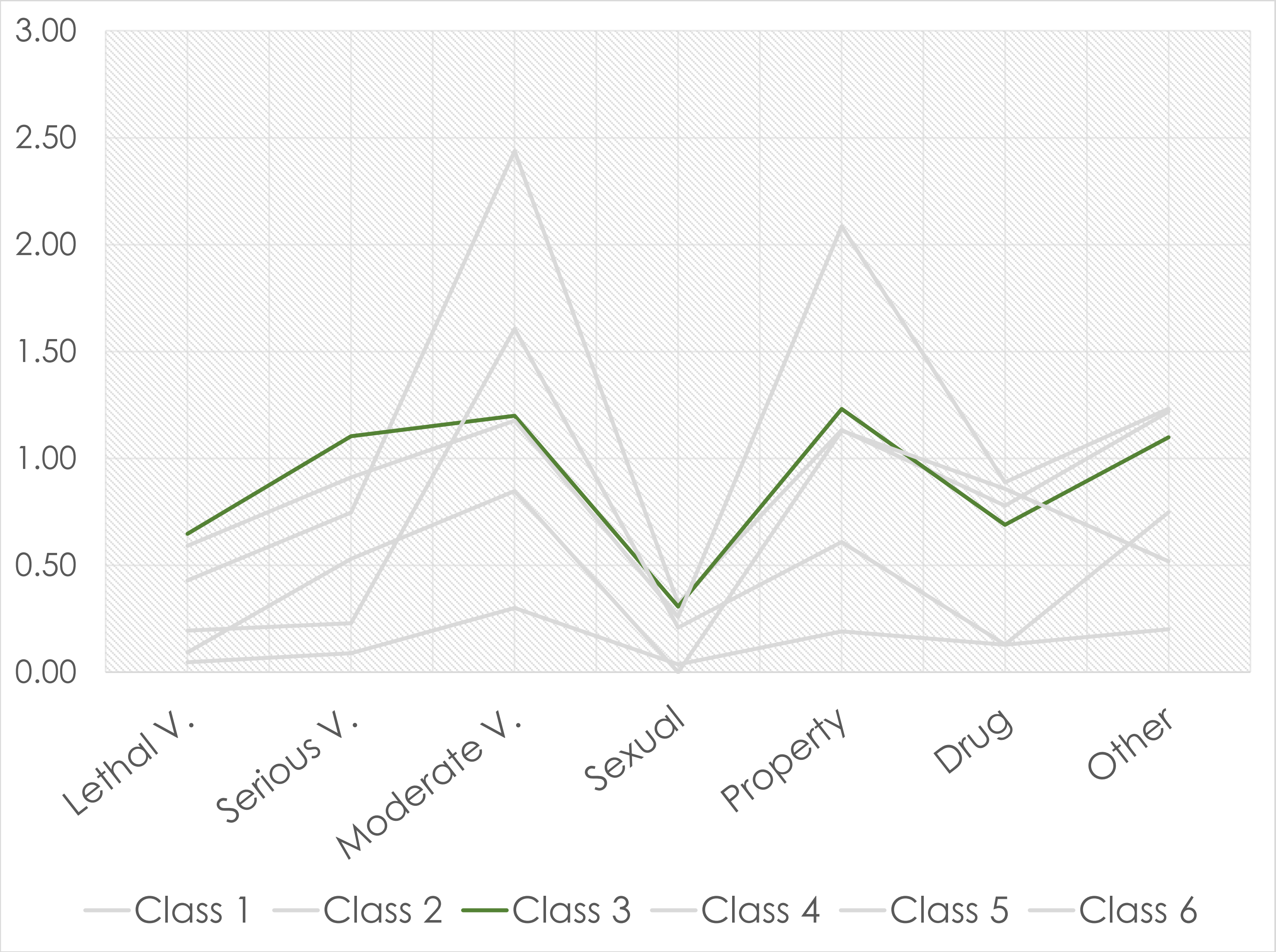
Results: Specialization

- **Class 1 (75.99%)** – Non-offenders
- **Class 2 (2.11%)** – Moderate-violent versatile offenders



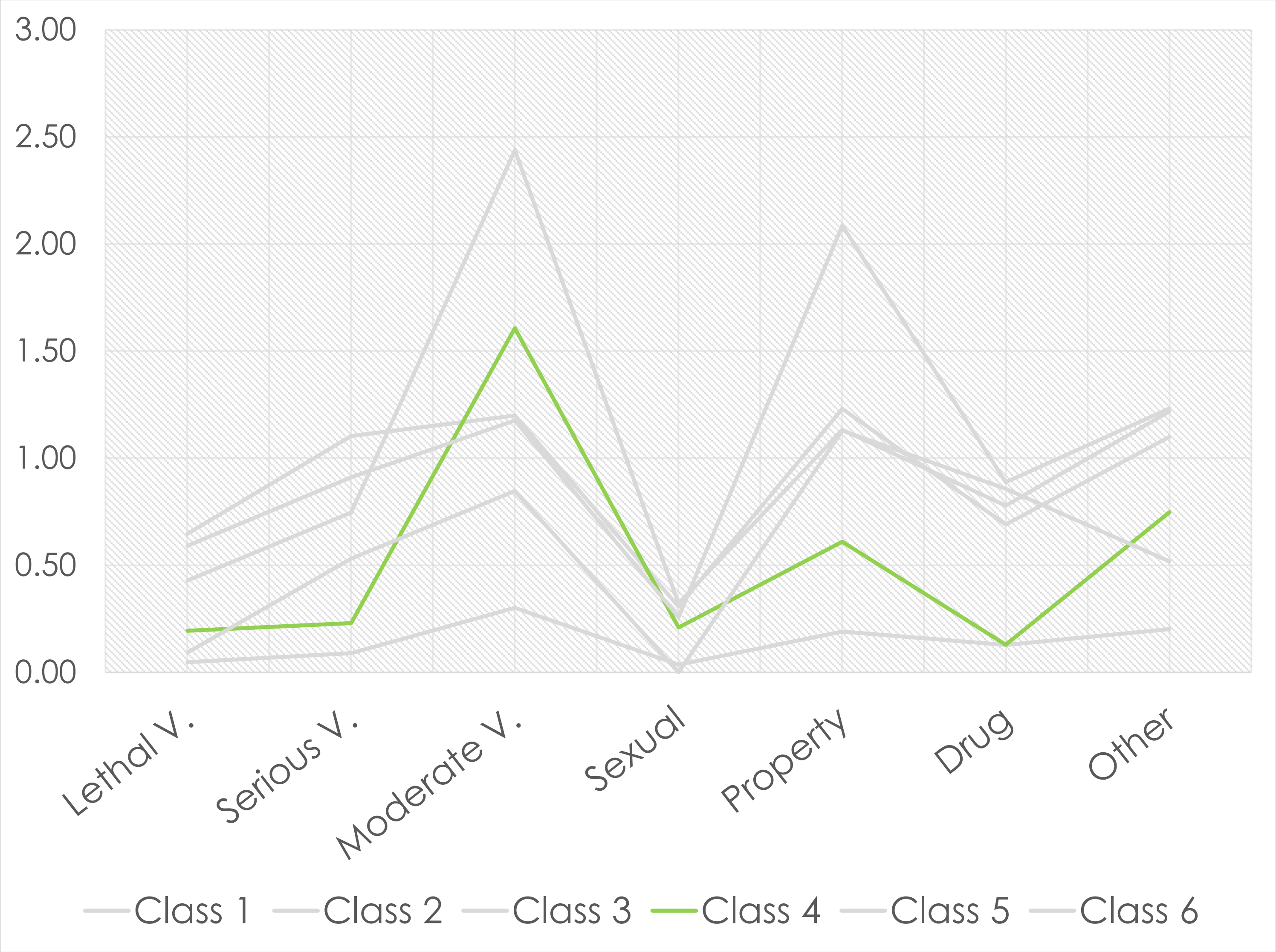
Results: Specialization

- **Class 1 (75.99%)** – Non-offenders
- **Class 2 (2.11%)** – Moderate-violent versatile offenders
- **Class 3 (1.48%)** – Serious-Violent versatile offenders



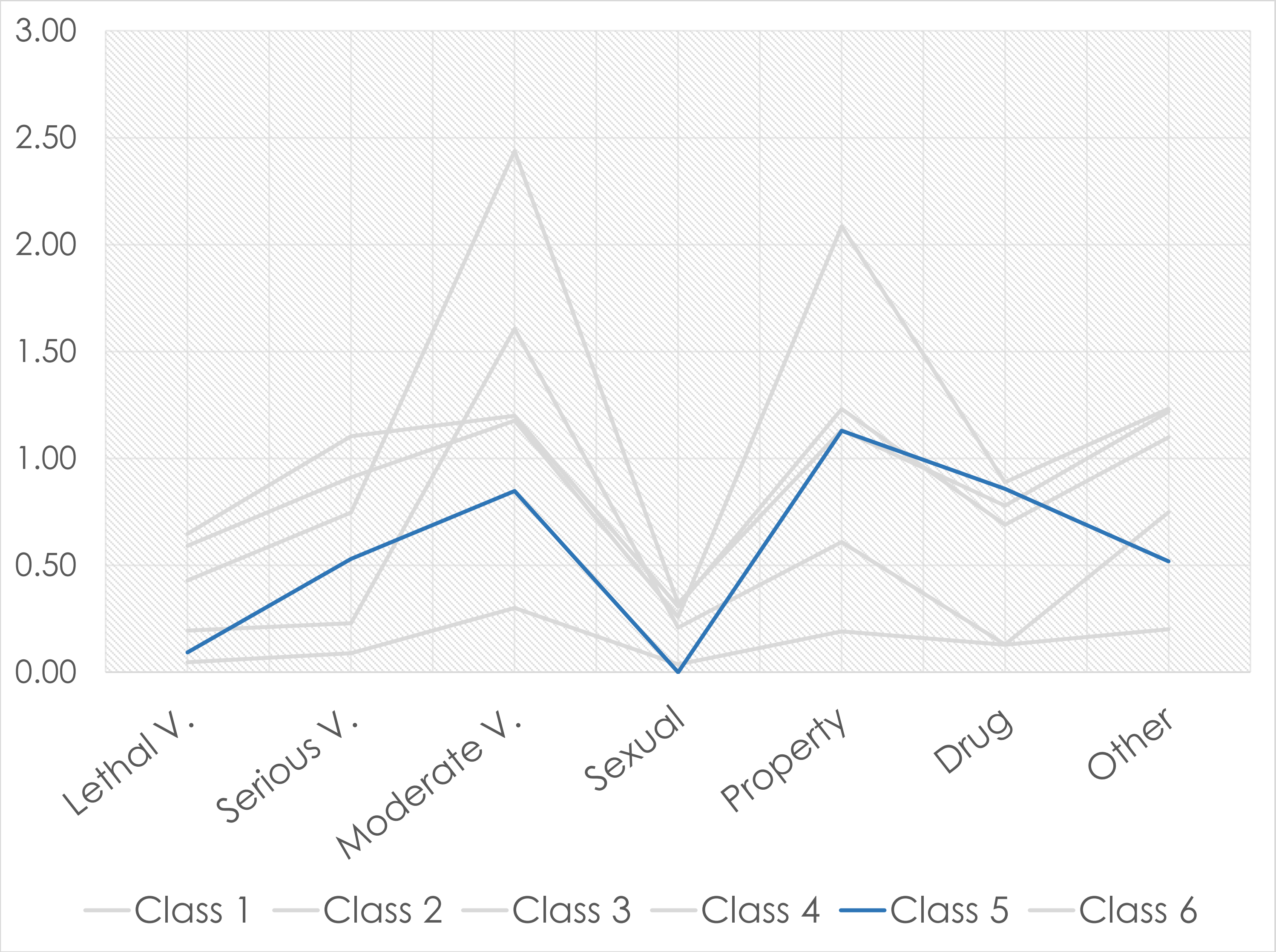
Results: Specialization

- **Class 1 (75.99%)** – Non-offenders
- **Class 2 (2.11%)** – Moderate-violent versatile offenders
- **Class 3 (1.48%)** – Serious-Violent versatile offenders
- **Class 4 (15.31%)** - Specialized moderate-violent offenders



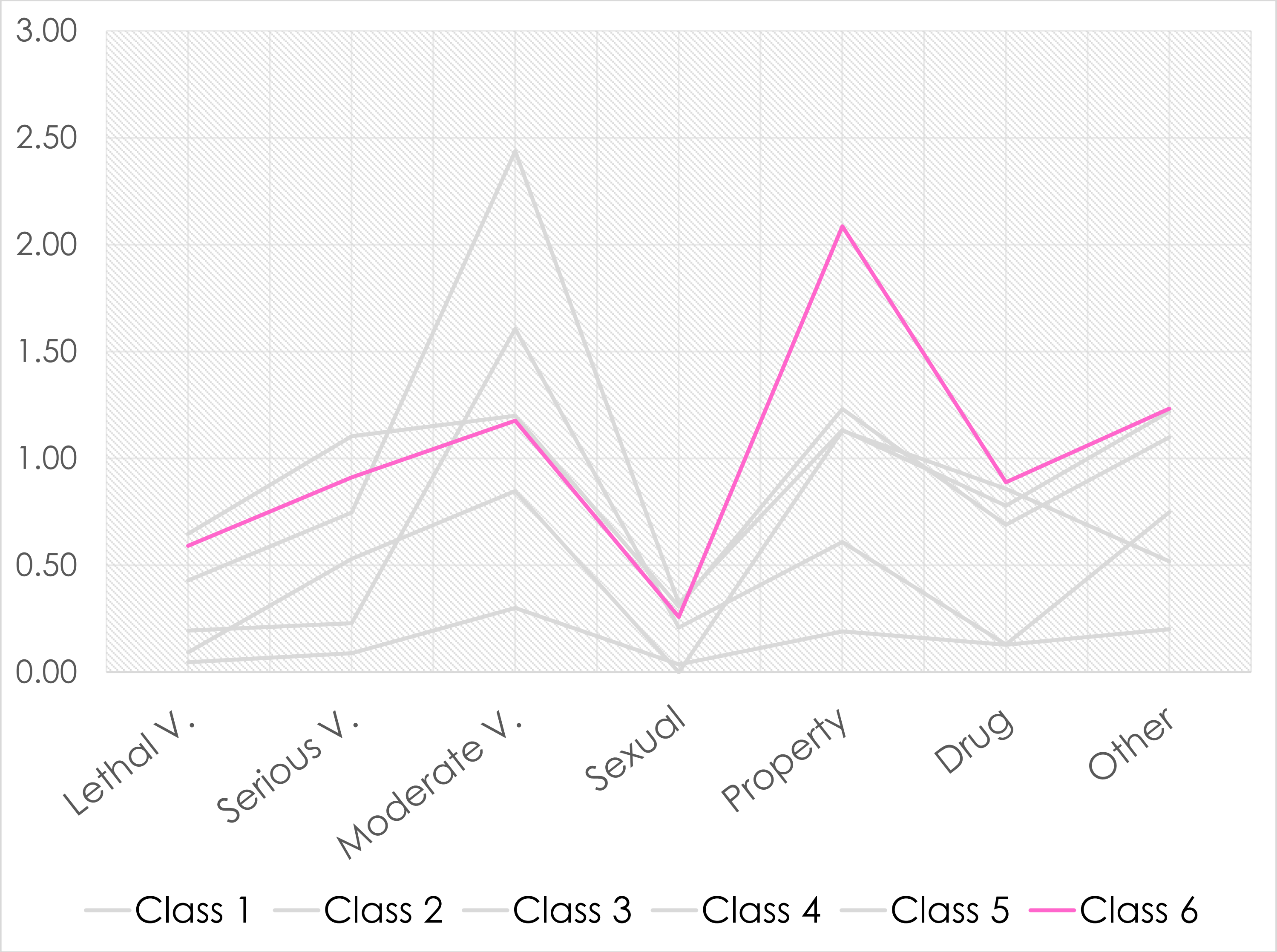
Results: Specialization

- **Class 1 (75.99%)** – Non-offenders
- **Class 2 (2.11%)** – Moderate-violent versatile offenders
- **Class 3 (1.48%)** – Serious-Violent versatile offenders
- **Class 4 (15.31%)** – Specialized moderate-violent offenders
- **Class 5 (4.59%)** – Low-violent offenders



Results: Specialization

- **Class 1 (75.99%)** – Non-offenders
- **Class 2 (2.11%)** – Moderate-violent versatile offenders
- **Class 3 (1.48%)** – Serious-Violent versatile offenders
- **Class 4 (15.31%)** – Specialized moderate-violent offenders
- **Class 5 (4.59%)** – Low-violent offenders
- **Class 6 (0.53%)** – Serious-Violent versatile offenders (high property)



Results: Specialization

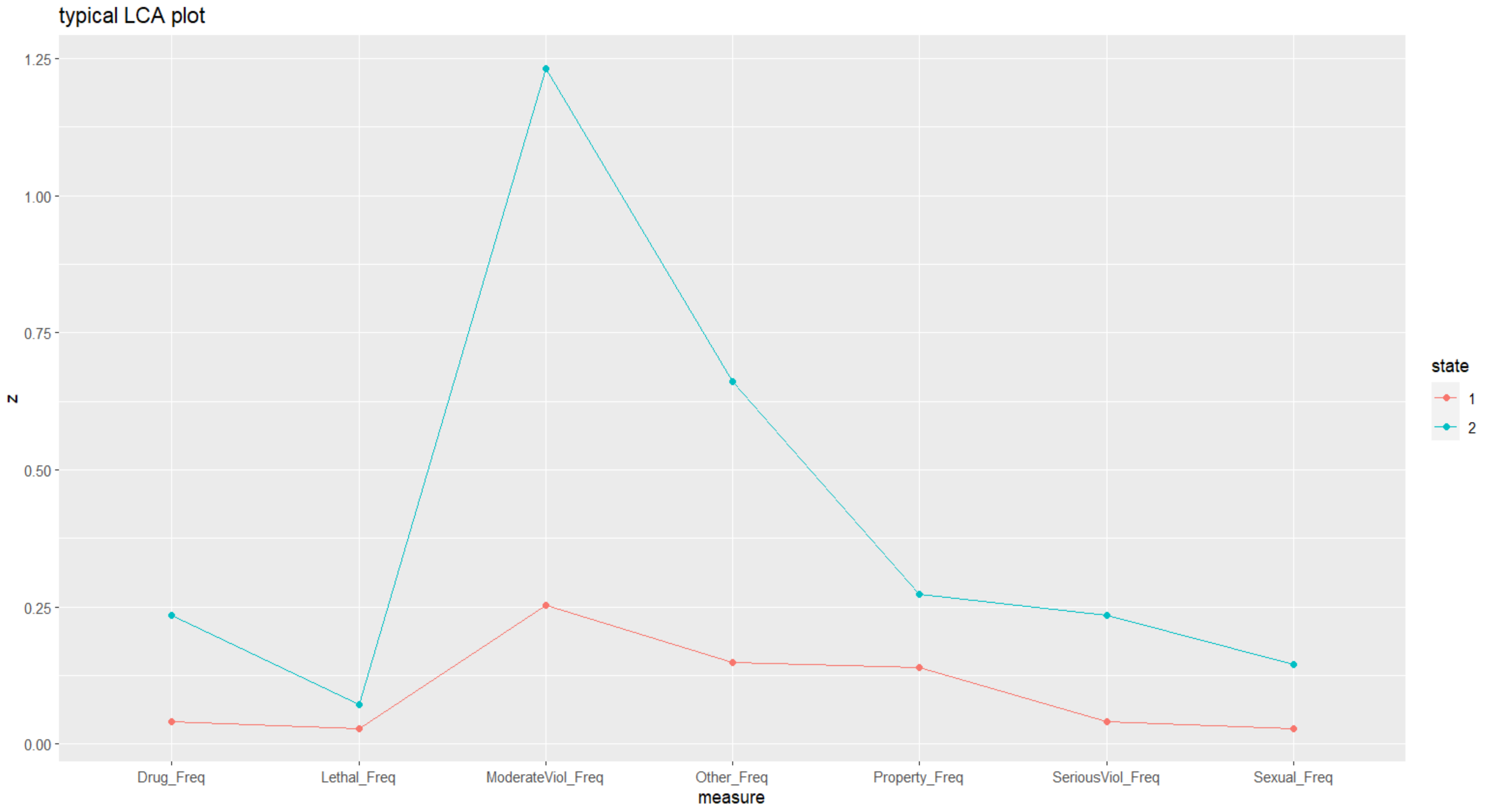
Latent Class Analysis (LCA) – for FEMALES

- Based on Bayesian Information Criterion (BIC = 5527), the 2-class model seems to best fit our data

Offending categories	Log(Intercepts)	
	Class 1 (92.70%)	Class 2 (7.30%)
1. Lethal Violent Offenses	-7.14	-5.23
2. Serious Violent Offenses	-6.26	-3.05
3. Moderate Violent Offenses	-2.68	0.71
4. Sexual Offenses	-7.01	-3.95
5. Property Offenses	-3.88	-0.68
6. Drug Offenses	-6.55	-2.16
7. Other Offenses	-3.77	-0.44

Results: Specialization

- Class 1 (92.70%) – Non-offenders
- Class 2 (7.30%) – Versatile offenders

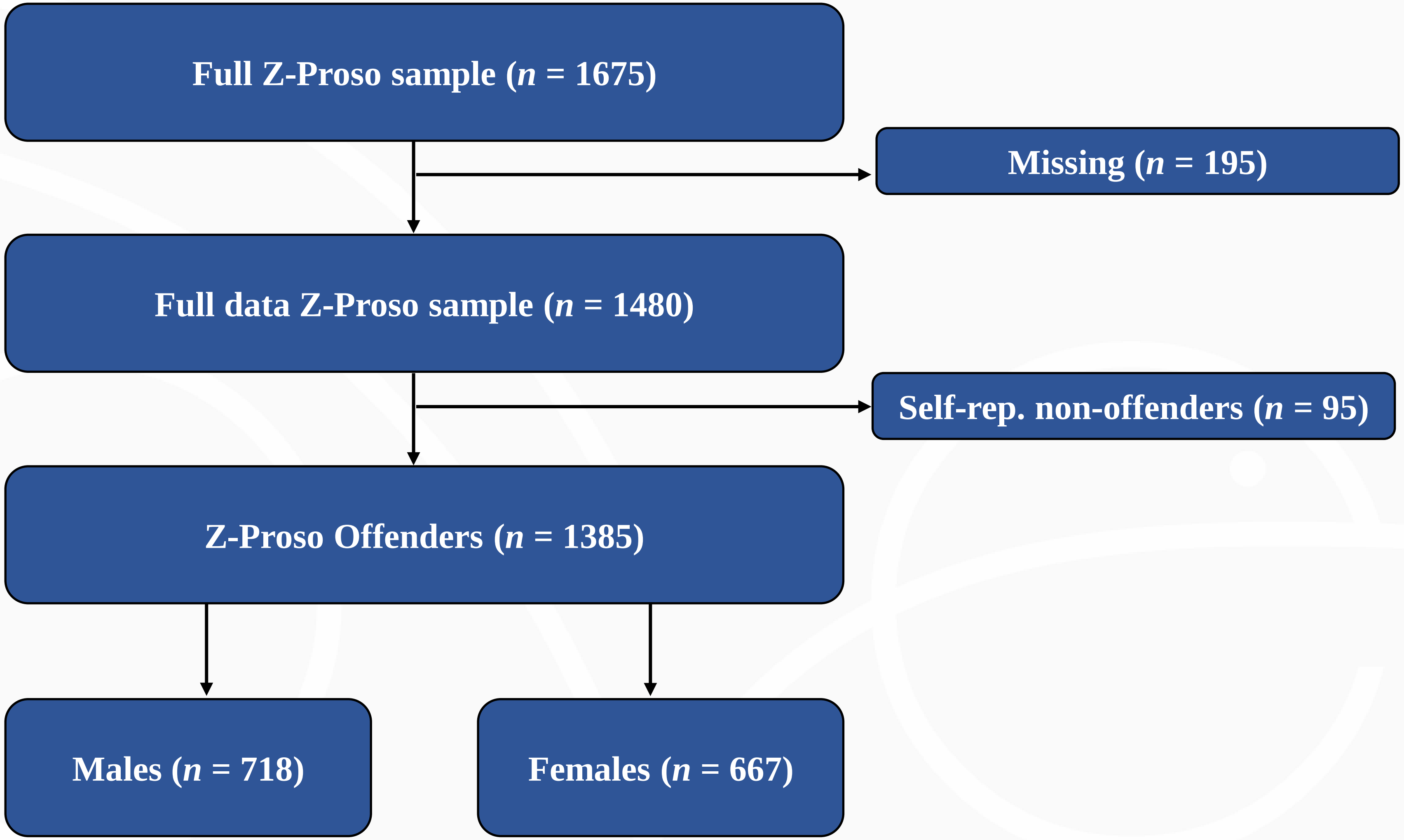


Current Study

Offender specialization among z-proso participants

Current Study

Participants



Current Study

Methods

- **Self-Reports of offending**

- According to previous studies (Murray et al., 2021), we considered seven types of delinquent behavior:
  - Stealing at home,
  - Shoplifting less than 50 CHF,
  - Shoplifting more than 50CHF,
  - Vehicle theft,
  - Fare dodging,
  - Vandalism, and
  - Assault.

- Based on these types of crimes, we have created composite variables that included information in waves K5-K9:
  - Delinquency prevalence, frequency, and variety.

DOVE

Current Study: Data Analysis

Data Analysis

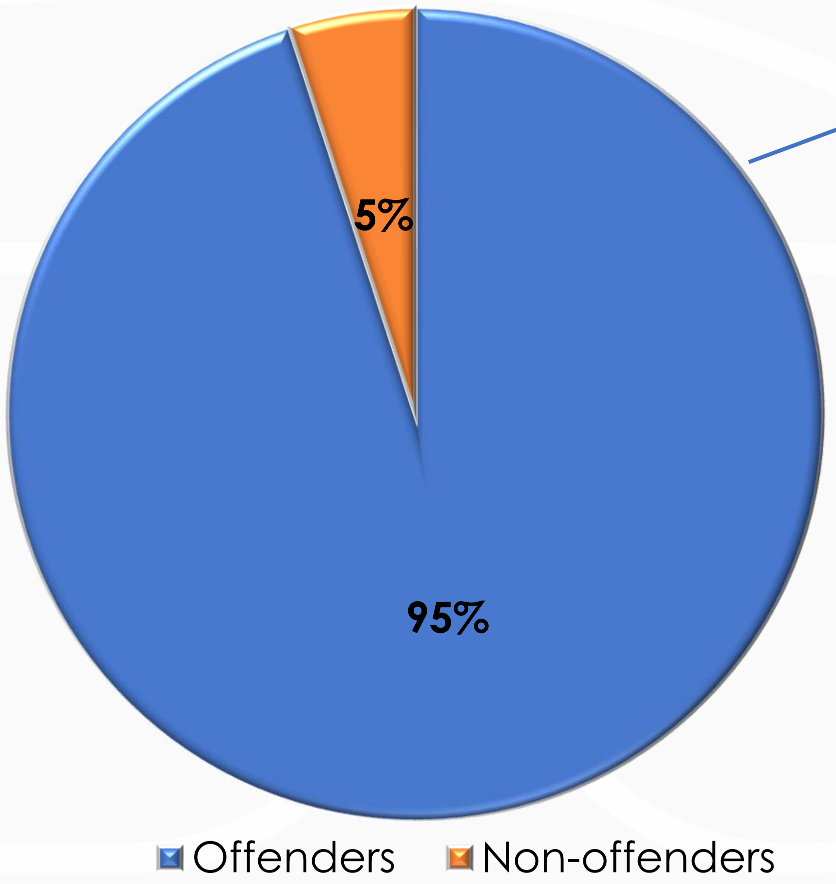
- Descriptive statistics
  - Prevalence, Frequency, and Variety of offending
  - Comparisons across participants' sex were carried out using:
    - Logistic regression for binary outcomes;
    - Negative binomial regression for continuous outcomes.

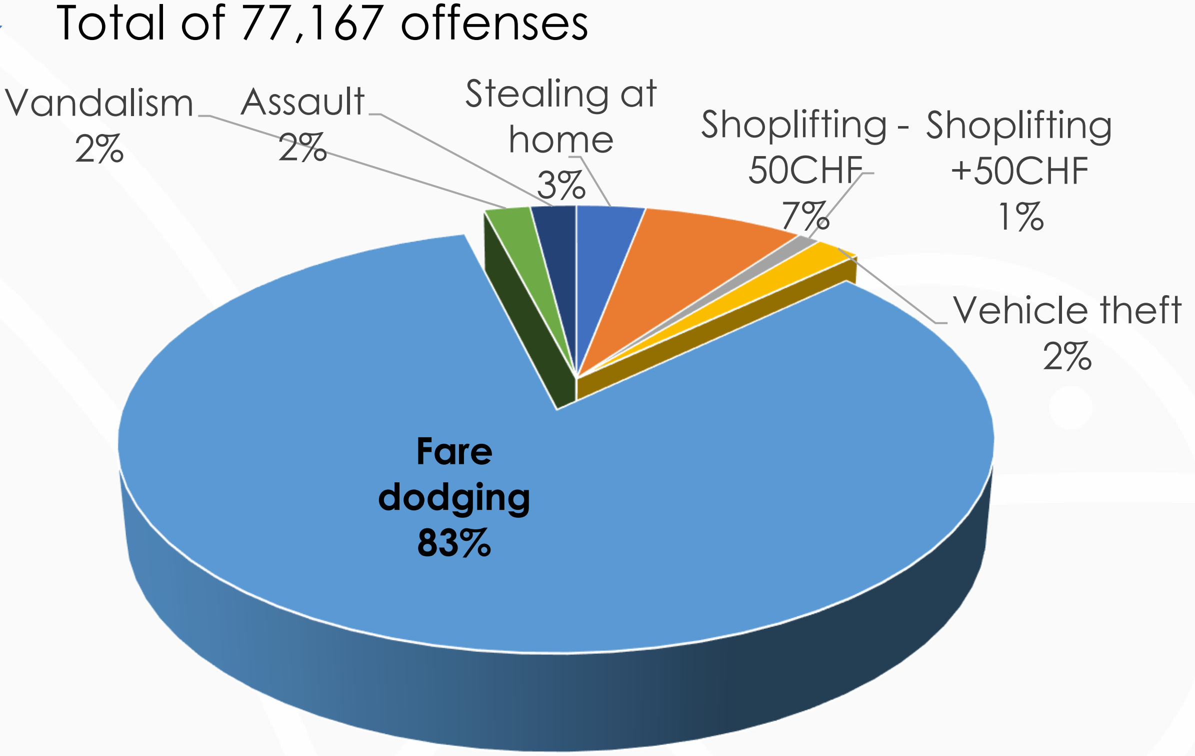
- Latent Class Analysis (LCA)
  - R package depmixS4 (Visser & Speekenbrink, 2010) - latent/ hidden Markov models
  - Allows to test LCA with <u>count data</u>

  - R package poLCA (Linzer & Lewis, 2011)
    - binary data

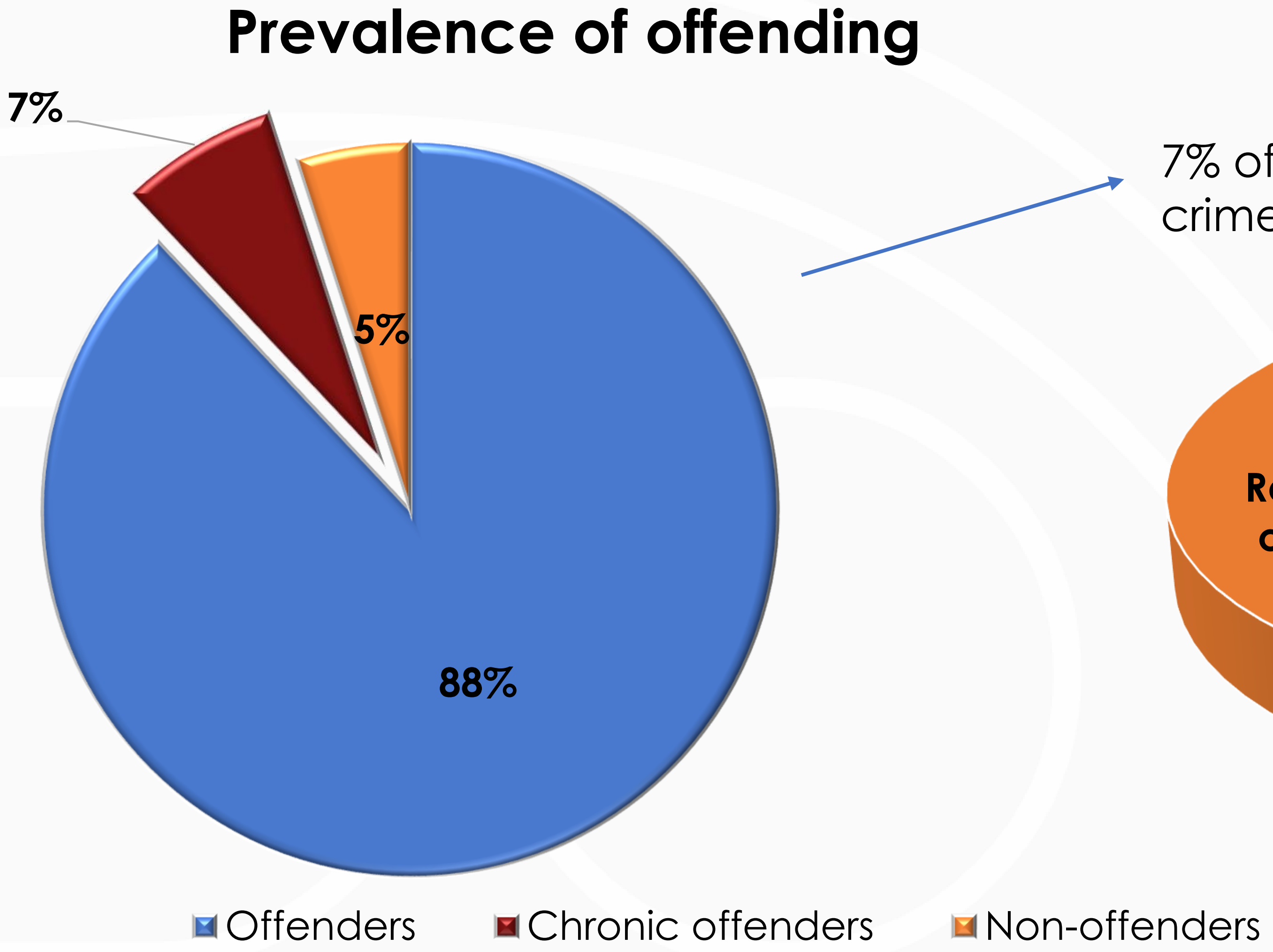
RESULTS: DESCRIPTIVE ANALYSIS

Prevalence of offending

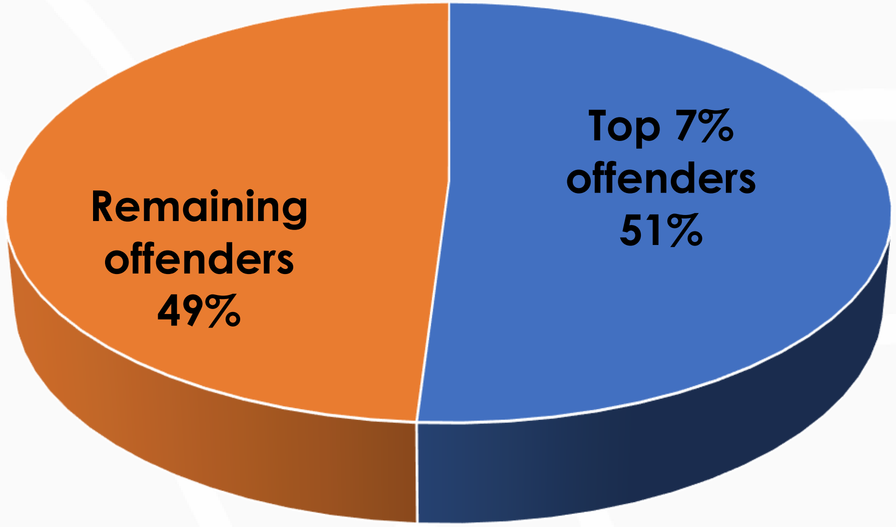




Results: Descriptive Analysis

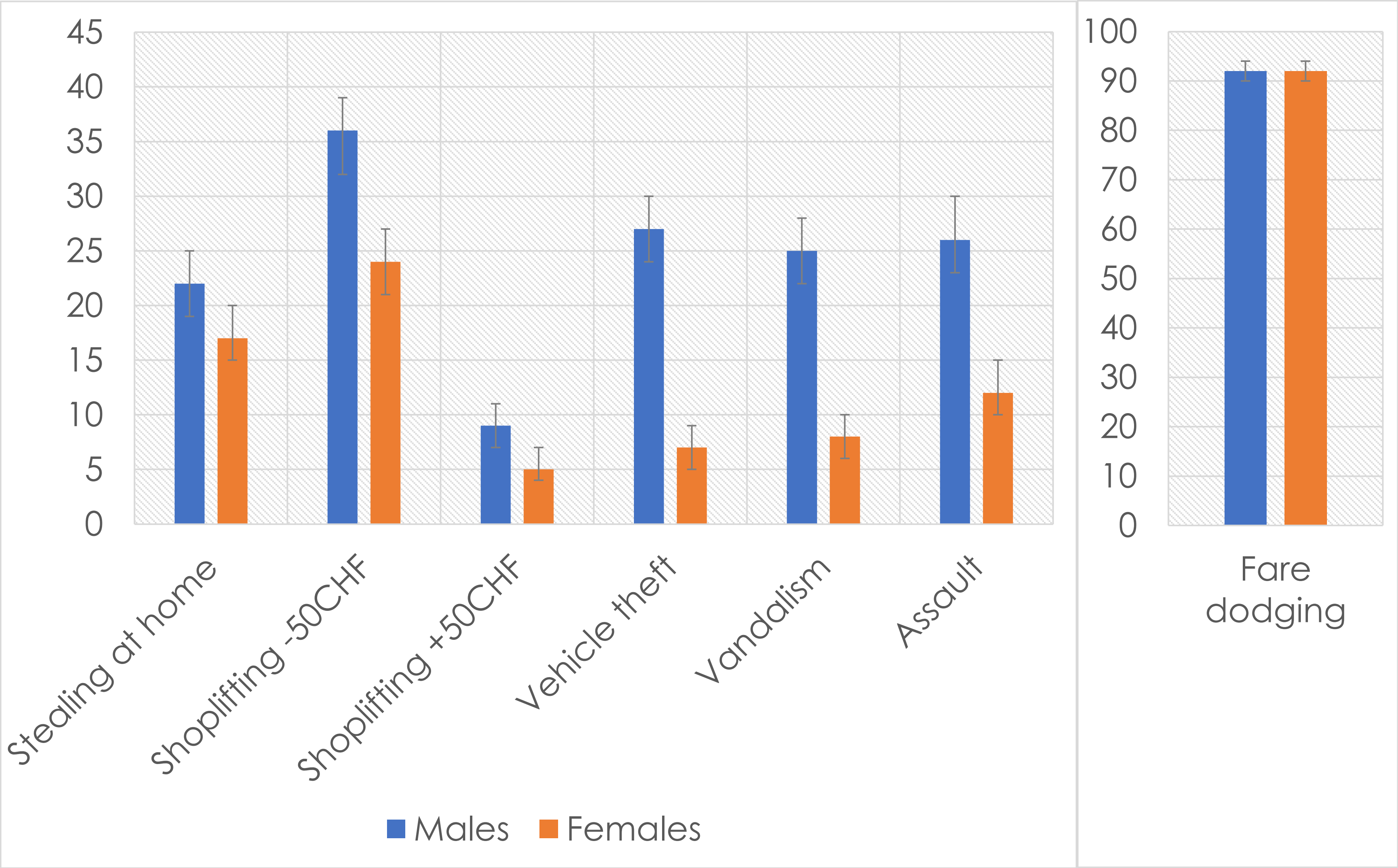


7% of participants are responsible for +50% of crimes.



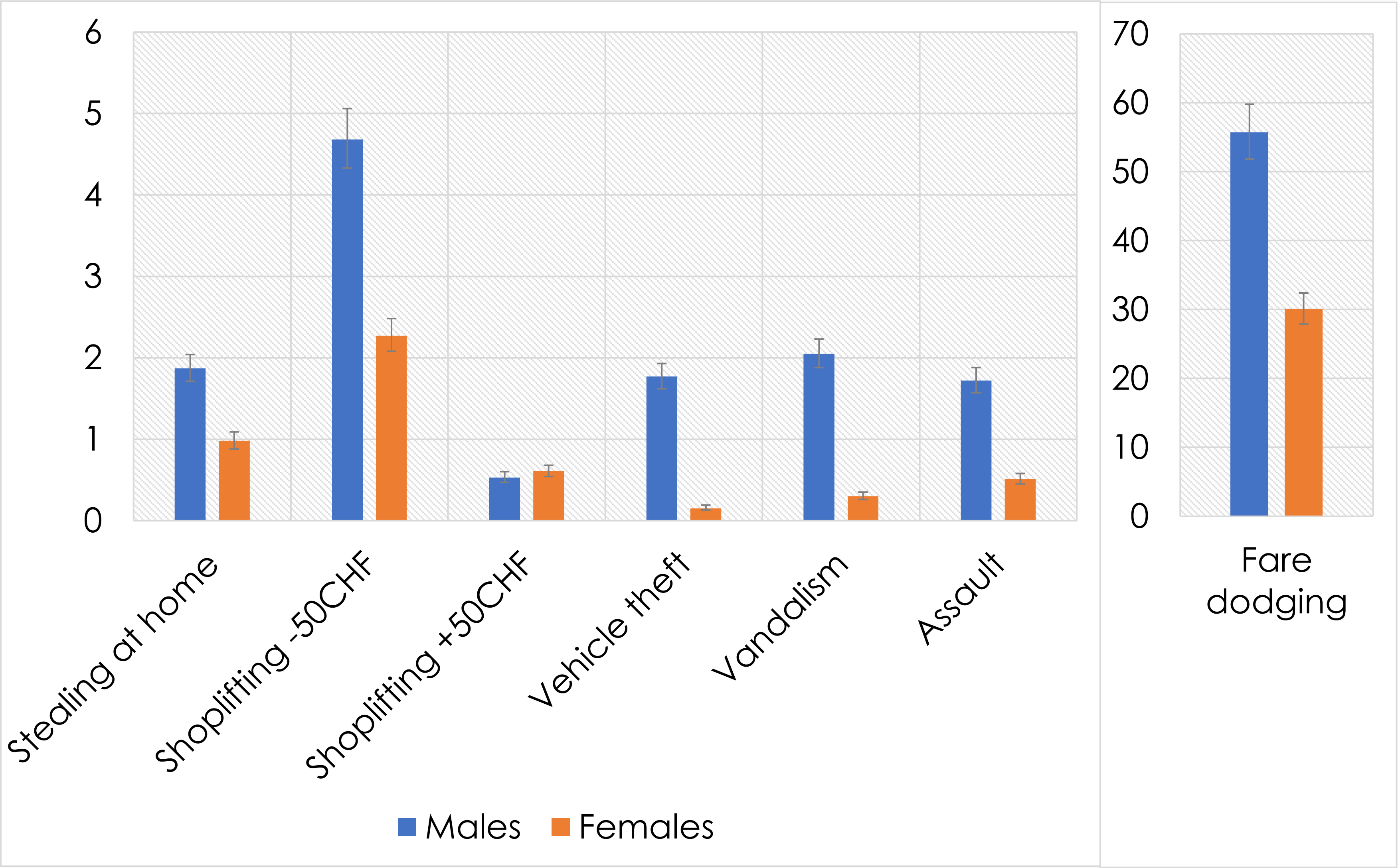
Results: Descriptive Analysis

Prevalence of offending



Results: Descriptive Analysis

Frequency of offending



Results: Specialization

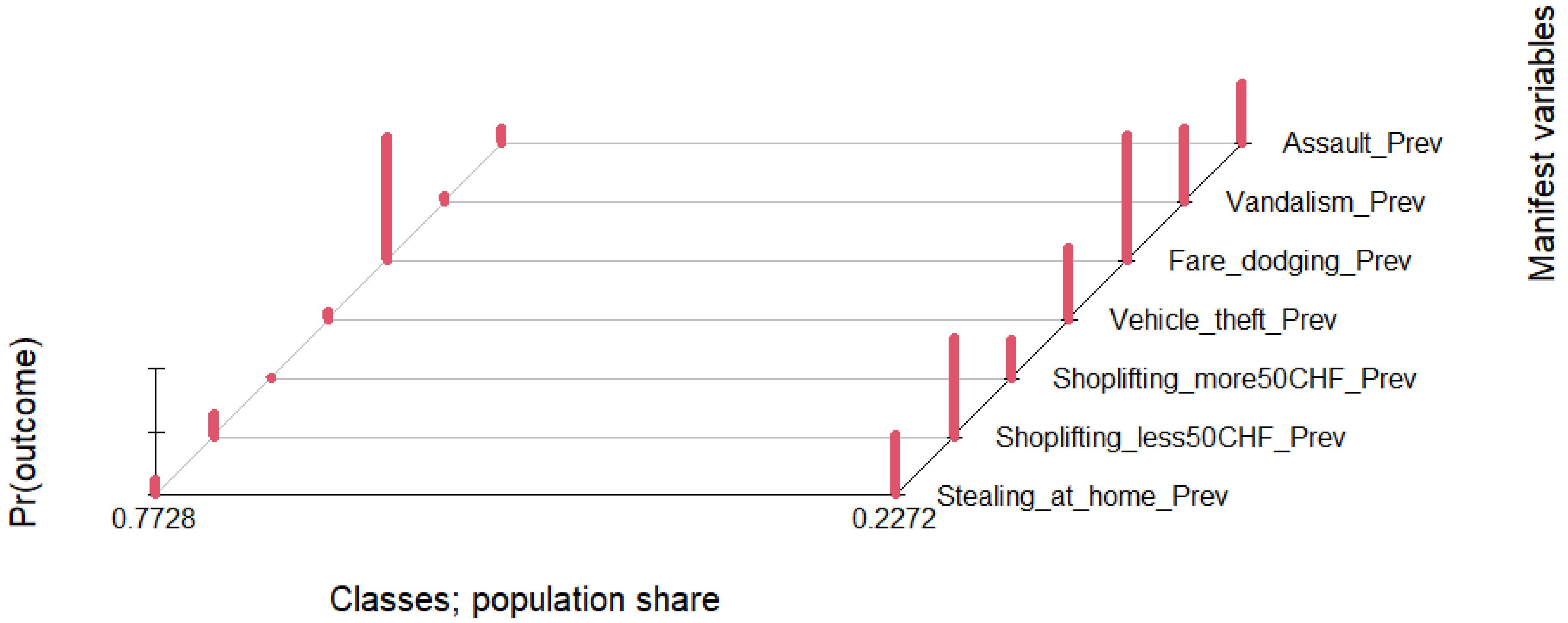
Latent Class Analysis (LCA) – full sample

- Based on Bayesian Information Criterion (BIC = 7606), the 2-class model seems to best fit our data

Fit statistics	2 classes	3 classes	4 classes	5 classes	6 classes
Likelihood	178.86	127.24	85.70	71.19	**63.13**
AIC	7527	7491	**7466**	7467	7475
BIC	**7606**	7611	7628	7672	7721
Group size %[a]					
C1	22.09%	8.59%	13.43%	6.06%	6.14%
C2	77.91%	28.66%	6.21%	63.39%	8.81%
C3		62.74%	63.39%	5.85%	12.35%
C4			16.97%	12.20%	13.43%
C5				12.49%	58.05%
C6					1.23%

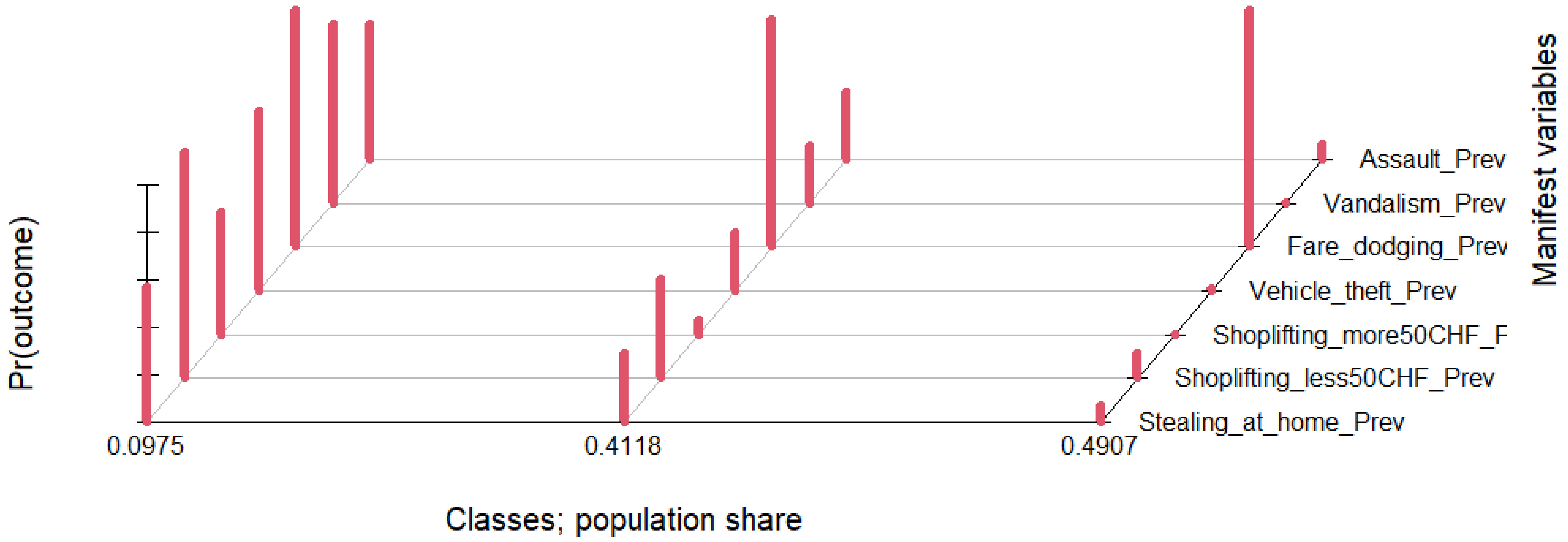
RESULTS: SPECIALIZATION

Latent Class Analysis (LCA) – full sample
2-class model



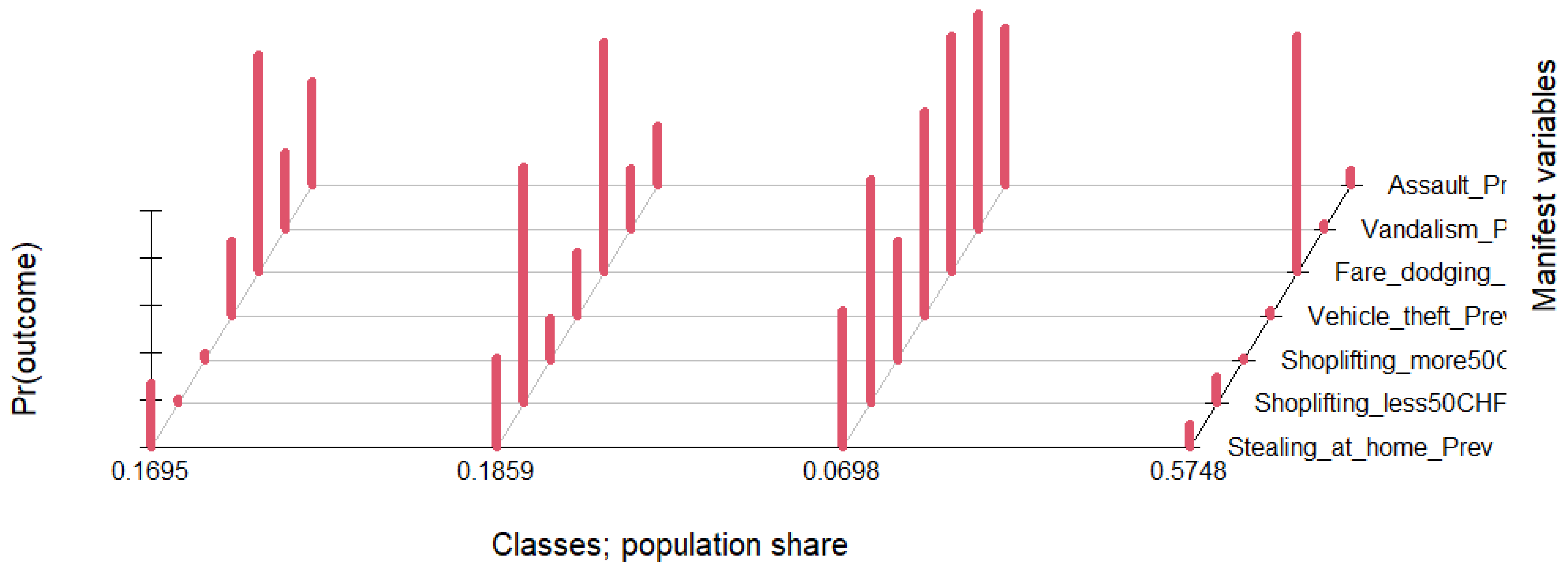
Results: Specialization

Latent Class Analysis (LCA) – full sample
3-class model



Results: Specialization

Latent Class Analysis (LCA) – full sample
4-class model



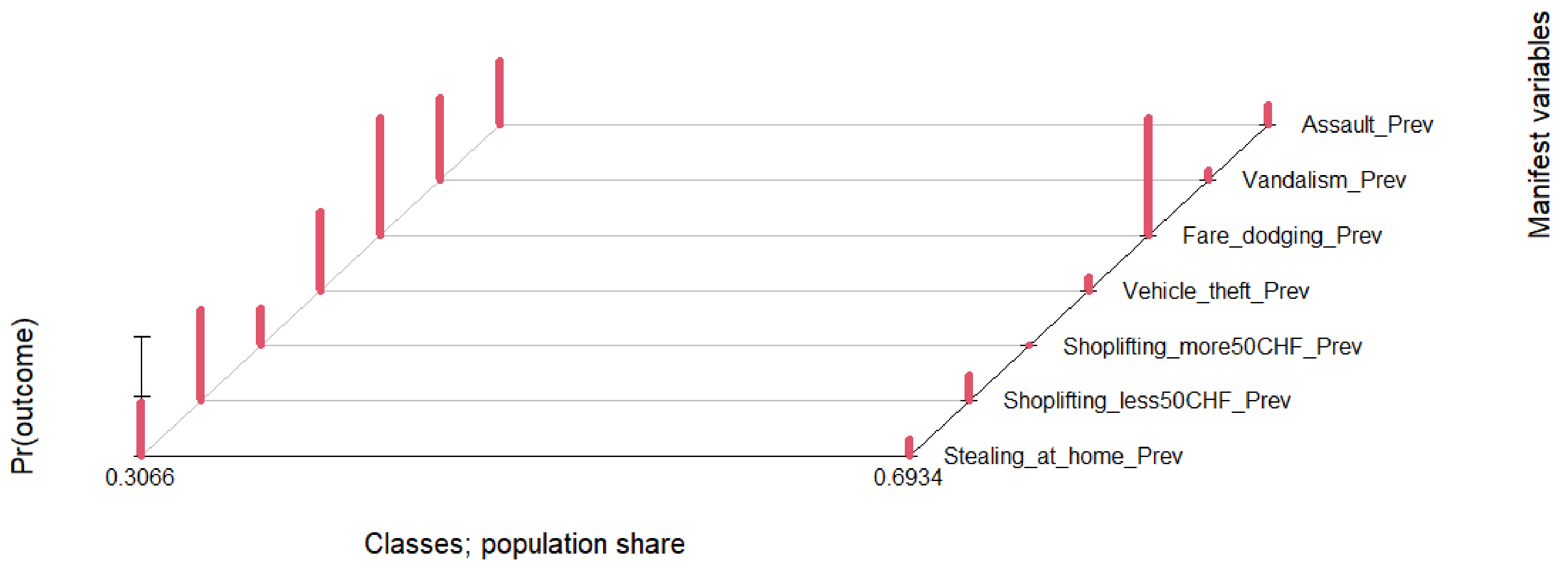
Results: Specialization

Latent Class Analysis (LCA) – Males

- Based on Bayesian Information Criterion (BIC = 4546), the 2-class model seems to best fit our data

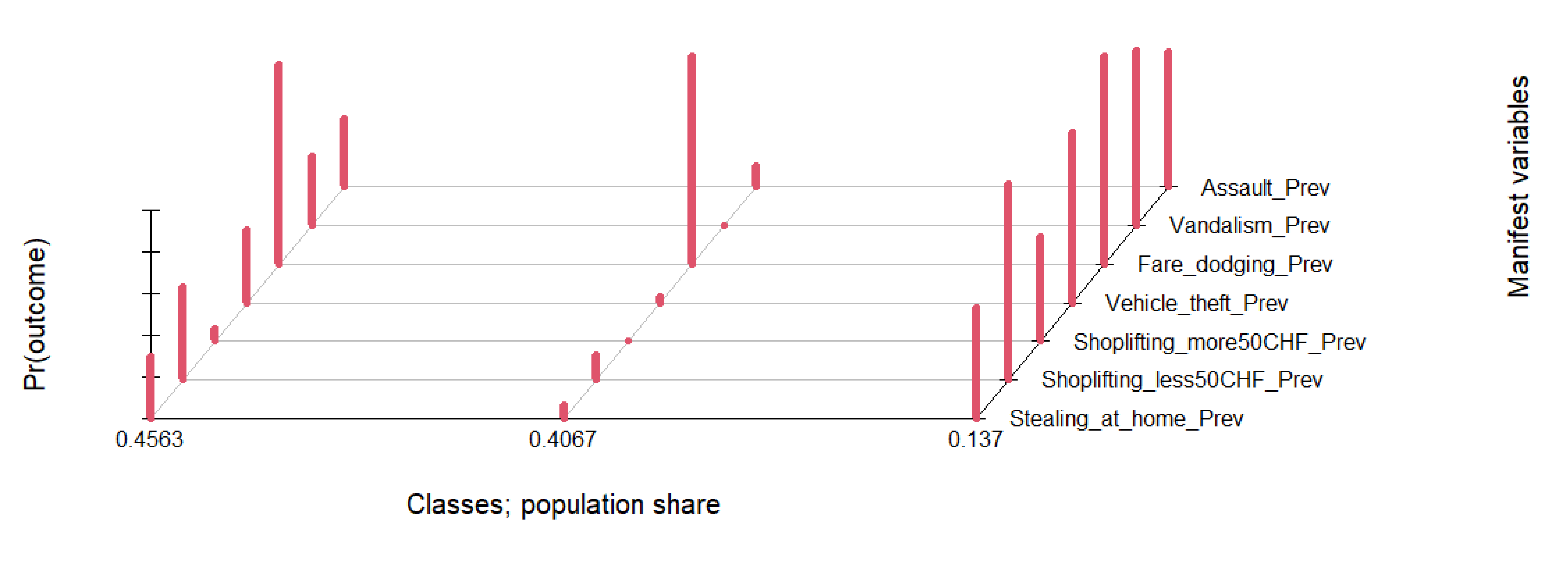
Fit statistics	2 classes	3 classes	4 classes	5 classes	6 classes
Likelihood	138.12	104.31	83.55	74.24	**61.08**
AIC	4478	4460	**4455**	4462	4465
BIC	**4546**	4565	4597	4640	4680
Group size %[a]					
C1	29.11	36.77	18.80	19.50	13.65
C2	70.89	50.84	21.03	18.11	50.97
C3		12.40	50.84	47.08	13.79
C4			9.33	7.94	13.51
C5				7.38	1.53
C6					6.55

Latent Class Analysis (LCA) – Males
2-class model



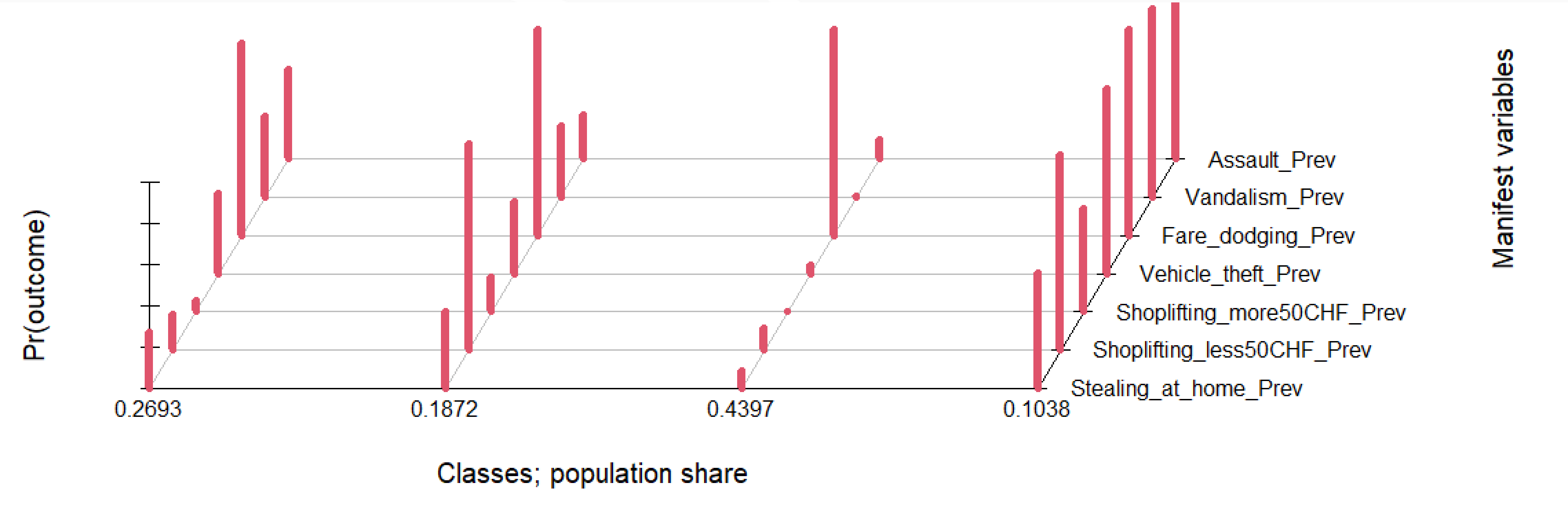
Results: Specialization

Latent Class Analysis (LCA) – Males
3-class model



Results: Specialization

Latent Class Analysis (LCA) – Males
4-class model



Results: Specialization

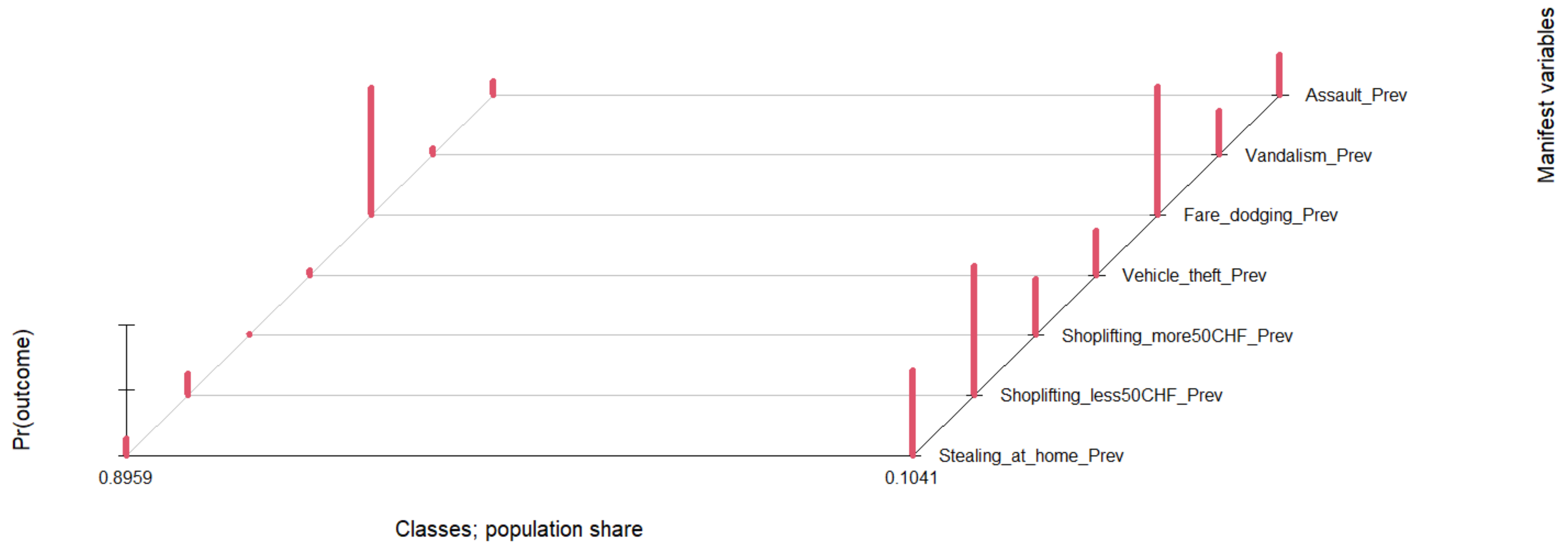
Latent Class Analysis (LCA) – Females

- Based on Bayesian Information Criterion (BIC = 2951), the 2-class model seems to best fit our data

Fit statistics	2 classes	3 classes	4 classes	5 classes	6 classes
Likelihood	86.80	59.89	54.15	51.28	**37.27**
AIC	2883	**2872**	2883	2896	2898
BIC	**2951**	2976	3022	3071	3109
Group size %[a]					
C1	91.45	11.69	7.50	10.49	71.66
C2	8.55	8.40	16.34	4.95	4.05
C3		79.91	65.97	17.84	4.50
C4			10.19	60.42	9.75
C5				6.30	2.40
C6					7.65

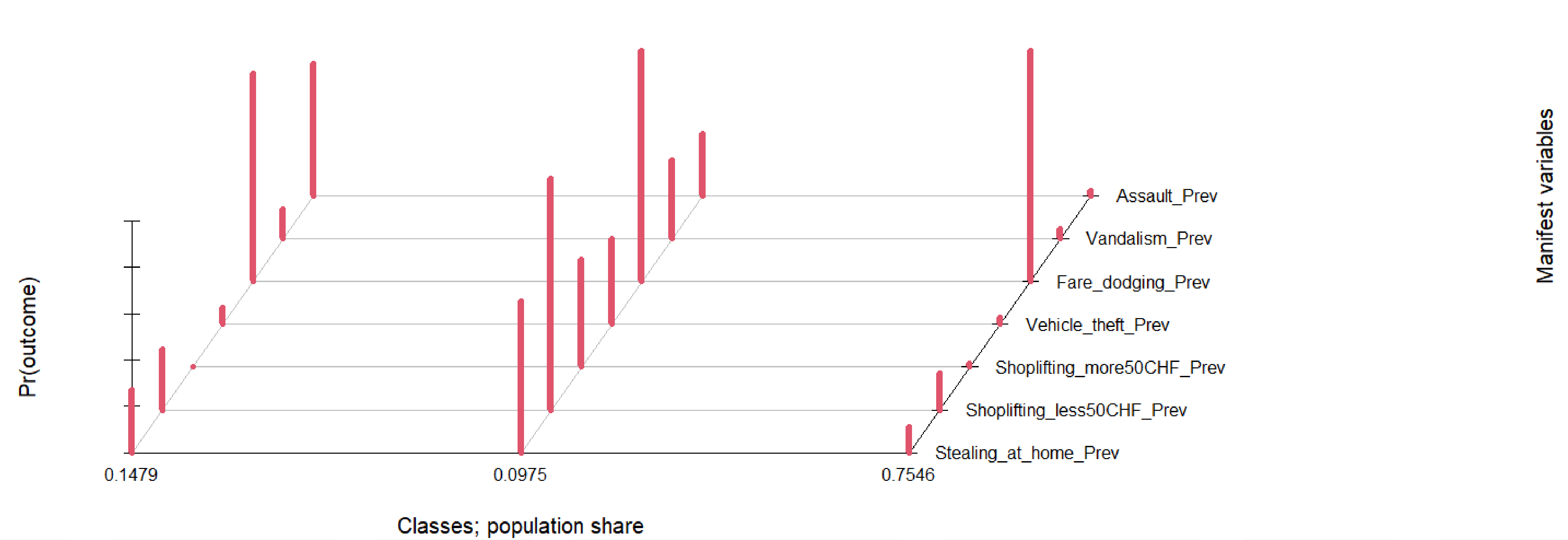
Results: Specialization

Latent Class Analysis (LCA) – Females
2-class model



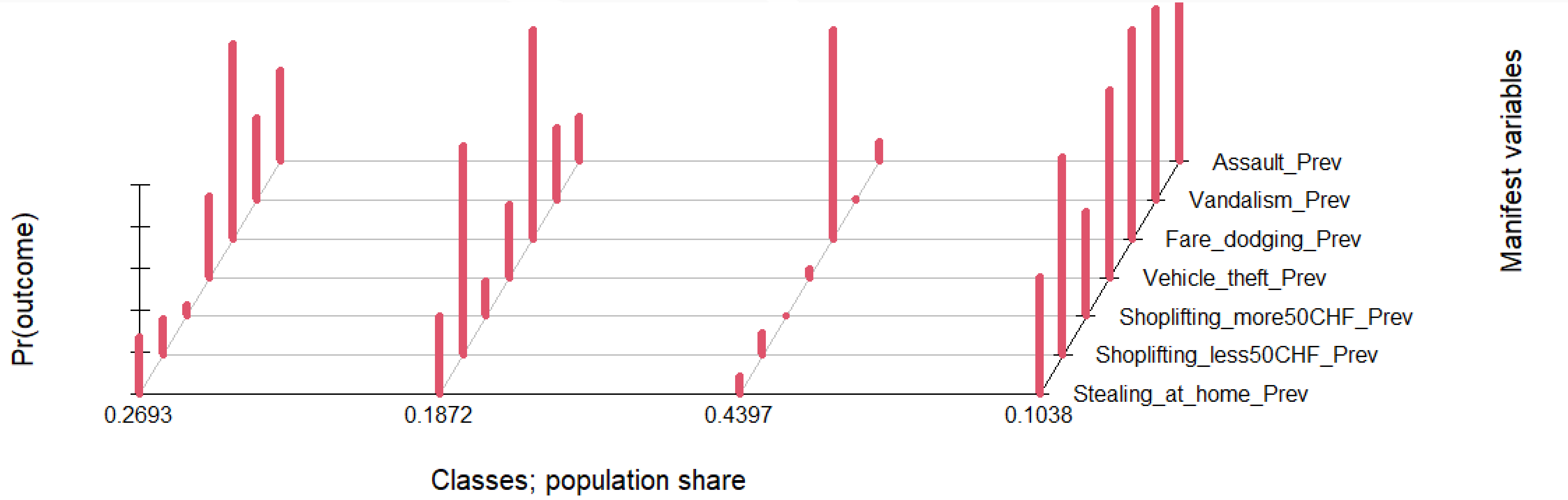
RESULTS: SPECIALIZATION

Latent Class Analysis (LCA) – Females
3-class model



RESULTS: SPECIALIZATION

Latent Class Analysis (LCA) – Males
4-class model



Conclusion

- Based on z-proso self-reports of offending we found no evidence of specialization.
- This finding gives support to the notion of general crime theories.
- Future directions:
  - Consider the frequency of offending.
  - Can we create a composite variable with low-frequency crimes (e.g., violent offenses)?
  - Comparison with officially recorded offending.
  - Does specialization change over the life-course?

DOVE
Centro de Pesquisas em
Desenvolvimento Humano
& Violência

Thank you!

UFPEL

Offender specialization among z-proso participants

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JACOBS CENTER

z-proso
The Zurich Project on the Social Development from Childhood to Adulthood

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14 September 2023