

They Took Our Crimes: Resolving the Immigration-Crime Puzzle

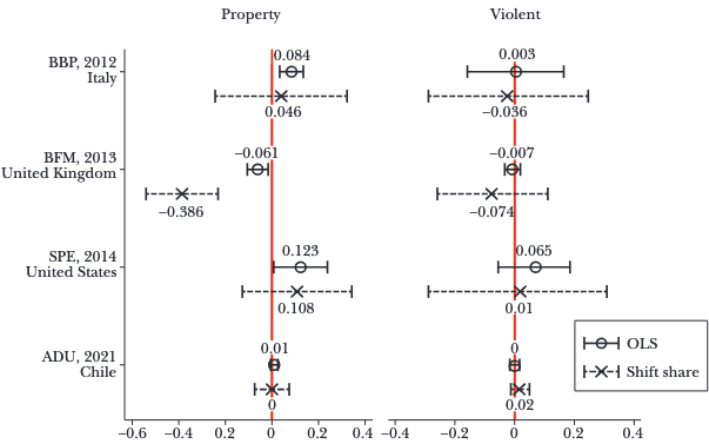
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Stylised fact 1: effect of immigration on (area level) crime is ≈ 0

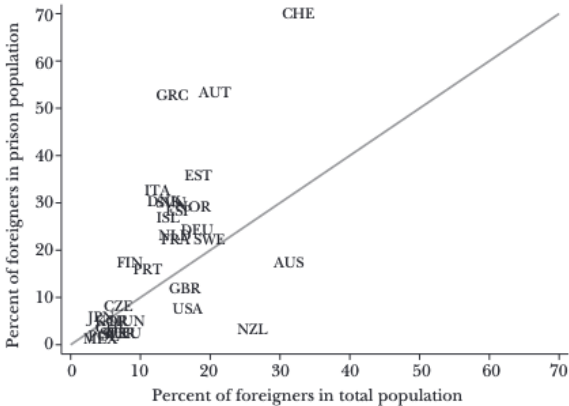
Summary of Estimates of the Impact of Immigration on Crime



Source: Marie & Pinotti (2024).

Stylised fact 2: migrants are overrepresented in crime statistics

Overrepresentation of Foreigners in Prison Populations



Source: Marie & Pinotti (2024).

Motivation: the crime–migration puzzle

- ▶ **Causal effect** of immigration on aggregate crime is $\approx$ zero
- ▶ **Immigrants** are overrepresented in Western prisons (except anglo-saxon countries)
- ▶ How can we reconcile these two stylized facts?
 - ▶ Selection on observables (age, income, education, risk attitudes)
 - ▶ Police (Goncalves and Mello, 2021) and judicial discrimination (Hanemaaijer et al., 2026)
- ▶ **Puzzle:** these two explanations alone cannot account for the native-migrant incarceration gap (Fasani et al., 2019)

Resolving the puzzle?

- ▶ We propose a novel explanation based on the literature on the effects of migration on labour markets (Card, 2001; Borjas, 2003; Dustmann et al., 2016). We argue that in crime markets:
 - ▶ **Substitution**: newcomers crowd natives *out of* crime
 - ▶ **Complementarity**: newcomers may draw some incumbents *into* crime
- ▶ *RQ*: How does a large refugee inflow affect the criminal behaviour of
 - ▶ **Natives**, **1st-generation migrants** (western and non-western), **2nd-gen migrants** (western and non-western)
- ▶ **Theory**: nested-CES labour-supply framework adapted to crime production
- ▶ **Empirics**: exploit the staggered opening of refugee centres between 2014-2016 in the Netherlands

Causal effect of immigration on crime is ≈ 0

- ▶ Immigration inflows: Bianchi et al. (2012); Bell et al. (2013); Spenkuch (2014); Marie and Pinotti (2024); Ajzenman et al. (2023); Fasani et al. (2019)
- ▶ Refugee inflows: Couttenier et al. (2019); Dehos (2021); Kayaoglu (2022); Kırdar et al. (2022); Megalokonomou and Vasilakis (2023); Akbulut-Yuksel et al. (2024); Lange and Sommerfeld (2024); Fasani et al. (2019)

→ Using rich Dutch data, we decompose the aggregate null effect into group-specific heterogeneity

Immigrants and labour market substitution & complementarity: Ottaviano and Peri (2012); Card (2009); Borjas (2003); Dustmann et al. (2013); Dustmann et al. (2016); Dustmann et al. (2017); Beerli et al. (2021); Llull (2018); Borjas et al. (2010)

→ Take framework to the crime market. Refugee inflow substitutes natives out of crime and complements incumbents likely to offend with newcomers

Co-offending and peer effects in crime: Glaeser et al. (1996); Bayer et al. (2009); Billings et al. (2019)

→ Inflow affects **second gen.** migrants with the highest ex-ante propensity to co-offend with **first gen. NW**, while **natives** exit networks

Theory: crime as a labour market

- ▶ A refugee inflow is a labour supply shock to the crime market: newcomers **substitute** some incumbents and **complement** others (Ottaviano and Peri, 2012)

Substitutes ($\sigma > 1$)

Compete for the same niche $\Rightarrow$ crowded out.
 $\Rightarrow$ marginal natives $\downarrow$

Complements ($\sigma < 1$)

Operate alongside newcomers $\Rightarrow$ drawn in.
 $\Rightarrow$ 1st-gen NW & 2nd-gen $\uparrow$

- ▶ Consistent with an overall 0 effect if price effects are weak ($\approx$ constant crime rents)
- ▶ Which group substitutes vs. complements is governed by the elasticities σ_1 , $\sigma_2 \rightarrow$ ultimately an empirical question

▶ Formal model

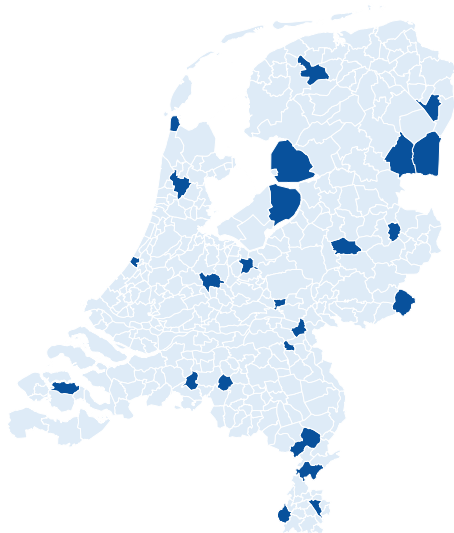
The opening of refugee centres 2014–2016

- ▶ **Shock:** 2014–2016 refugee inflow (mostly Syrian): 83,000 asylum requests in NL (*Algemene Rekenkamer, 2022*)
- ▶ **Rapid roll-out:** capacity pressures on the sheltering agency (COA) led to centres opening in 70 municipalities between Jan 2014 and Dec 2016
- ▶ **Half-yearly capacity decisions:** centres opened, closed, downsized, or expanded every six months by predicted need
- ▶ **Decision & criteria:** municipalities have no hosting mandate but had **limited scope to refuse** during the crisis. Openings driven by cost, even geographic distribution, and site flexibility/quality
- ▶ **Work ban:** refugees cannot work until they have a residence permit (≥ 6 months). Shuts down labour market competition channel

Asylum centres in the Netherlands, 2014–2016

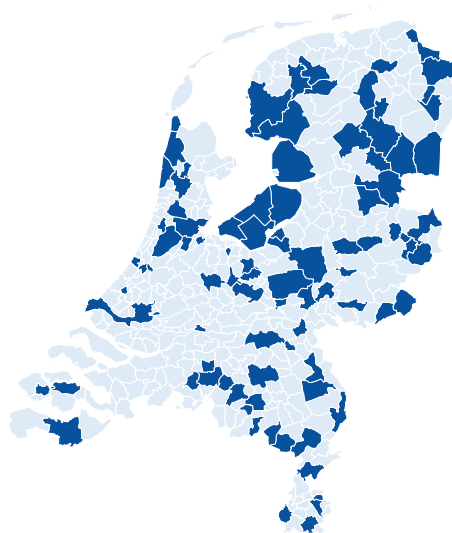
► Allocation

AZCs operating, 2013



No AZC AZC operating in 2013

AZCs operating, 2016



No AZC AZC operating in 2016

- ▶ Administrative microdata, Statistics Netherlands (CBS). Individual-year panel 2010–2021
→ Match sources via time-consistent individual identifier
 - ▶ **Demographics**: birth year, sex, generation, country of origin
 - ▶ **Address spells**: residential municipality at year-end
 - ▶ **Asylum cohort**: detailed data on arrival, placement municipality, status changes
 - ▶ **Crime**: police suspect register, incident–suspect link, co-offender pairs at the crime-id level
 - ▶ **Incidents and victimization data**: can match the victim of crimes (if known) in the data. Find out arrest history and gender of victims
- ▶ Sample: men aged 15–54, residing in matched treated or control municipalities
- ▶ **Note**: refugees identifiable only from 2014; pooled with 1st-gen non-Western in all analyses

Treatment and matching

- ▶ **Treatment:** living in a municipality in which refugee centre opened in $g \in \{2014, 2015, 2016\}$
- ▶ **Matching:** centres opened in rural areas
 - ▶ 1:1 propensity-score nearest-neighbour at municipal level, by treatment cohort, no replacement
 - ▶ Match (probit) on: baseline 1st-gen share, baseline population, lagged unemployment, lagged mean age, 4 lags of the arrest rate for non-traffic crimes
 - ▶ Match individuals to the municipality they live in
 - ▶ No double controls: each treated municipality has a unique control
- ▶ **67** out of **70** treated municipalities are matched

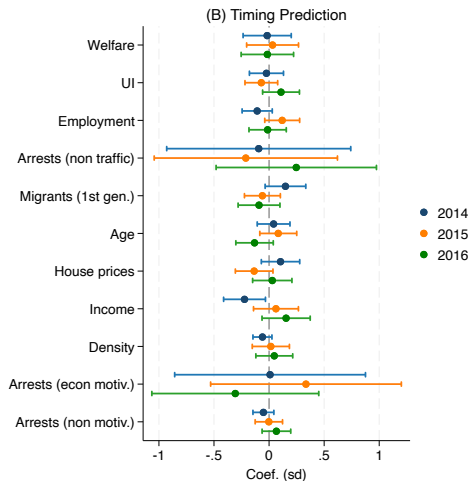
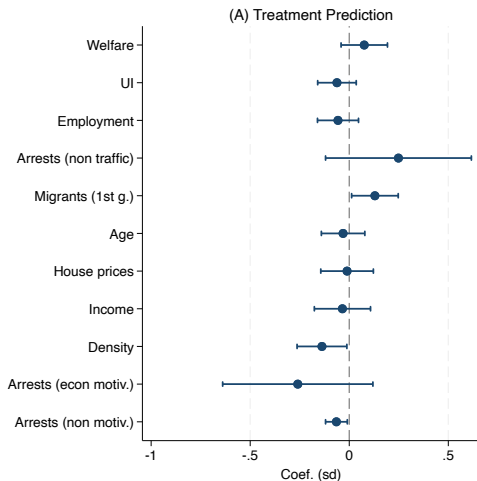
Balancing table: municipal-level pre-period covariates

	Unmatched				Matched			
	Treated	Control	<i>p</i> -value	Norm. diff.	Treated	Control	<i>p</i> -value	Norm. diff.
<i>Panel A. i-level</i>								
Age	35.287	35.762	0.032	−0.040	35.302	35.653	0.152	−0.030
First gen.	0.139	0.097	0.000	0.132	0.139	0.126	0.319	0.039
Second gen.	0.099	0.079	0.002	0.070	0.099	0.100	0.886	−0.003
Welfare	0.038	0.023	0.000	0.089	0.038	0.031	0.029	0.042
UI	0.060	0.055	0.003	0.027	0.060	0.059	0.446	0.008
Disability ben.	0.041	0.039	0.318	0.010	0.041	0.041	0.993	0.000
Employed	0.729	0.755	0.000	−0.062	0.729	0.744	0.069	−0.035
Arrest (ext.)	0.025	0.021	0.000	0.032	0.026	0.025	0.828	0.002
Number of arrests	0.028	0.023	0.000	0.033	0.029	0.028	0.669	0.003
Econ. mot.	0.023	0.018	0.000	0.033	0.023	0.022	0.792	0.002
Non-motivated	0.006	0.006	0.669	−0.002	0.006	0.007	0.059	−0.009
Obs.	1,220,000	2,180,000			1,220,000	963,000		
<i>Panel B. Municipal</i>								
House prices	225.7	251.7	0.004	−0.417	226.7	236.5	0.409	−0.149
Pop. density	1,107.7	800.8	0.063	0.284	1,018.1	1,335.3	0.147	−0.262
Population	86,398	31,631	0.001	0.607	66,353	54,116	0.136	0.270
Male pop.	42,477	16,256	0.000	0.605	33,312	27,154	0.114	0.275
Municipalities	69	258			67	67		

Exogeneity of openings

- ▶ Cannot predict openings on observables

▶ Politics

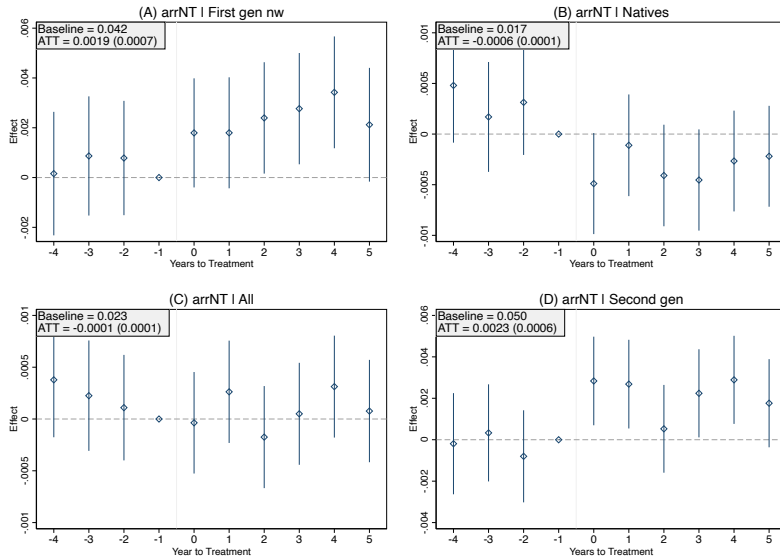


$$Y_{i,d,t} = \alpha_{d,t} + \phi_{i,d} + \sum_{\substack{\tau=-4 \\ \tau \neq -1}}^{+5} \beta_{\tau} \mathbf{1}\{t - T_d^* = \tau\} \cdot D_i + \varepsilon_{i,d,t} \quad (1)$$

- ▶ $Y_{i,d,t}$: outcome of interest
- ▶ $T_d^* \in \{2014, 2015, 2016\}$; $D_i = 1$ if i lived in a treated municipality at $t = T_d^* - 1$
- ▶ $\alpha_{d,t}$: cohort $\times$ year FE; $\phi_{i,d}$: individual FE
- ▶ Reference period: $\tau = -1$
- ▶ Per-cohort event-time window: $\tau \in [-4, +5]$
- ▶ Estimated for everyone and by immigration category: **All**, **Natives**, **1st-gen + refugees**, **2nd gen**

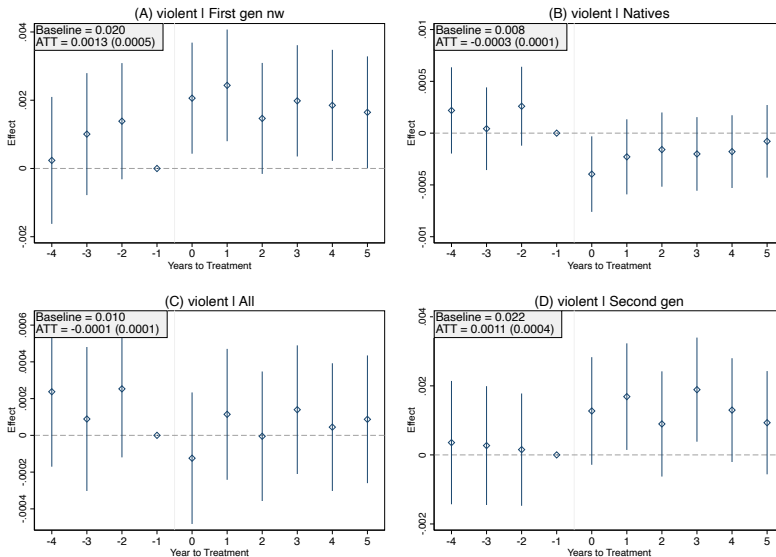
Main result: arrests (non-traffic), by migration background ► Intensive

Overall: 0 effect; 1st gen. NW ↗; natives ↘; 2ndgen ↗. Note: $S_{Fgen}\beta_{Fgen} + S_{Sgen}\beta_{Sgen} + S_{Nat}\beta_{Nat} \approx 0$



Main result: violent crime, by migration background

► Overall: 0 effect: 1st gen. NW ↗: natives ↘: 2ndgen ↗
► EconMotiv ► Property



Who are the displaced?

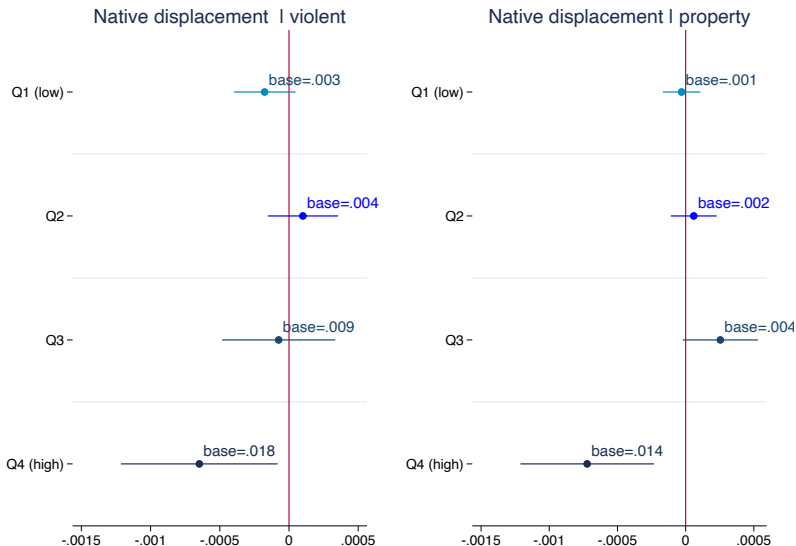
- ▶ DiD on arrests shows ↘ for natives
- ▶ But can we really speak of displacement out of crime?
- ▶ Understand **who** are the natives exiting criminal activities

Predict which natives are most likely to offend

- Run penalised logit to predict pre-treatment crime-risk for natives. **Idea:**
1. Devise a training and test sample (honest approach)
 2. Using $\tau = -2$ covariates, predict who is going to offend in $\tau = -1$. Check predictions against realizations in $\tau = -1$
 3. Assign individuals a score based on their likelihood to offend pre-treatment
 4. Run DiD by quartile of the propensity score

Penalized logit: results

- Displaced natives are those most likely to have offended pre-treatment [► Dis. arrests](#)



Networks: patterns in co-offending

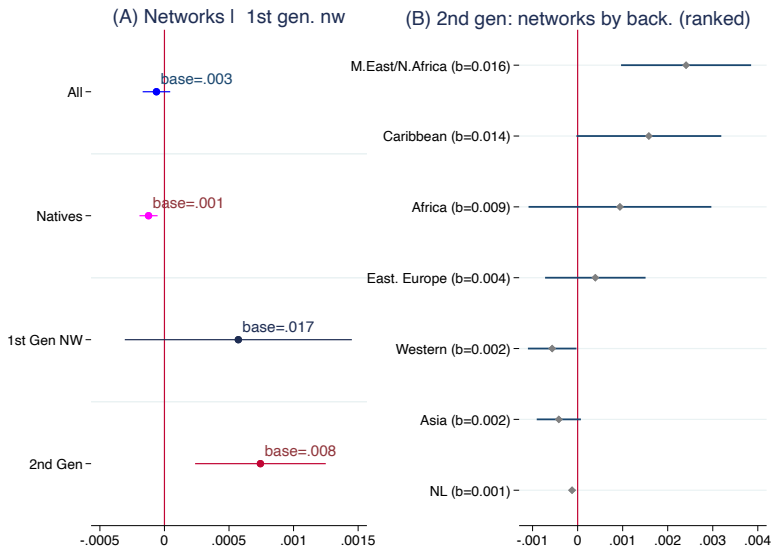
Questions

- ▶ Are the results (native ↘, 1st & 2nd gen ↗) reflected in co-offending?
- ▶ Is the ↗ for 2nd gen due to discrimination or a real increase in crime?
- ▶ Is there heterogeneity in 2nd gen responses to refugee inflows? → Some more complementary to refugees than others

Unique dutch police data

- ▶ Dutch police records a **unique arrest event code** → can track co-offending (netsize ≥ 2)
- ▶ From now on: *networks* $\iff$ co-offending in year y
- ▶ Check whether co-offending patterns **corroborate the main finding**
- ▶ Inspect co-offending with 1st gen. non-west. → unpack the 2nd gen response

(A) Main result reflected in co-offending (B) Sec. gen. with high propensity to co-offend with 1st gen.
 NW ↗ ↗

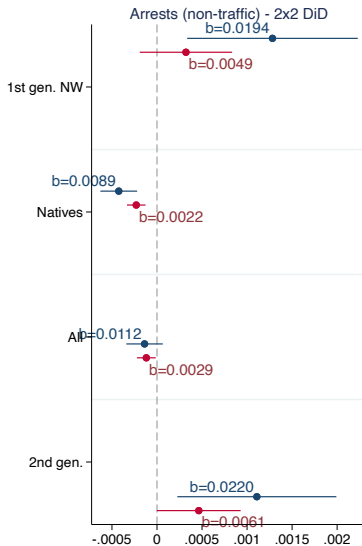
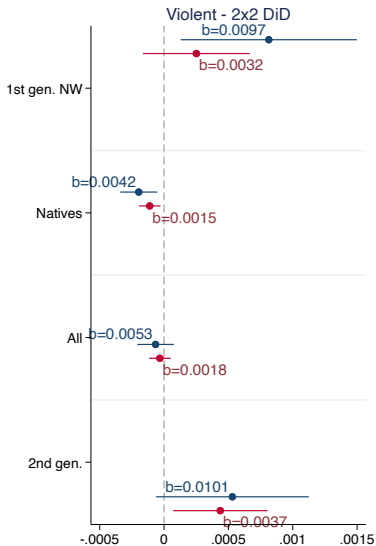


Why decompose?

- ▶ Main result shows that results are driven by **violent** arrests
- ▶ View violence as a key **input** in the production of criminal activities (i.e. fighting for the corners)
- ▶ If this is the case, we should see **relatively** larger effects **on** violence for previously arrested individuals ($\approx 10\%$ of victims)
- ▶ Investigate this using **unique victimization data**

PRELIMINARY - Arrests by victim type: clean victims vs arrested victims

Violent crimes by victim type → SecGen: 5% vs 12.2%, possibly due to between group competition



Placebo outcome: sexual crimes and unclassified crimes

► Sexual

► Other

→ Would not expect to be affected by migration flows → find 0 effect

Rule out domestic violence

- Distinguishes intimate / household violence (female victim) from street violence (male victim) → rule out that domestic violence drives our results on violent crime

Policing-capacity

- Monthly police priority calls reaction time around refugee centre openings
- No evidence of behavioural response by police

► ReactionTime

- ▶ **Bridge two stylized facts:**
 - ▶ Migrants are overrepresented in european prisons
 - ▶ Immigration has no causal effect on crime
- ▶ We provide evidence that **natives** are substituted out of the crime market, whereas **1st gen.** and some **2nd gen.** are drawn into crime
- ▶ **2nd gen.** with higher baseline propensity to offend with **1st gen.** offend more → complementarity
- ▶ Victimization data shows relatively larger effects on previously arrested individuals → possibly competition across groups (more work needed here)

Thanks for your attention!

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Groups differ in substitutability σ_j in crime production (Ottaviano & Peri, 2012):

$$C = [\theta_N N^{\rho_1} + \theta_M M^{\rho_1}]^{1/\rho_1}, \quad M = [\theta_R R^{\rho_2} + \theta_I I^{\rho_2}]^{1/\rho_2}, \quad \sigma_j = \frac{1}{1-\rho_j}.$$

Top: natives N vs non-Western composite M . Bottom: refugees R vs incumbents I .

Returns scale with a fixed illicit pie, $\pi_g = (\bar{P}/C) MP_g$; Fréchet productivity $\Rightarrow$ offending share $s_g \propto \pi_g^\kappa$.

Predictions after $R \uparrow$:

- ▶ Refugee crime $\uparrow$ (mechanical).
- ▶ Natives $\downarrow$ if **substitutes** ($\sigma_1 > 1$).
- ▶ Incumbent migrants $\uparrow$ if **complements** ($\sigma_2 < 1$).
- ▶ Aggregate sign ambiguous $\Rightarrow$ empirical.

Returns $\pi_g = (\bar{P}/C) \text{MP}_g$ with CES marginal products; in logs

$$\log \pi_N = \text{const} + \left(\frac{1}{\sigma_1} - 1\right) \log C - \frac{1}{\sigma_1} \log N.$$

Log-linearise $R \uparrow$ with $s_M = \theta_M M^{\rho_1} / C^{\rho_1}$, $s_R = \theta_R R^{\rho_2} / M^{\rho_2}$, so $d \log C = s_M s_R d \log R$ and $d \log M = s_R d \log R$. Using $s_g \propto \pi_g^\kappa$ (N, I fixed):

$$d \log s_N = \kappa \left(\frac{1}{\sigma_1} - 1 \right) s_M s_R d \log R < 0 \iff \sigma_1 > 1,$$

$$d \log s_I = \kappa s_R \left[\left(\frac{1}{\sigma_1} - 1 \right) s_M + \left(\frac{1}{\sigma_2} - \frac{1}{\sigma_1} \right) \right] d \log R > 0 \text{ if } \sigma_1 \geq 1, \sigma_2 < 1.$$

Refugees: the level shift in R dominates $\Rightarrow$ refugee crime $\uparrow$.

Sufficient for the empirical pattern: $\sigma_1 > 1$ (substitution), $\sigma_2 < 1$ (complementarity).

Appendix: the Dutch asylum system

- ▶ **Two agencies.** COA runs reception centres (AZCs) – shelter, guidance; IND processes asylum applications.
- ▶ **Arrival & allocation.** Register at *Ter Apel*, then within days moved to **the next available bed** (food, shelter, medical care, 40 EUR/week) ⇒ within-centre composition **plausibly exogenous** to municipal characteristics.
- ▶ **Confined & immobile.** Must stay until assigned permanent housing; **cannot** relocate to another centre.
- ▶ **Length of stay:** ≥ 6 months, often longer (social-housing congestion + administrative delays).
- ▶ **Labour-market ban.** No work before a residence permit; *only if* the IND has not ruled **within 6 months**, max **24 weeks/year** (employer also needs a work permit).
- ▶ **Three centre types.** POL (high turnover, first arrival, always open); *permanent* centres (applicants + awaiting housing); *emergency shelters* (quick open/close) – **our focus**.

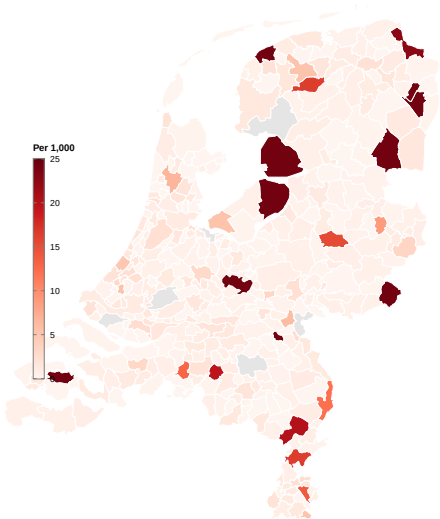
Procedure (more detail). Rest-and-preparation period (≥ 6 days) → *General Asylum Procedure* (IND interviews + decision, short track) → *Extended Procedure* if further investigation is needed → if granted, a temporary asylum residence permit (initially 5 years) unlocks full labour-market access. (*See Appendix B.*)

◀ Back to main slide

Allocation of refugees in NL: 2013 vs 2016

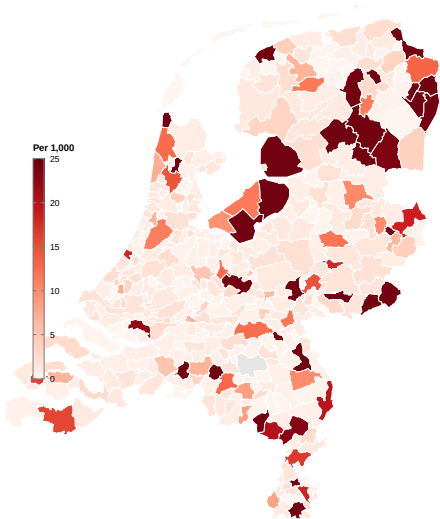
Refugee–origin immigration by municipality, 2013

Immigrants from Syria, Eritrea, Afghanistan, Iraq, Somalia, Iran per 1,000 pop.



Refugee–origin immigration by municipality, 2016

Immigrants from Syria, Eritrea, Afghanistan, Iraq, Somalia, Iran per 1,000 pop.

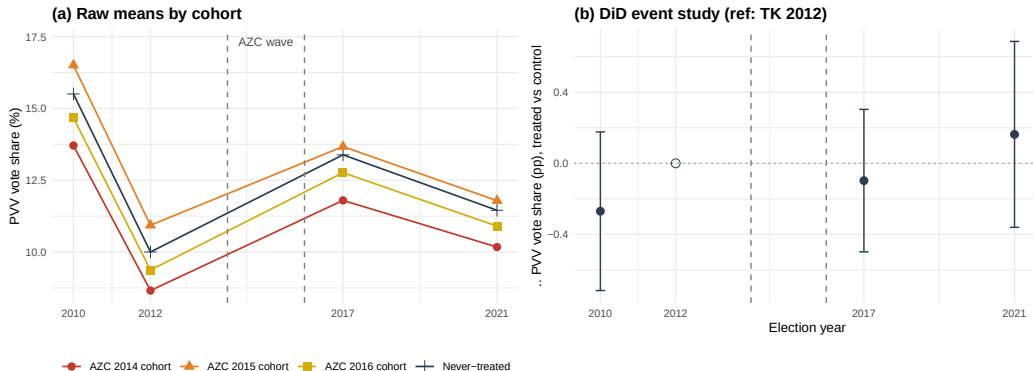


Exogeneity of openings: politics

- Political party in power locally does not explain openings [► Back](#)

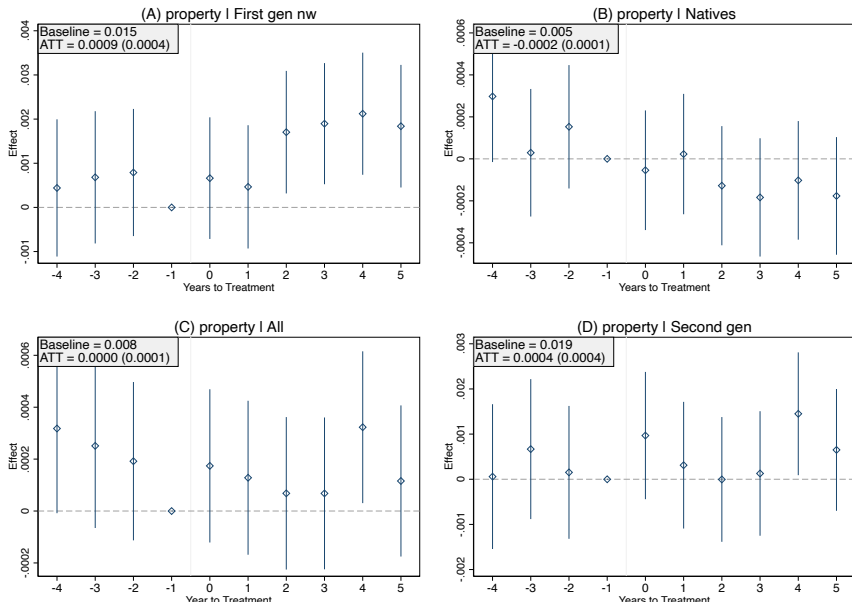
AZC openings and right-wing political composition

PVV vote share at Tweede Kamer elections, treated vs never-treated gemeenten

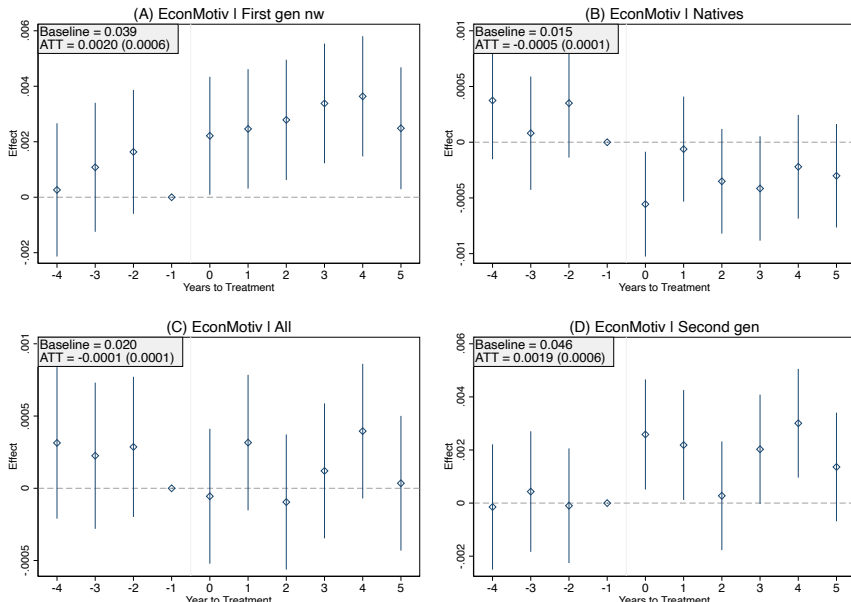


Sources: Kiesraad TK 2010, 2012, 2017, 2021; panel_refugee_centers_2017.dta.
95% CIs clustered by gemeente. Cohorts 2014–2016 only; pre-2014 and post-2016 openers excluded.

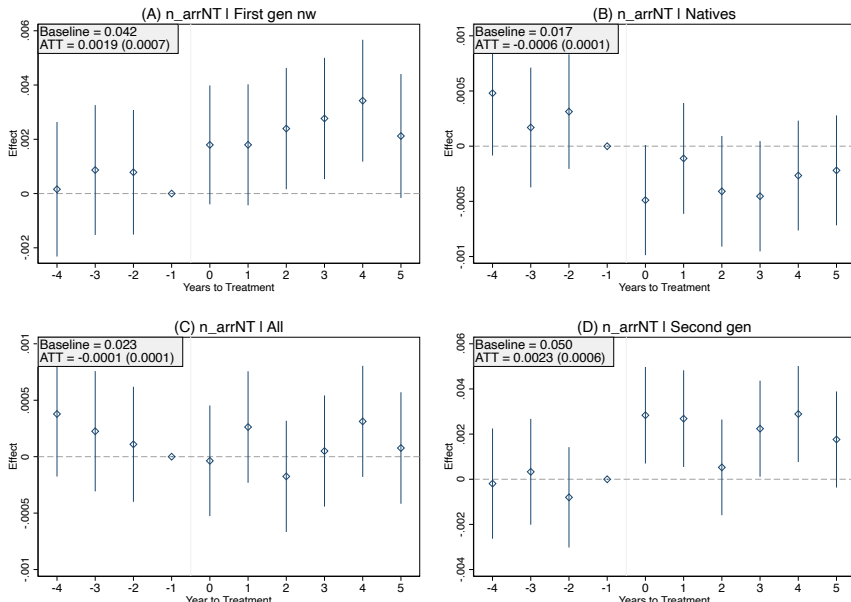
Main result: property crime, by migration background

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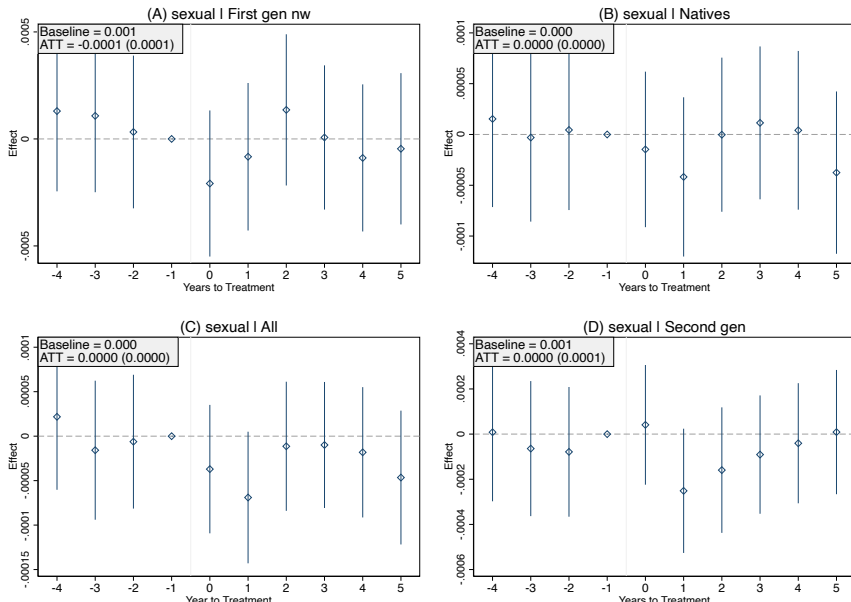
Main result: economically motivated crime, by migration background

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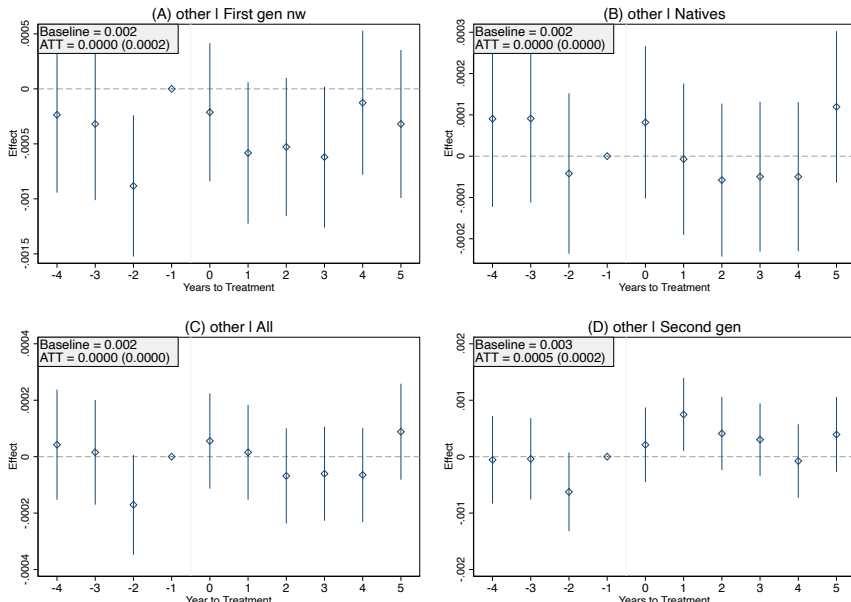
Main result: number of crimes (non-traffic), by migration background

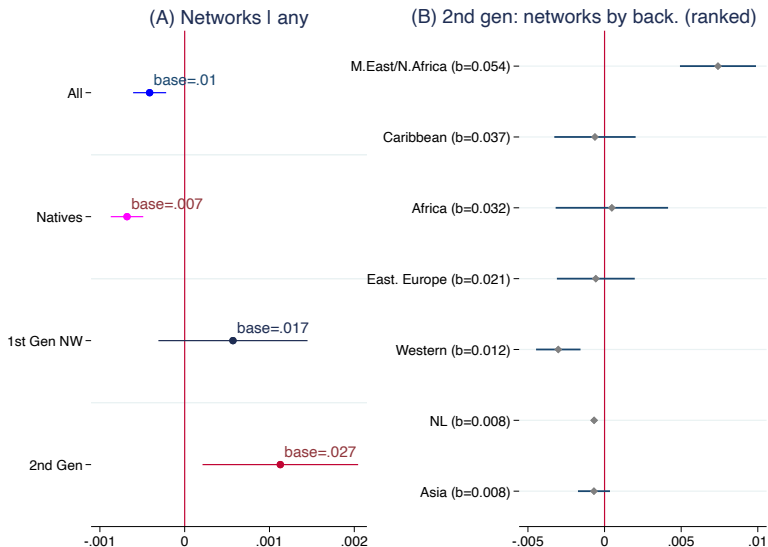
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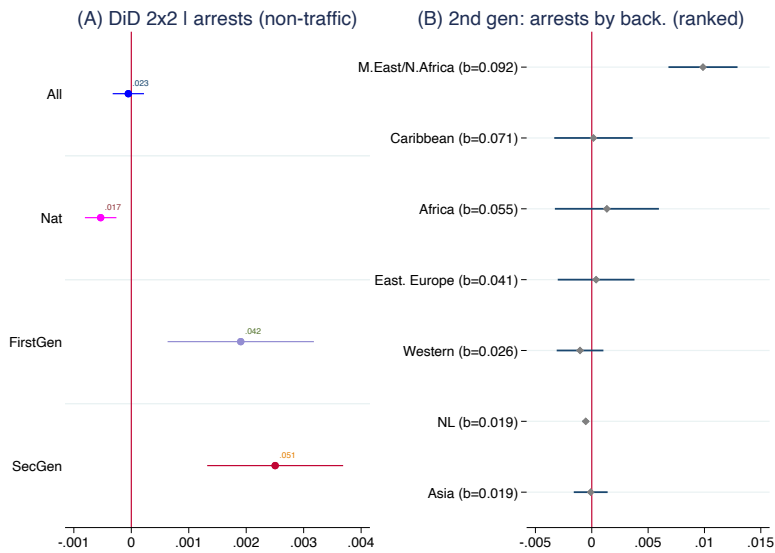
Main result: sexual crimes, by migration background

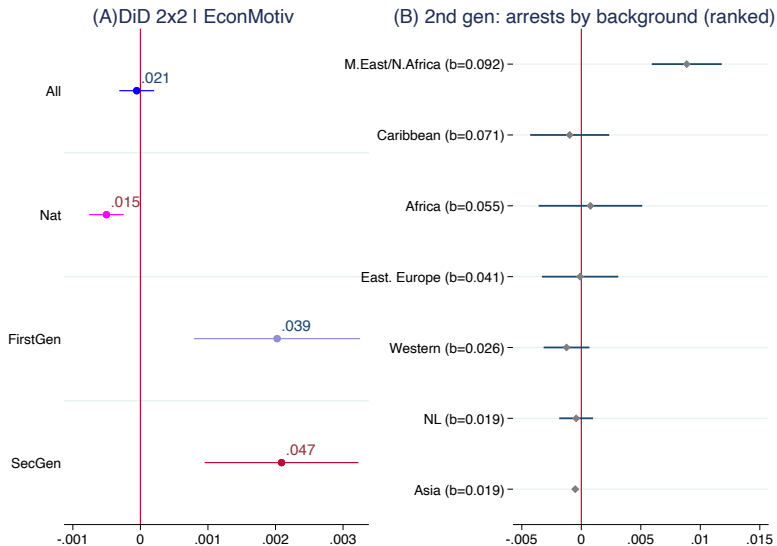
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Main result: unclassified crimes, by migration background

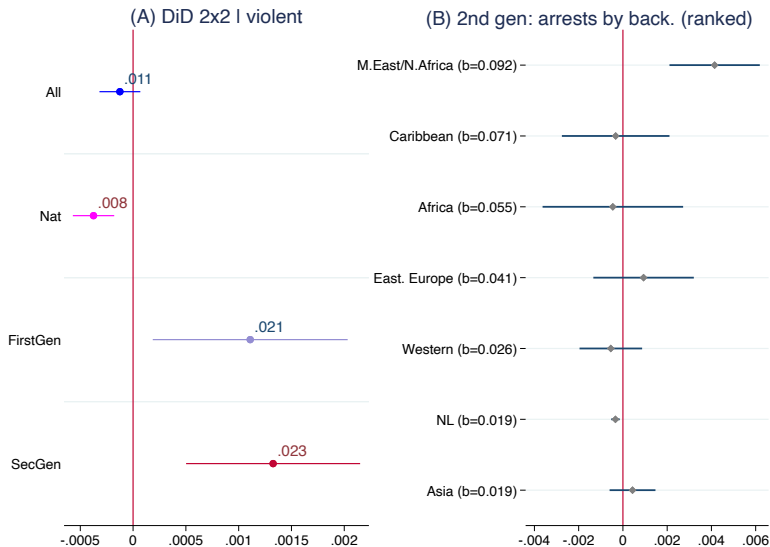
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Violent: 2x2 and **secon gen.** decomposition [▶ Back](#)



Definitions: immigration categories

Categories (GBAPERSOONTAB + ASIELCOHORT + MIGMOTIEFBUS):

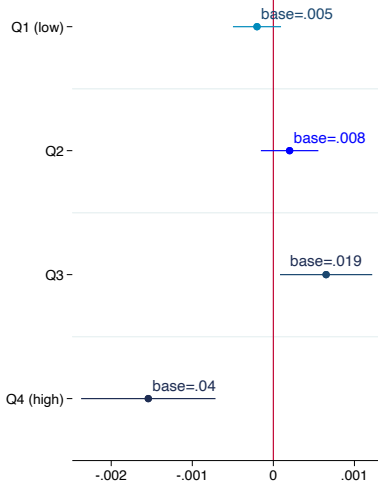
- ▶ **Natives** ($cat = 1$): born in NL, both parents born in NL
- ▶ **2nd-gen** ($cat = 2$): born in NL, ≥ 1 parent born abroad
- ▶ **Western 1st-gen** ($cat = 3$): excluded from analysis
- ▶ **Non-Western 1st-gen + refugees (combined)** ($cat \in \{4, 5\}$):
 - ▶ Refugees flagged from 2014 (MIGMOTIEFBUS codes 31, 32, 34, 35, 36; or ASIELCOHORT)
 - ▶ Pre-2014: refugees indistinguishable from other non-Western 1st-gen

Crime classification :

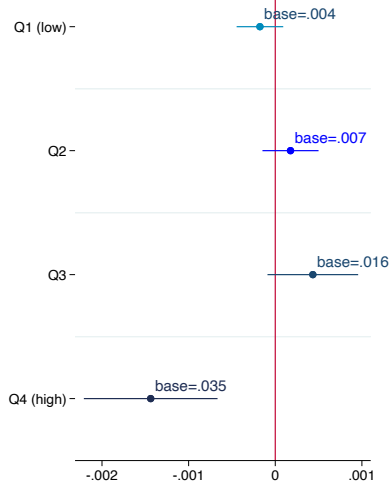
- ▶ Property: stealing, arson, petty property crime, auto theft
- ▶ Violent: assault, violent robbery, intimidation, attacks
- ▶ Sexual (placebo): rape, sexual assault, harassment
- ▶ Drugs: articles 2 and 3 of the opium law
- ▶ Traffic (placebo)
- ▶ Other: unclassified, vandalism

Economically motivated: property, violent, drugs. Non economically motivated: traffic, sexual, other

Native displacement | Arrests (non-traffic)



Native displacement | EconMotiv



Police reaction time to priority calls around opening event (Sun-Abraham)

Reaction time, 2015 + 2016 AZC openings, quarterly

