

Excluded by design: the effects of restricting neighbourhood access on incumbent residents

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- ▶ The **neighbourhood** we live in shapes our economic outcomes, social networks, and overall well being (e.g. Chetty et al., 2016)
- ▶ Literature focuses on **moves** into new environments to estimate contextual effects
- ▶ We study a unique policy affecting the composition and work incentives in selected neighbourhoods
- ▶ Do changes in neighbourhood composition and place-based incentives affect **incumbent** residents?

Research question(s)

- ▶ We study the effects of the *Rotterdam Wet*, a policy:
 - ▶ Banning workless individuals with less than 6 years of residency in the region from moving into selected disadvantaged neighbourhoods
 - ▶ Displacing residents with less than 6 years residency at lease renewal if they are workless
- ▶ Did the policy affect the composition of targeted neighbourhoods?
- ▶ Did changes in neighbourhood composition and incentives affect long-term residents? Look at:
 - ▶ Labour market outcomes & benefits dependence
 - ▶ Criminal behaviour
 - ▶ Children and teenage schooling outcomes
- ▶ Disentangle incentive effects from peer effects
 - ▶ Do conditionalities on housing spur employment?
 - ▶ Do changes in peer composition affect adult outcomes?

Agenda

1. Related literature
2. Institutional context
3. Descriptives and sample selection
4. Difference-in-differences and direct effects of the policy
5. Incumbents analysis and indirect effects
6. Triple differences and threat effects
7. Heterogeneity analysis using causal forests

Related literature

Neighbourhood effects

- ▶ **Long-run youth outcomes:** Chetty and Hendren (2018); Chyn and Katz (2021); Chyn (2018); Derenoncourt (2022); Britto et al. (2022); Kawano et al. (2024); Webbink et al. (2025); Carrillo et al. (2023); **through school quality** Laliberté (2021); **peers** Deutscher (2020); Chetty et al. (2026)
- ▶ **Adult health outcomes:** Ludwig et al. (2012); Hasager and Jørgensen (2024)

→ **We show neighbourhoods influence adult employment, welfare, and criminal behaviour through place-based incentives**

Welfare dependence: Dahl et al. (2014); Card and Hyslop (2005); Dahl and Gielen (2021)

→ **Investigate whether local peer composition affects welfare dependence**

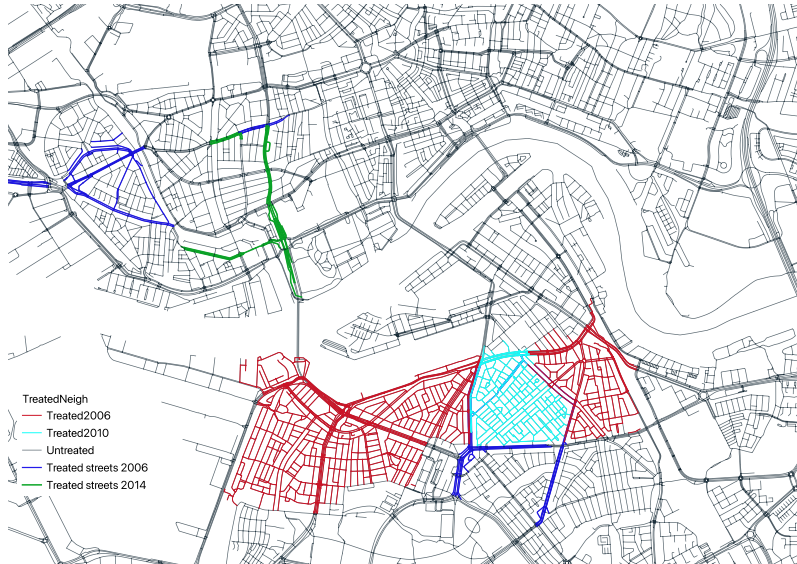
Sorting and amenities

- ▶ **Ethnic sorting** Card et al. (2008); **school quality** Bayer et al. (2007); **crime** Autor et al. (2017)
- ▶ **Role of expectations and stigma:** Bayer et al. (2016); Govind et al. (2025); Koster and Van Ommeren (2024)

→ **We show moving restrictions can significantly alter sorting patterns.** Future analyses will look at the effects on **excluded** individuals

- ▶ Bars workless if living < 6 years in Rotterdam region from moving within or into neighbourhoods and selected streets
 - ▶ Workless in-movers are barred
 - ▶ Workless incumbents whose lease expires or move within-neighbourhood are displaced
 - ▶ Applies to all housing in the regulated sector ($< 615\text{€}$ rent in 2006)
 - ▶ Around 75% of housing in treated areas is rented in 2006, virtually all fall under the regulated rent
 - ▶ We drop all individuals in neighbourhoods in which only some streets are treated
- ▶ Enforced between 2006 and 2022 in parts of R'dam
- ▶ Policy intention
 - ▶ Improve liveability and social mix in targeted areas
 - ▶ Municipality has discretion to decide which neighbourhoods to target ▶ Crit.

The Rotterdam Wet II



- ▶ Administrative data from Statistics Netherlands. Construct panel of all individuals having lived in Rotterdam from 1999 to 2019 → Match all sources via time-consistent* individual and household identifiers
 - ▶ **Housing** spells for all individuals in the *Gemeentelijke Basisregistratie (GBA)*
 - ▶ **Demographics**: age, gender, migration background, origin, marital status, marriage divorce year
 - ▶ **Household** characteristics: number of children, household composition, household type
 - ▶ **Employment**: Employment income from the job in which most hours are worked, contract type (flexible/non-flexible)
 - ▶ **Government benefits**: welfare (*bijstand*), unemployment benefits (*WW*), disability/sickness benefits (*AOW*)
 - ▶ **Education**: exam scores, schooling establishment, and exam location for the test passed at 11-12 (*cito toets*), and the final exam (*centraal examen*). Additional information on in-school scores, teacher advice, and language spoken at home
 - ▶ **Crime**: data from Dutch courts. Information on crime type, time of crime, municipality in which crime is committed

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Descriptives: neighbourhood composition

► Share in employment ↗, share on welfare ↘

► Inflows

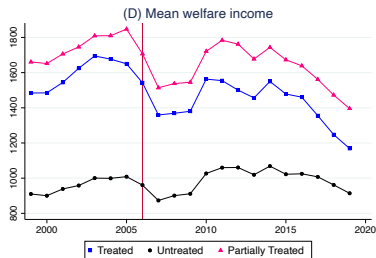
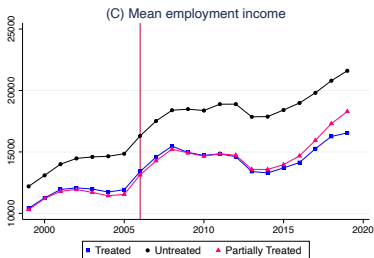
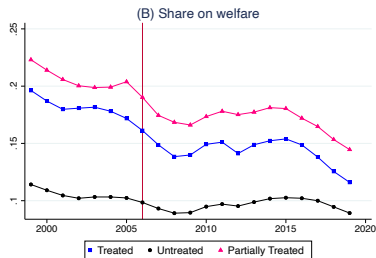
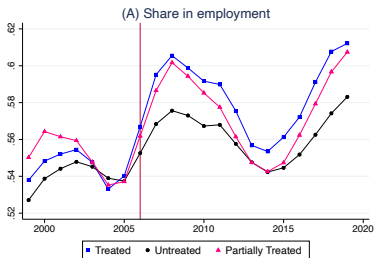
► Turnover

► Add. stat.

► Add. in

► Out.

► Add. out



Balancing table: full sample - R'dam region & the Hague ► Kclust

	Full Sample				K-clust. trim			
	Treated	Control	Norm. Diff	P-val	Treated	Control	Norm. Diff	P-val
Age	38.28	41.44	-0.253	0.000	38.28	39.04	-0.061	0.262
Male	0.53	0.50	0.054	0.000	0.53	0.51	0.033	0.006
Single parent	0.10	0.08	0.075	0.001	0.10	0.11	-0.037	0.130
Turkish	0.16	0.05	0.368	0.004	0.16	0.09	0.208	0.086
Moroccan	0.07	0.03	0.184	0.000	0.07	0.08	-0.011	0.809
Antillian	0.05	0.02	0.166	0.000	0.05	0.04	0.078	0.033
Surinamese	0.12	0.07	0.185	0.000	0.12	0.14	-0.033	0.397
Native	0.37	0.65	-0.577	0.000	0.37	0.43	-0.118	0.315
First Gen.	0.52	0.26	0.548	0.000	0.52	0.46	0.113	0.288
Second Gen.	0.11	0.09	0.064	0.005	0.11	0.11	0.003	0.886
Crime	0.02	0.01	0.087	0.000	0.02	0.02	0.025	0.039
Employed	0.60	0.68	-0.148	0.013	0.60	0.62	-0.033	0.589
Welfare	0.19	0.08	0.313	0.000	0.19	0.15	0.094	0.122
Unemployment	0.08	0.05	0.108	0.000	0.08	0.06	0.062	0.000
Sickness Ben.	0.10	0.09	0.057	0.004	0.10	0.10	-0.004	0.853
Obs. (N)	36,714	899,676			36,714	245,262		

Empirical model: event study difference-in-differences

$$Y_{i,n,t} = \alpha_t + \phi_i + \sum_{k=-4}^{-2} \beta_k^{pre} [\mathbb{1}\{G_i = g\} \cdot \mathbb{1}\{t - 2006 = k\}] + \sum_{k=0}^9 \beta_k^{post} [\mathbb{1}\{G_i = g\} \cdot \mathbb{1}\{t - 2006 = k\}] + \varepsilon_{i,n,t} \quad (1)$$

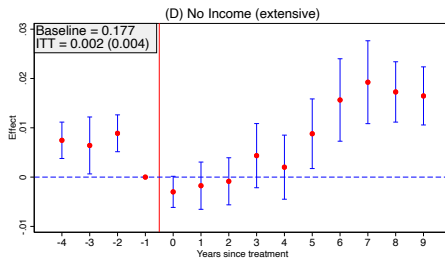
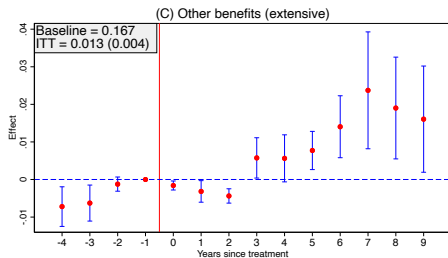
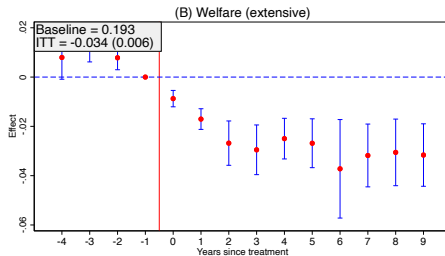
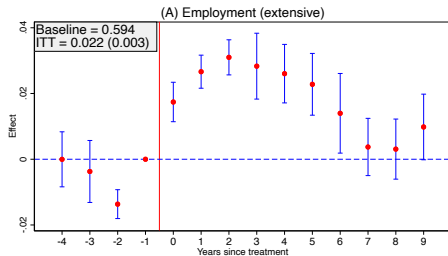
- ▶ $Y_{i,n,t}$: outcome of interest
- ▶ β_t : coefficient of interest for year t
- ▶ $\mathbb{1}\{G_i = g\}$: indicator function for treated neighbourhoods
- ▶ $\mathbb{1}\{t - 2006 = k\}$: indicator for time relative to 2006
- ▶ Estimate on **two samples**
 - ▶ All individuals: compositional effect + indirect effect on incumbents = total effect
 - ▶ Residents living in the same neighbourhood in the two years before treatment: isolate the policy effect on incumbents

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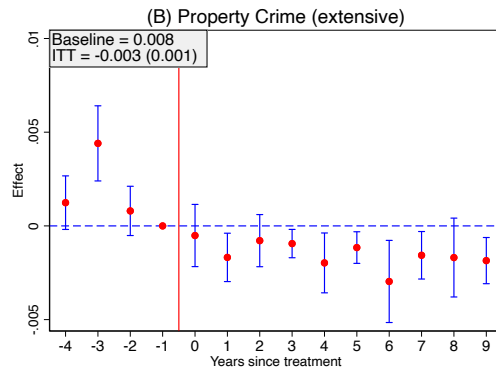
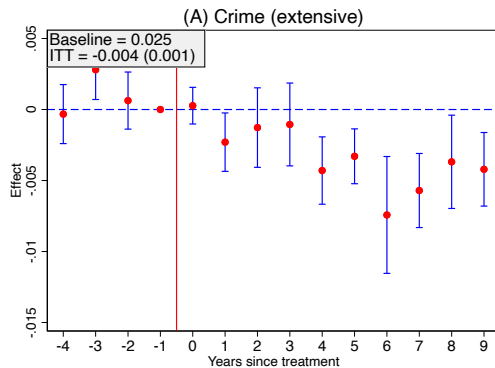
Results: labour market and welfare outcomes - all individuals

- Employment ↗ by 3 pp (5.6%); welfare take-up ↘ by 2.2 pp (12.9%) ► Int. margin



Results: crime - all individuals

- Criminal offences ↘ by 0.32 pp (14.6%)



Beyond sorting: why focus on incumbents?

- ▶ The Rotterdam Wet mechanically reduces the entry of workless individuals

Looking at incumbents

- Isolates the **behavioural response** of a population to changes in place-based incentives (threat of displacement) and peer composition
- Look at how existing residents alter their labour and welfare decisions

Sample definition

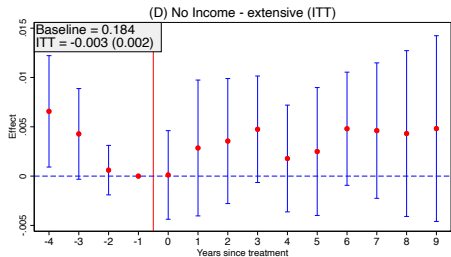
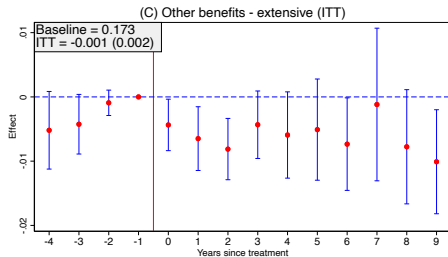
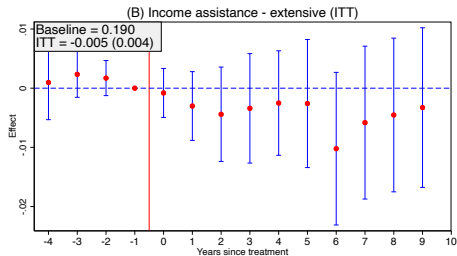
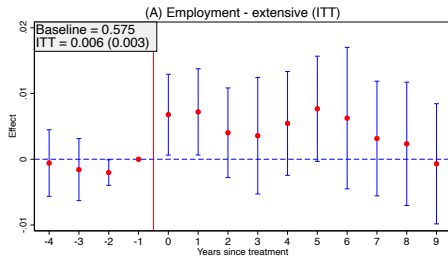
- ▶ Individuals residing in the exact same neighbourhood in the two years prior to treatment (2004 and 2005) [▶ Table](#)
- ▶ Do not condition on individuals staying post treatment → intention to treat (**ITT**)

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Results: labour market and welfare - incumbents [▶ Move](#)

▶ Employment ↗ by 0.8 pp (1.3%); welfare take-up ↘ by 0.45 pp (2.4%) [▶ Int. margin](#) [▶ Crime](#) [▶ WOZ](#)



Adding a third difference: the 6-year rule

- ▶ The policy's housing restrictions specifically target workless individuals with **less than 6 years** of regional residency.

Mechanisms: disentangling the response

- **Targeted incumbents** (< 6 years): face the direct **threat of displacement** at lease renewal
- **Exempt incumbents** (≥ 6 years): experience shift in **peer composition**
- Isolate displacement threat, do not rule out peer effects: peers could matter only for the **targeted**

A cleaner counterfactual

- Sweeps out time-varying neighbourhood confounders (e.g. other local policies or gentrification trends)
- Uses exempt long-term residents living in the *exact same streets* as a comparable, within-area control group

Model: triple difference

$$\begin{aligned} Y_{i,n,t} = & \alpha_t + \phi_i \\ & + \sum_{\substack{k=-4 \\ k \neq -1}}^9 \gamma_k [\mathbb{1}\{G_i = g\} \cdot \mathbb{1}\{t - 2006 = k\}] + \sum_{\substack{k=-4 \\ k \neq -1}}^9 \delta_k [\textcolor{red}{S}_i \cdot \mathbb{1}\{t - 2006 = k\}] \\ & + \sum_{k=-4}^{-2} \beta_k^{pre} [\mathbb{1}\{G_i = g\} \cdot \textcolor{red}{S}_i \cdot \mathbb{1}\{t - 2006 = k\}] + \sum_{k=0}^9 \beta_k^{post} [\mathbb{1}\{G_i = g\} \cdot \textcolor{red}{S}_i \cdot \mathbb{1}\{t - 2006 = k\}] \\ & + \varepsilon_{i,n,t} \end{aligned} \tag{2}$$

- ▶ Add a third interaction dummy $\textcolor{red}{S}_i$, equal to one if i living < 6 years in R'dam region
- ▶ $\mathbb{1}\{G_i = g\}$:= indicator for treated neighbourhoods
- ▶ $\mathbb{1}\{t - 2006 = k\}$:= indicator for time relative to 2006
- ▶ Interaction $\mathbb{1}\{G_i = g\}$ and S_i (treatment $\times$ 6 years) is absorbed by the individual FE

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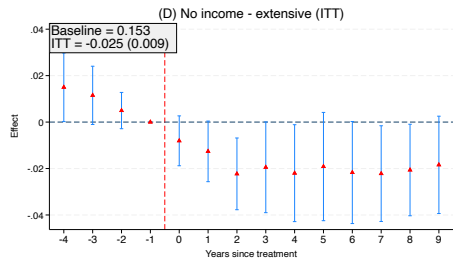
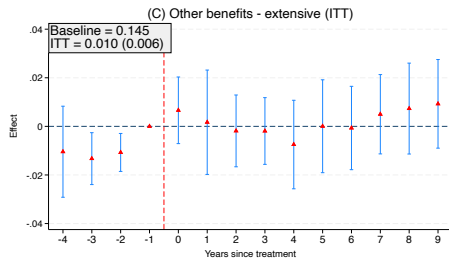
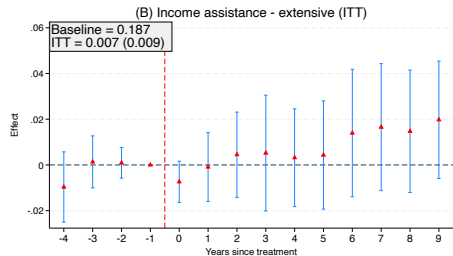
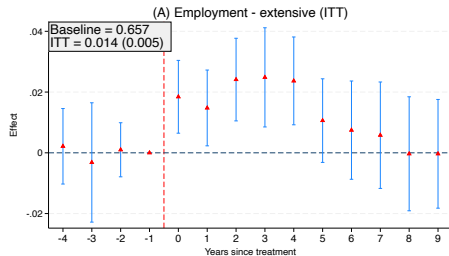
Balancing table: incumbents triple difference (age 20-45)

	Treated		Control		P-val DiD	Norm.DiD
	- 6 years	+ 6 years	- 6 years	+ 6 years		
Age	30.09	33.69	30.28	34.17	0.288	-0.045
Male	0.53	0.51	0.52	0.49	0.474	0.027
Single head hh	0.09	0.13	0.08	0.16	0.000	-0.168
Turkish	0.11	0.23	0.06	0.10	0.007	0.275
Moroccan	0.08	0.09	0.06	0.09	0.100	-0.069
Antillian	0.04	0.03	0.06	0.03	0.002	-0.093
Surinamese	0.11	0.14	0.08	0.13	0.068	-0.068
Native	0.28	0.34	0.40	0.44	0.507	0.051
First Generation	0.64	0.51	0.49	0.39	0.214	-0.079
Second Generation	0.08	0.15	0.11	0.16	0.180	0.050
Criminal Record	0.03	0.02	0.02	0.02	0.100	-0.054
Employed	0.64	0.68	0.69	0.71	0.384	0.039
Welfare	0.17	0.18	0.12	0.16	0.101	-0.091
Unemployment Insurance	0.08	0.09	0.05	0.08	0.023	-0.050
Sickness Benefits	0.06	0.08	0.04	0.07	0.331	-0.020
Observations (N)	5,647	14,629	15,484	43,704		

Results: labour market and welfare - incumbents - triple diff.

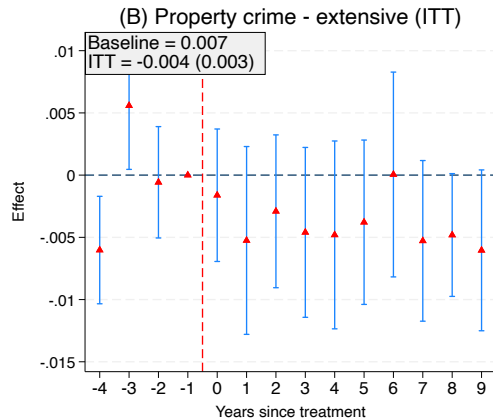
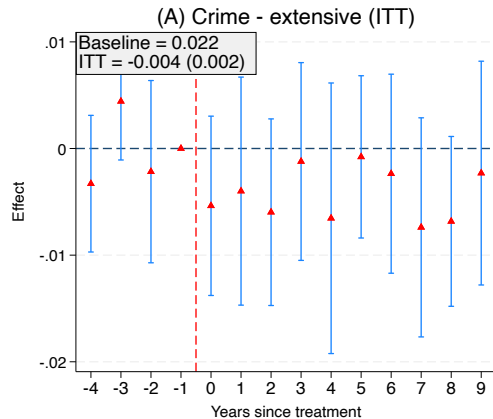
[▶ HeadHH](#)[▶ HadKids](#)[▶ Move](#)

▶ Employment ↗ by 1.75 pp (2.65%); undeclared income ↘ by 2.1 pp (13.7%)

[▶ Int. margin](#)[▶ WOZ](#)

Results: crime - incumbents - triple diff.

- Criminal offences by incumbent residents ↘ by 0.5 pp (22.7%) [WOZ](#)



Heterogeneity analysis with causal forests

- ▶ Find out **who** reacts to the policy
- ▶ **Causal forests** identify all interactions and non-linearities determining TE heterogeneity
- ▶ Estimate the Conditional Average Treatment Effect (CATE)

$$CATE = E[Y_{1i} - Y_{0i} | X_i = x] \quad (3)$$

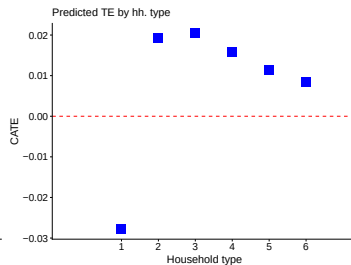
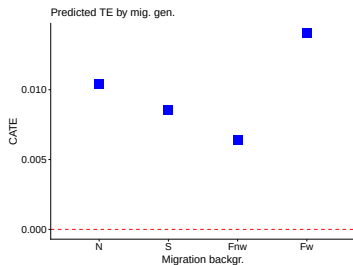
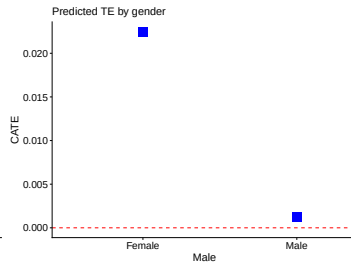
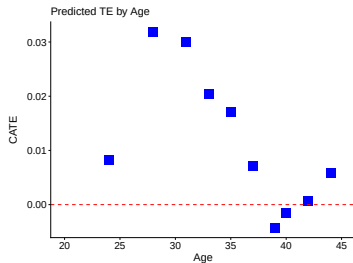
- ▶ Assess heterogeneity by all observable variables on the triple difference estimate
- ▶ **Intuition:** the algorithm splits the data by maximizing an objective function to maximize across-leaf variance in treatment effects while minimizing within-leaf variance

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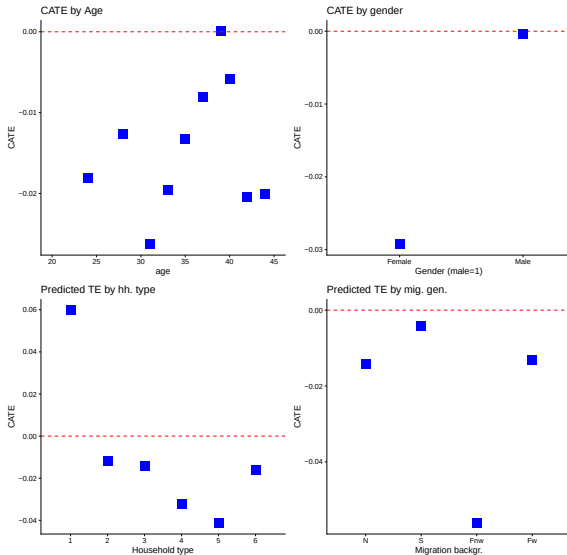
Heterogeneity: employment (extensive)

- ▶ Young women drive the effects (CATE=0.03) ▶ [Inter.](#)



Heterogeneity: having no legal income

- Driven by women and non-western migrants (CATE= -0.04)

[► Inter.](#)[► OB](#)[► InterOB](#)[► Welf](#)[► InterW](#)

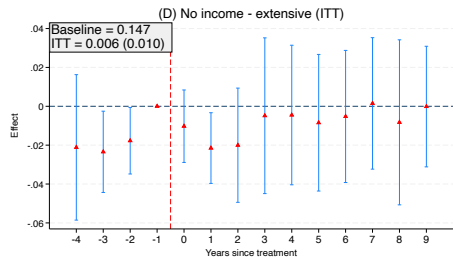
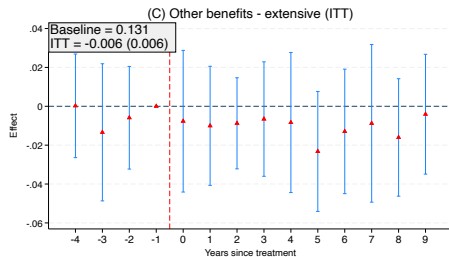
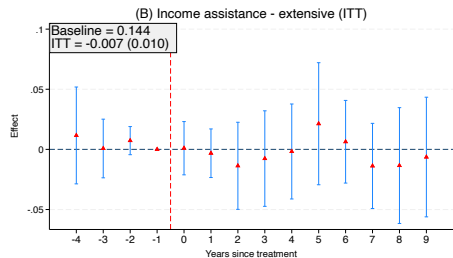
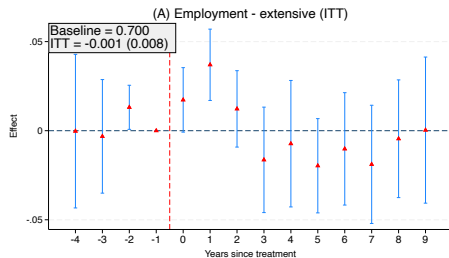
Placebo: re-run analysis on random neighbourhoods - incumbents

► Spill

► Crime

► Indirect

► Ind. crime



Conclusion & next steps

- ▶ Study a unique policy banning workless individuals from moving into specific neighbourhoods
- ▶ Policy $\nearrow$ the share of residents in employment, $\searrow$ share of residents on welfare, and $\searrow$ share of criminal offenders
- ▶ Indirect effects on **incumbent** residents: $\nearrow$ employment, $\searrow$ informal work, $\searrow$ criminal offences
- ▶ Triple difference suggests threat effects of policy spurred work adoption
- ▶ Future analyses will look at possible role of **peer effects**

Thanks for your attention!

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Criteria selection R'dam wet

- ▶ To be included a neighbourhood needs to have > 5.000 housing units, 25% of inhabitants without a paid job, and/or 45% households with a 'low income'
- ▶ Minister has to grant permission for the law to be applied in a neighbourhood, and its application has to be extensively justified by the municipality
- ▶ Municipality targeted neighbourhoods based on:
 - ▶ *Problem cumulation score*: a weighted average of 12 objective indicators (% single-family houses; % vacancy ; % long-term housing ; % overcrowding; % unemployed jobseekers; % cheap private housing; % newcomers (individuals < 2 years in NL); % receiving benefits; % mobility (moving); % WOZ-value per room; % reports from neighbors; % reports on violence). Weights unknown
 - ▶ Eventually (but not sure when) switched to the *Liveability score*, which is also an indicator of neighbourhood quality. It relies on a (high) number of neighbourhood level indicators. The weights are determined through surveys asking residents to rank the variables by importance
- ▶ The selection process is not transparent. Based on these indicators and observables in the admin data, it looks like other neighbourhoods in R'dam were just as vulnerable as treated areas but were not selected

Share of residents with a migration background

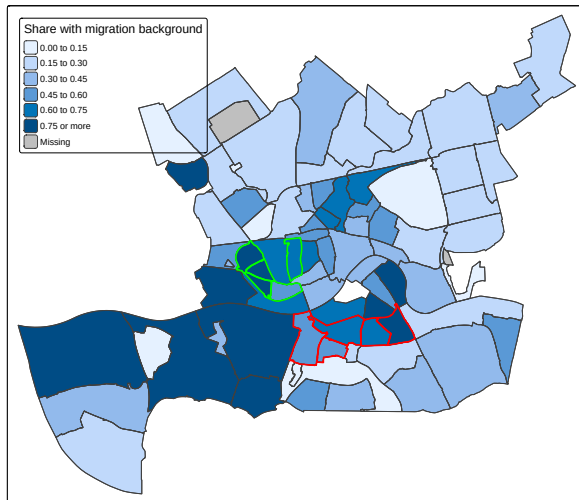
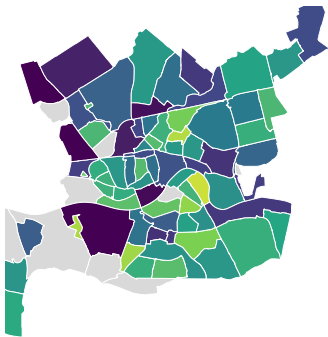
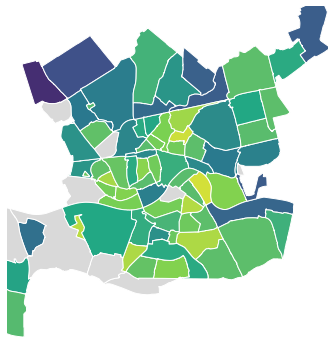


Figure: Share of residents with a migration background by neighbourhood in Rotterdam. Source: CBS Statline.

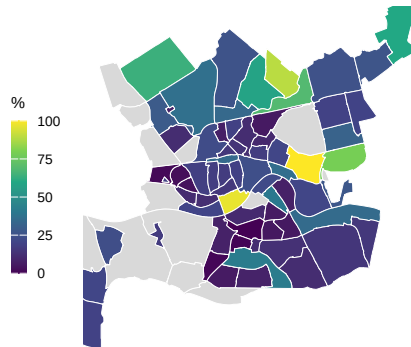
(A) Public housing share
2009



(B) Rental housing share
2009



(C) Mean property value
2006



Neighbourhood signalling score by neighbourhood

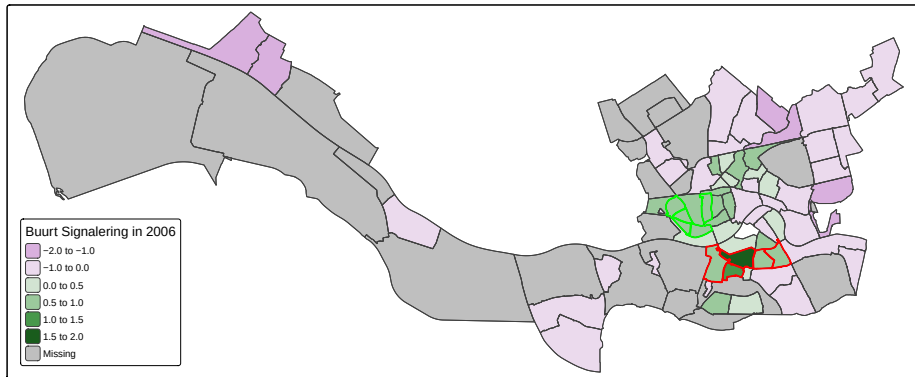


Figure: Neighbourhood signalling (*Buurt signalering*) score by neighbourhood in Rotterdam

Share of residents perceiving welfare benefits

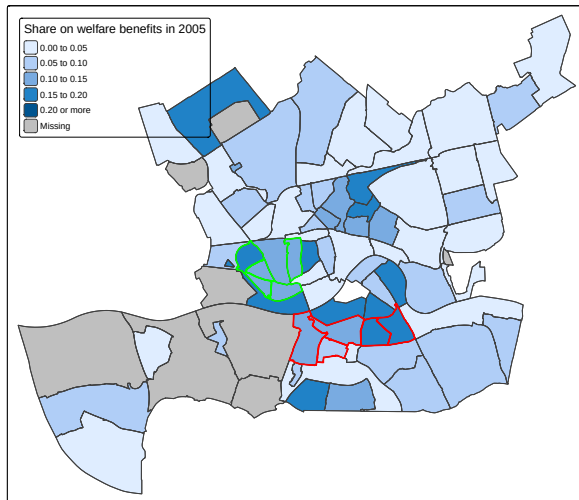


Figure: Share residents perceiving welfare benefits by neighbourhood in Rotterdam. Source: CBS Statline.

Liveability score by neighbourhood

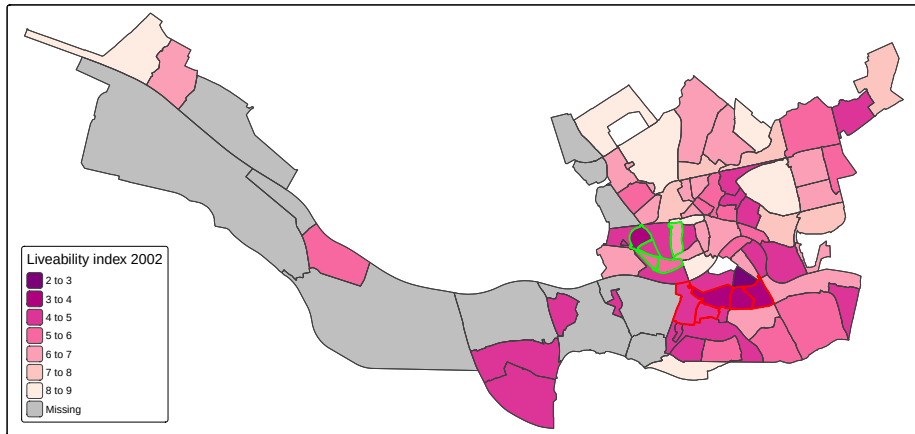


Figure: Liveability score (*leefbarometer*) by neighbourhood in Rotterdam

- ▶ **Data correction:** Feb 26, 2005, Rotterdam erroneously added 25,000 individuals—excluded from all analyses
- ▶ **Demographics**
 - ▶ First-gen migrants: born abroad, 1 parent born abroad
 - ▶ Second-gen migrants: born in NL; origin = mother's birth country, or father's if mother born in NL
- ▶ **Work & Benefits**
 - ▶ **Flexible jobs:** temp agency, 0-hour contracts; **Stable:** all others
 - ▶ Welfare, unemployment (UI), and sickness/disability (DI) benefits merged (DI = sickness + disability)
- ▶ **Education**
 - ▶ *Cito Toets* (age 11–12) from 2007 to 2019 and *Eind Examen* (end of high school), from 2006 to 2019
 - ▶ Data on attainment (all years) + enrolment (2003–2019)
- ▶ **Crime**
 - ▶ Court records (2001–2019); 5 categories: property, violent/sexual, traffic, drug, other
 - ▶ Use residence, not location of crime (Damm and Dustmann, 2014)

Descriptives: balancing table - all residents

Table: Descriptive statistics on individuals in treated and control neighbourhoods

Variable	Group		P-Value
	Treated	Control	
Age	42.14	47.30	0
Single parents	0.10	0.09	0
Turkish Origin	0.15	0.05	0
Moroccan Origin	0.07	0.04	0
Antillian Origin	0.05	0.02	0
Surinam Origin	0.12	0.07	0
Native	0.41	0.63	0
1st Gen. Migrant	0.48	0.27	0
2nd Gen. Migrant	0.11	0.10	0
Crime	0.02	0.01	0
Welfare	0.17	0.10	0
Unemployment	0.07	0.05	0
Disability	0.09	0.07	0

Descriptives: balancing table - incumbent residents

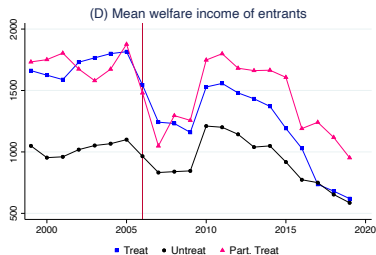
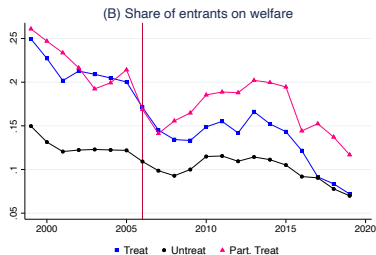
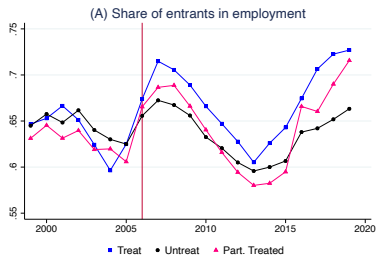
Variable	Group		P-Value
	Treated	Control	
Sge	42.14	47.30	0.00
Single Parents	0.097	0.086	0.00
Turkish Origin	0.148	0.048	0.00
Moroccan Origin	0.069	0.038	0.00
Antillian Origin	0.048	0.024	0.00
Surinam Origin	0.116	0.074	0.00
Native	0.413	0.635	0.00
1st Gen. Migrant	0.478	0.270	0.00
2nd Gen. Migrant	0.110	0.095	0.00
Crime	0.021	0.0109	0.00
Welfare	0.174	0.104	0.00
Unemployment	0.068	0.046	0.00
Disability	0.0888	0.068	0.00

Descriptives: balancing table - residents receiving welfare benefits

	Group	
	Treated	Control
Age	41.40	43.60
Turkish Origin	0.20	0.11
Moroccan Origin	0.12	0.13
Antillian Origin	0.11	0.08
Surinam Origin	0.14	0.15
Native	0.21	0.30
1st Gen. Migrant	0.70	0.60
2nd Gen. Migrant	0.09	0.10
Single Parent	0.23	0.28
Crime	0.05	0.04
Welfare	1.00	1.00
Unemployment	0.04	0.04
Disability	0.04	0.04

Descriptives: inflows into neighbourhoods

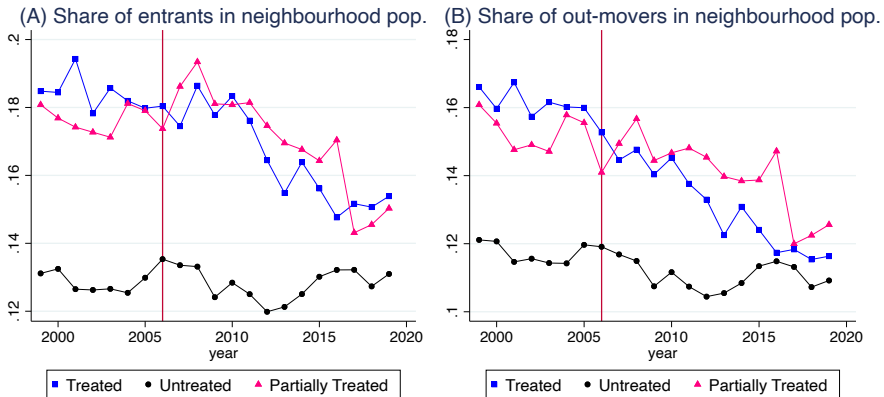
► Share of entrants on welfare ↘ ↘, share of entrants in employment ↗ ↗ [► Back](#)



Summary statistics: share of entrants and leavers

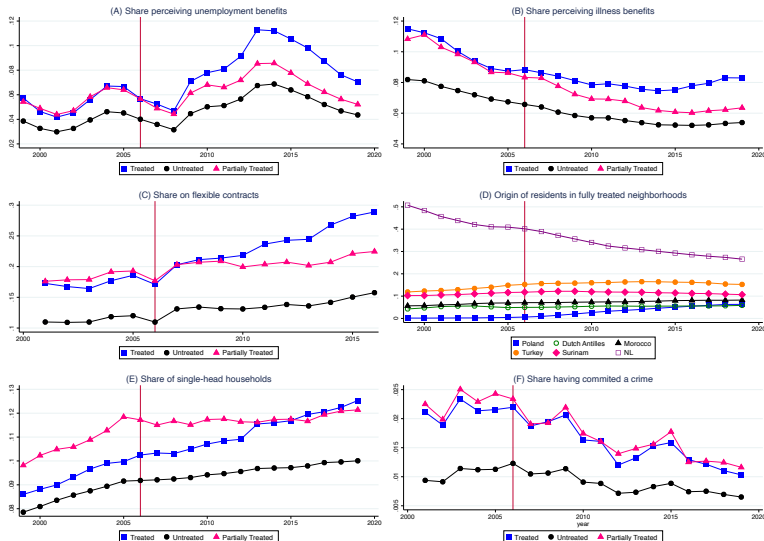
► Turnover ↘

► Back



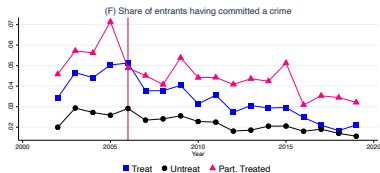
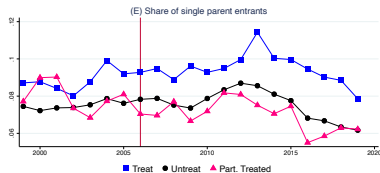
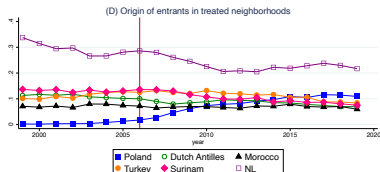
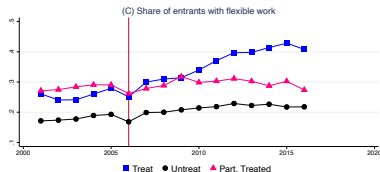
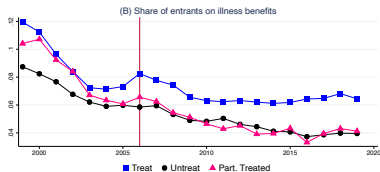
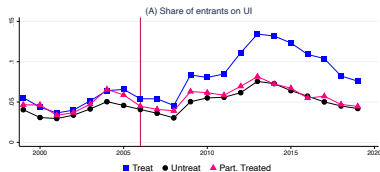
Summary statistics: composition - other outcomes

► UI ↘, flexwork ↗, crime ↘ [► Back](#)



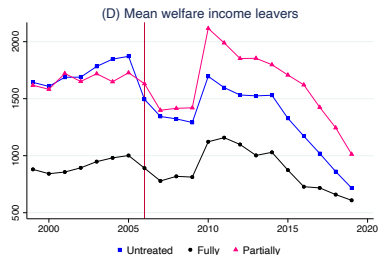
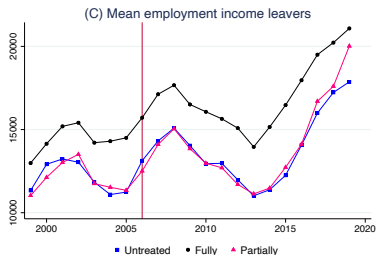
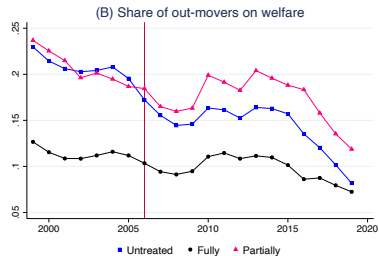
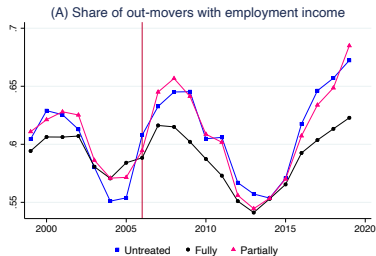
Summary statistics: entrants - other outcomes

► Back



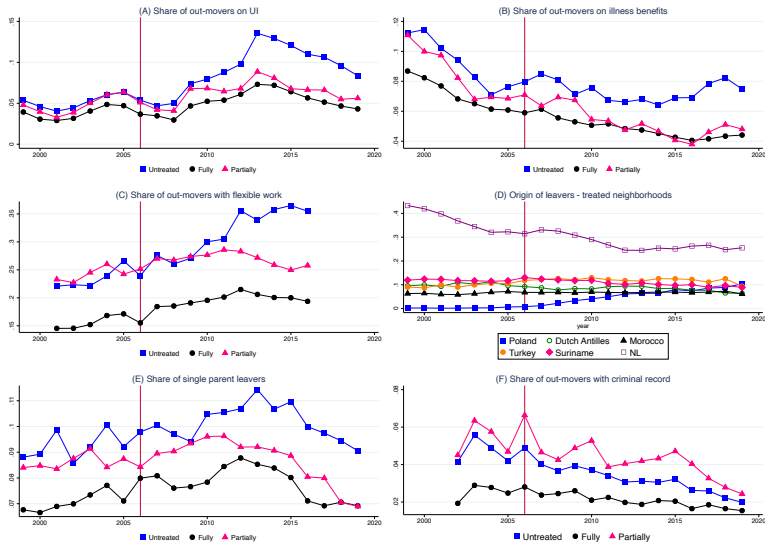
Summary statistics: leavers - labour market outcomes

► Back



Summary statistics: leavers - other outcomes

► Back



- ▶ Exposure measured as

$$E_{it} = (\bar{B} - \text{age in 2006}_{it}) \times \mathbb{1}[\text{age}_{it} \leq \bar{B}] \quad (4)$$

- ▶ Where $\bar{B}$ is the age at which individual i passes the exam
- ▶ Identify effects of years of exposure on youth outcomes

$$Y_{it} = \beta_t E_{it} + \mathbf{X}'_{it} \Omega_{itm} + \epsilon_{it} \quad (5)$$

- ▶ Estimate for *cito* (11-12) and *eind examen* (15-18)

Trimming the Sample with K-Means Clustering

The Problem

Treated and control neighborhoods are too different (treated areas are poorer and more diverse)

K-Means Intuition

- ▶ Groups data into K distinct clusters based on shared traits.
- ▶ Unsupervised clustering, not a matching algorithm
- ▶ Units inside the same cluster are very similar on observables
- ▶ Still N treated $\ll$ N control. We do not pick controls

▶ Back

Implementation

1. **Group:** Sort all neighbourhoods into 30 clusters based on their traits.
2. **Keep:** Only keep control neighbourhoods if they share a cluster with a treated one.

We drop controls that are too dissimilar to treated group

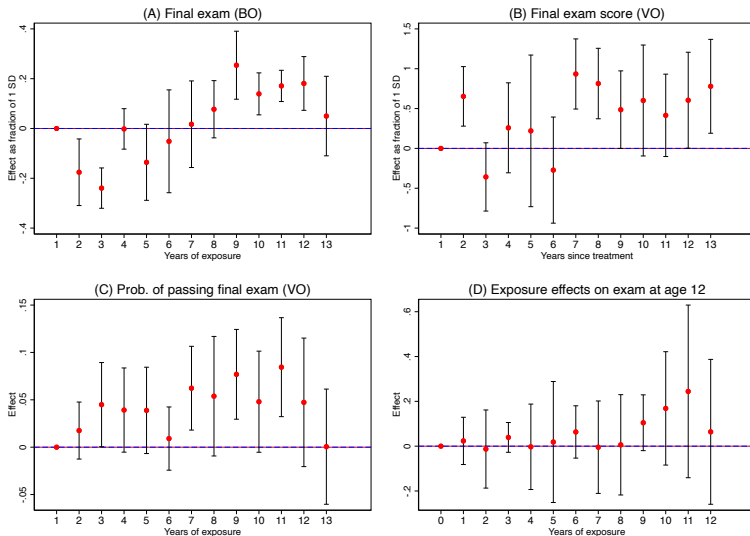
Robustness Check

Keeping only the 25% of neighbourhoods with the lowest house prices in the region (WOZ) gives a similar set of controls, and unchanged results

Results: Youth outcomes

► Null and imprecisely estimated exposure effects

► [Back](#)

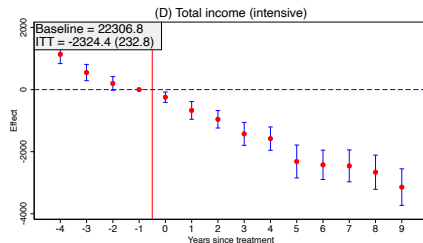
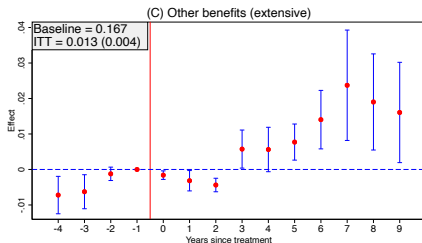
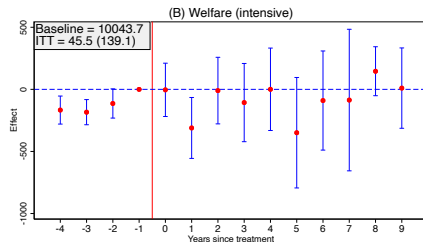
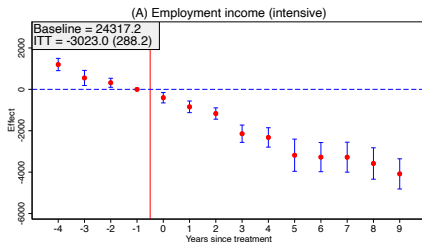


Goal: Flexibly estimate heterogeneous treatment effects (CATEs) across subpopulations

- ▶ Causal forests build on regression trees: split the data based on covariates to uncover variation in treatment effects
- ▶ At each node, the algorithm selects the split maximising a criterion function; the resulting data splits are called *leaves*
- ▶ The tree is complete when no further splits are possible given a stopping rule
- ▶ To detect heterogeneity, Athey and Imbens (2016) propose splitting to maximize treatment effect variance across leaves and minimize it within leaves
- ▶ A causal forest is a collection of many decorrelated trees, each built on a slightly different subsample
- ▶ The Conditional Average Treatment Effect (CATE) is estimated by averaging across trees
- ▶ *honest approach*: To prevent overfitting, the sample is split in two. One half for learning, the other for estimating treatment effects (Athey et al., 2019)

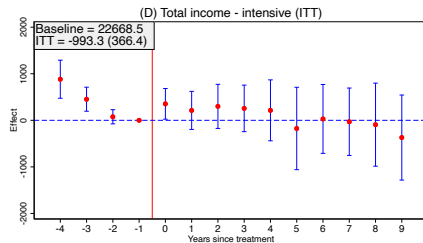
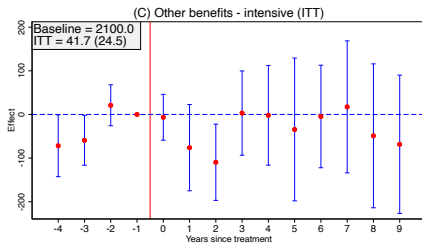
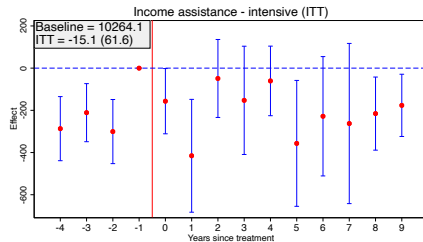
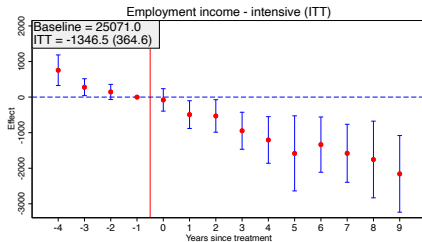
Results: composition - intensive margin

- Income ↘, UI ↘ (poor jobs). No change in other benefits [► Back](#)



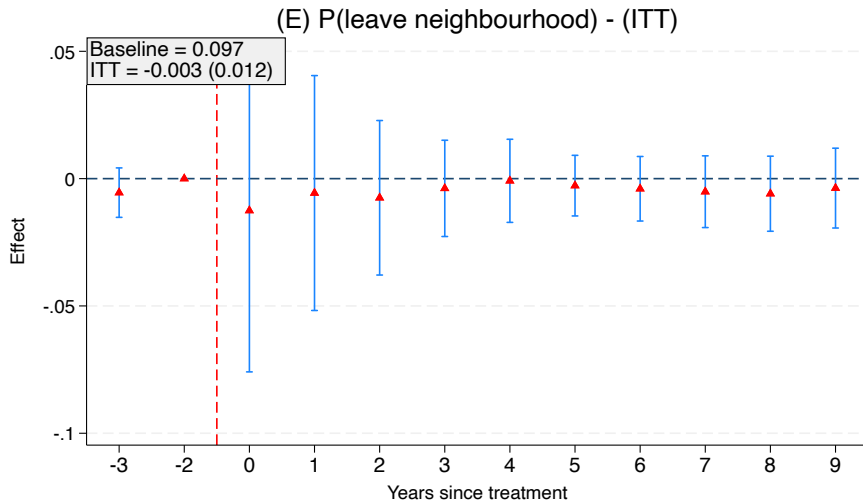
Results: ITT - intensive margin

► Income ↘, No change in benefits amounts [► Back](#)

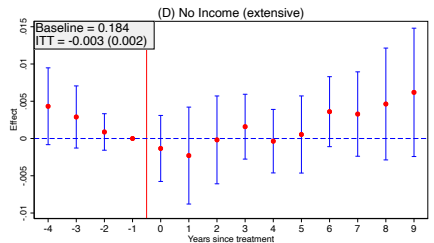
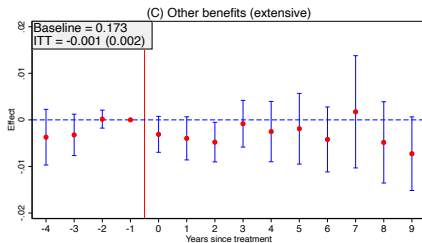
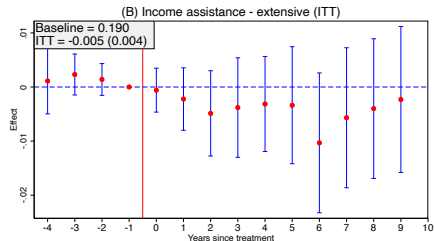
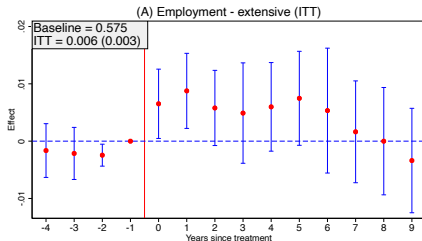


Results: ITT - P(move out of hood)

► No change [► Back](#)



Results: labour market outcomes (extensive) - incumbents - WOZ trimmed sample

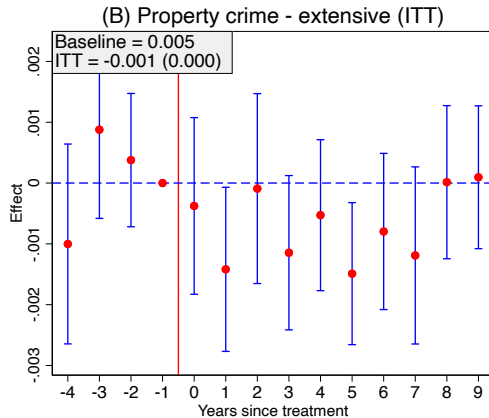
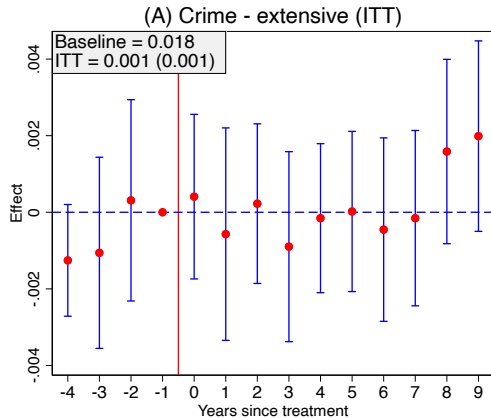


Results: crime - incumbents

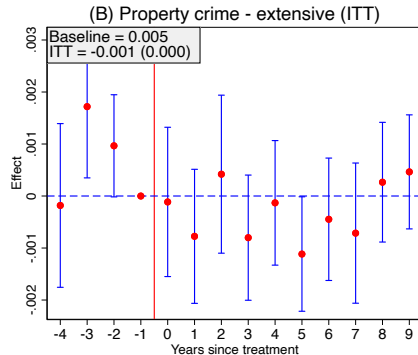
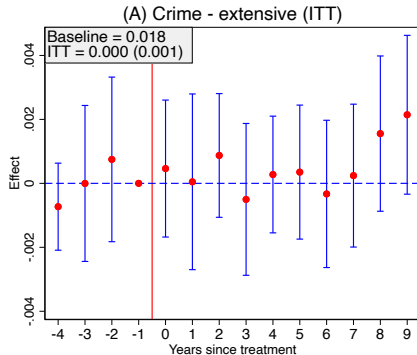
- Property crime offences by incumbent residents ↘ by 0.13 pp (26%)

► Youth

► WOZ crime



Results: crime - WOZ trimmed sample

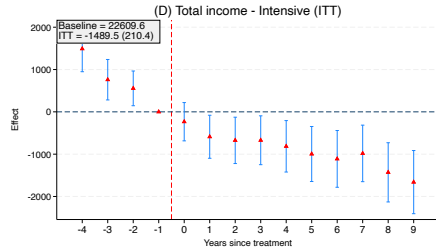
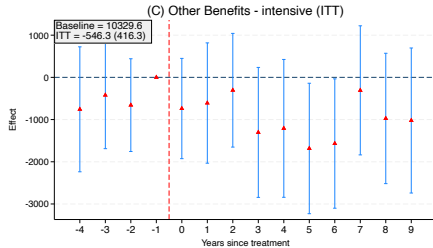
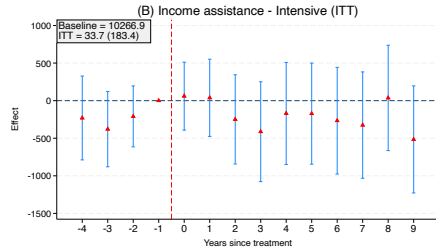
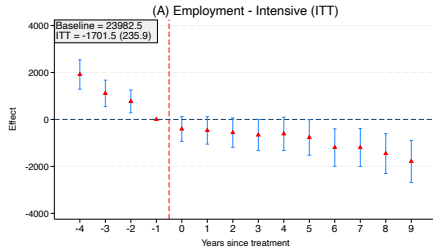


► Back

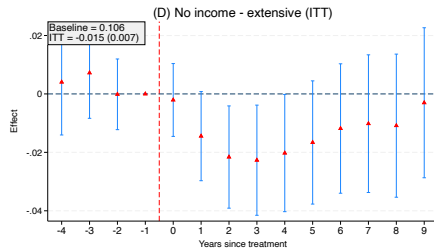
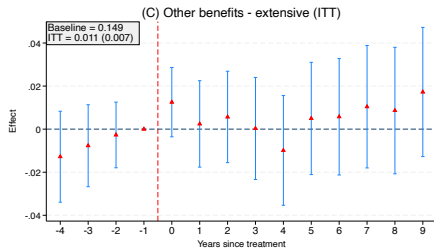
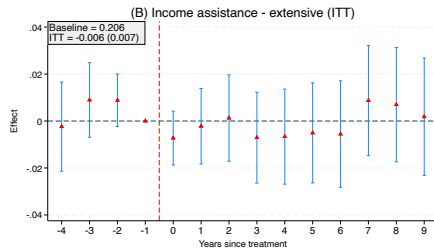
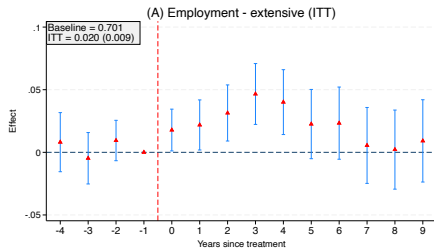
Balancing table: incumbents sample - R'dam region & the Hague

	Full Sample				K-clust. trim			
	Treated	Control	Norm. Diff	P-val	Treated	Control	Norm. Diff	P-val
Age	39.95	42.82	-0.236	0.000	39.95	40.72	-0.063	0.259
Male	0.51	0.50	0.040	0.002	0.51	0.50	0.025	0.081
Single head hh	0.11	0.08	0.083	0.001	0.11	0.12	-0.043	0.111
Turkish	0.17	0.05	0.399	0.003	0.17	0.09	0.230	0.074
Moroccan	0.07	0.03	0.194	0.000	0.07	0.08	-0.012	0.799
Antillian	0.04	0.02	0.137	0.000	0.04	0.03	0.050	0.147
Surinamese	0.12	0.07	0.191	0.000	0.12	0.14	-0.042	0.301
Native	0.39	0.66	-0.575	0.000	0.39	0.44	-0.103	0.409
First Generation	0.51	0.25	0.566	0.000	0.51	0.46	0.107	0.359
Second Generation	0.10	0.09	0.041	0.040	0.10	0.10	-0.010	0.627
Criminal Record	0.02	0.01	0.068	0.000	0.02	0.02	0.008	0.535
Employed	0.59	0.67	-0.160	0.009	0.59	0.61	-0.034	0.597
Welfare	0.19	0.08	0.320	0.000	0.19	0.15	0.084	0.172
Unemployment Insurance	0.08	0.05	0.113	0.000	0.08	0.06	0.062	0.000
Sickness Benefits	0.11	0.09	0.067	0.002	0.11	0.11	-0.006	0.807
Observations (N)	30,317	781,677			30,317	204,023		

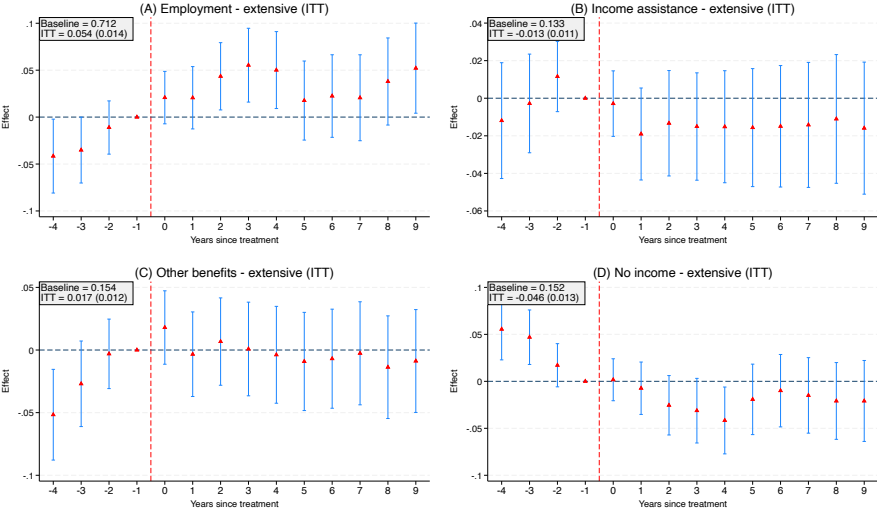
Results DDD: labour market outcomes (intensive) - incumbents - KNN trimmed sample

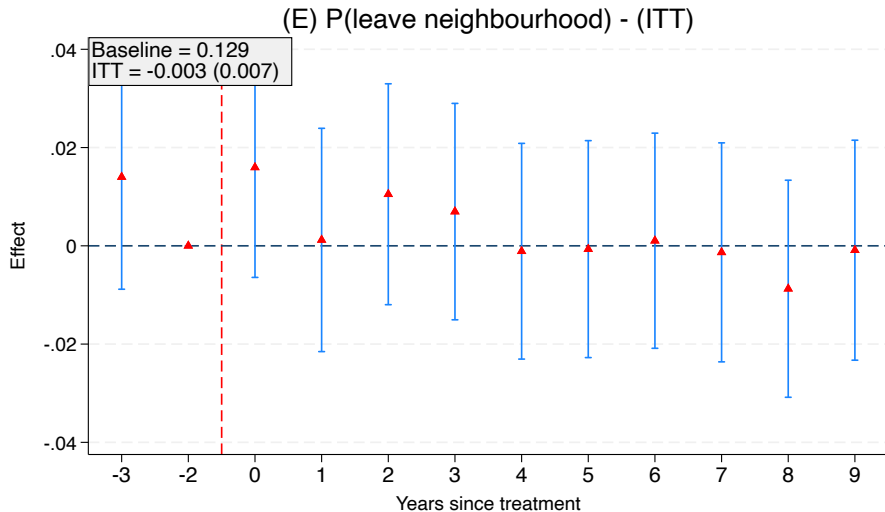


Results DDD: labour market outcomes (extensive) - incumbent heads of household - KNN trimmed sample

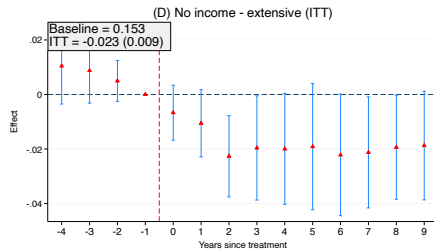
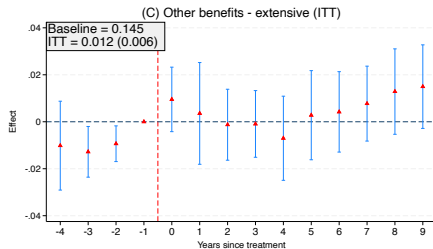
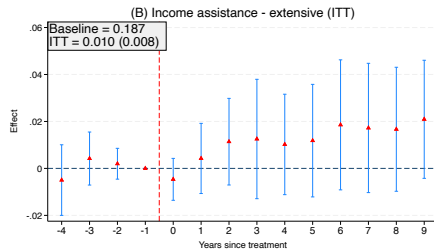
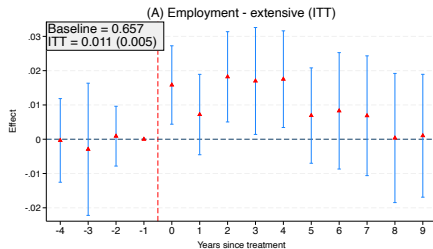


Results DDD: labour market outcomes (extensive) - incumbents who had a first kid - KNN trimmed sample

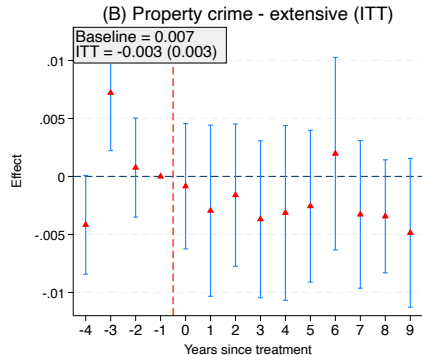
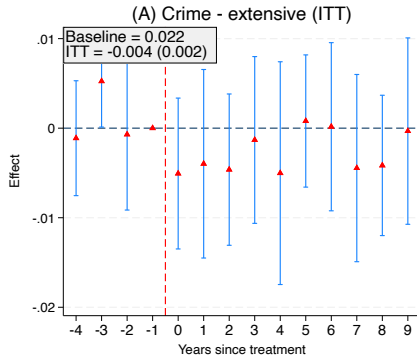


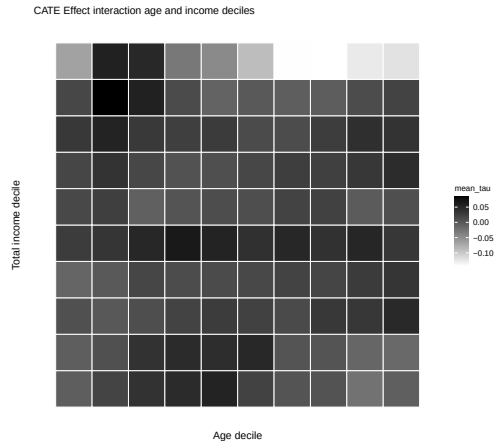
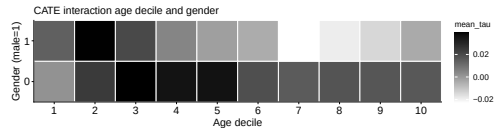


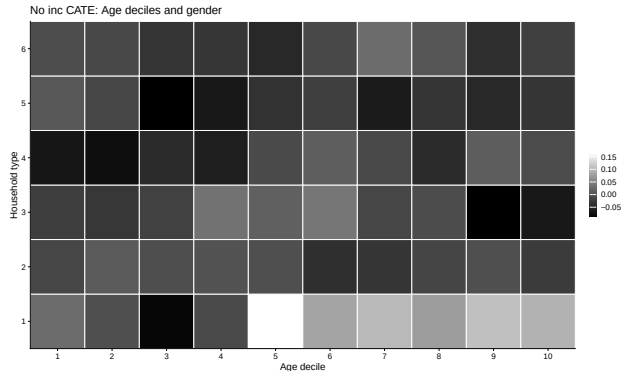
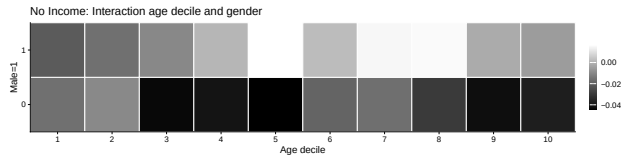
Results DDD: labour market outcomes (extensive) - incumbents - WOZ trimmed sample



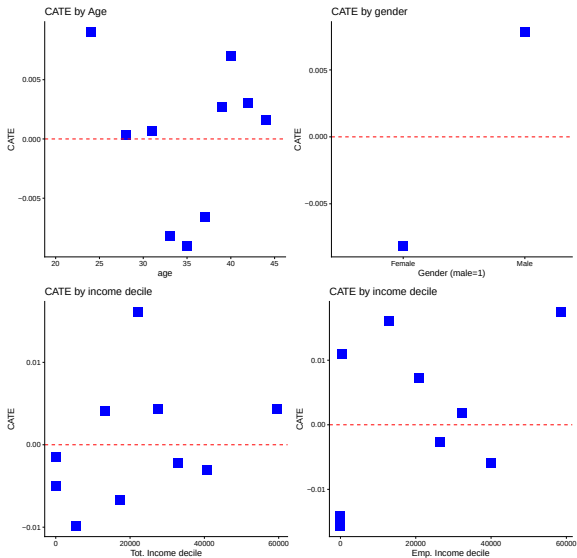
Results DDD: crime - WOZ trimmed sample

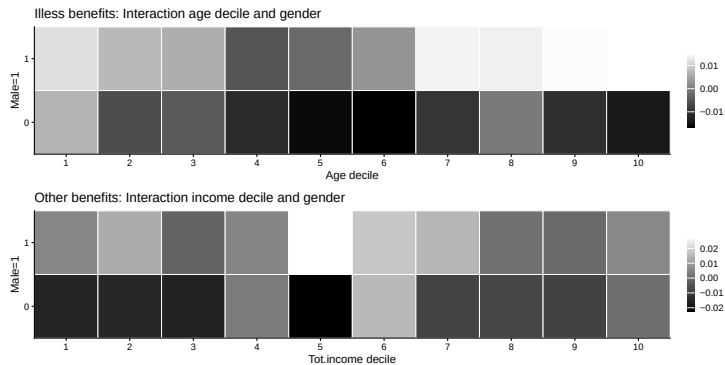


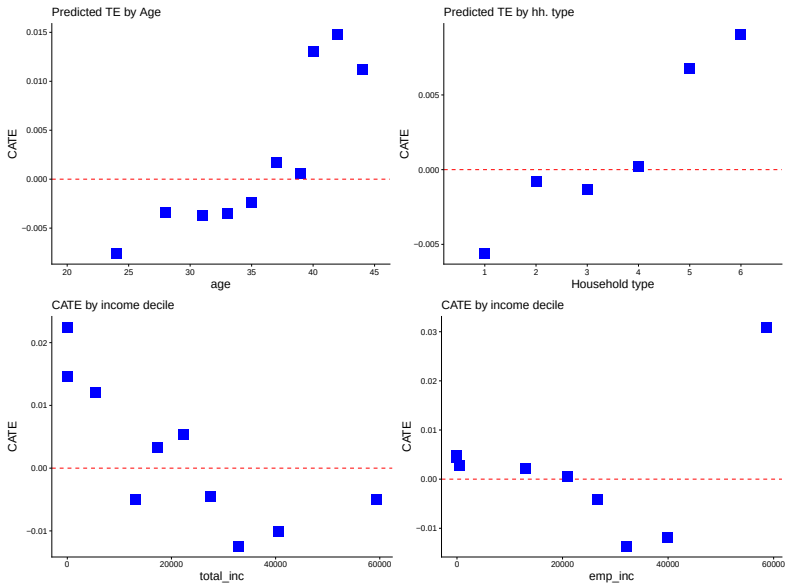


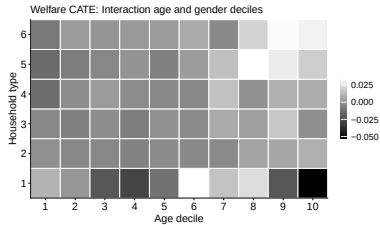
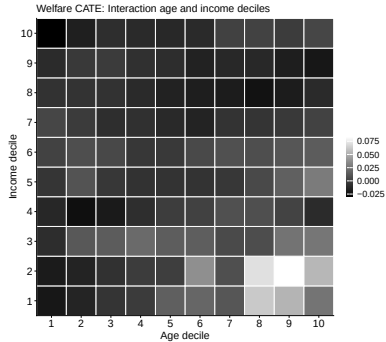


CATE Illness Benefits

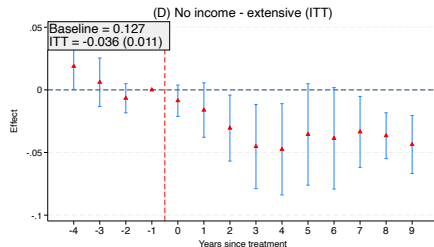
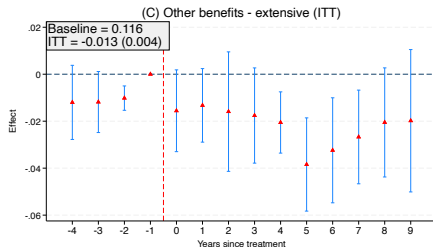
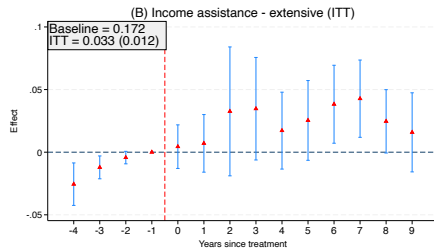
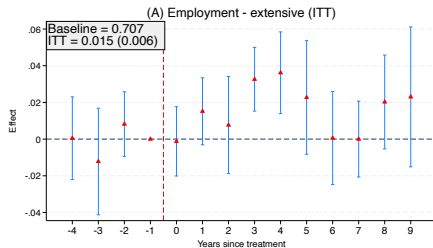


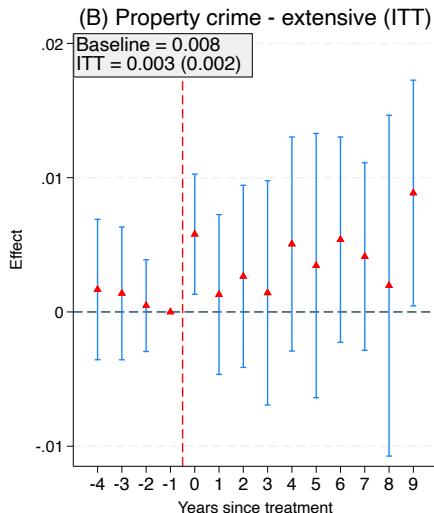
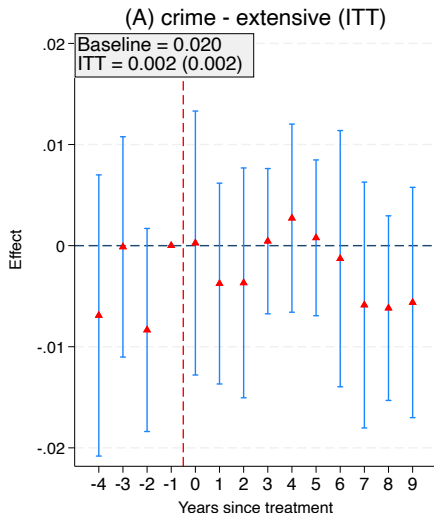






▶ Consistent with treatment spillovers around treated area





Spillover: re-run analysis on non-adjacent nearby neighbourhoods [▶ Back](#)

