What do NEETs Need?
The Effect of Activation Policies and Cash Transfers

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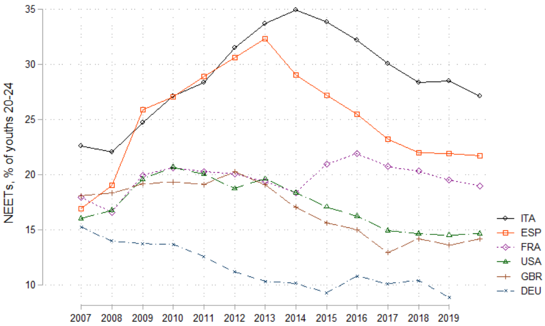
What do NEETs Need?

Youth Not in Employment, Education or Training (NEETs) are a persisting problem in some European countries and some sub-populations



Source: OECD

- Education/training? Trade/tech generating mismatch? Institutions (e.g. minimum wage)?
  Quintini (2011); Eichhorst et al. (2012); Cahuc et al. (2013)
- Higher labor-market frictions ⇒ "scarring" unemployment and poverty trap
  Ioannides and Datcher Loury (2004); Marinescu and Rathelot (2018); Oreopoulos et al. (2012); Rothstein (2019); Brunello and De Paola (2014)

Motivation

Social protection is widespread in Europe (Data), but...

Problem: **passive policies** (cash transfers, UI) risk reducing labor supply and job search (Moffitt, 1985)

- Pure moral hazard/liquidity effect (Card et al., 2007; Chetty, 2008)
- Distorsive **implicit taxation** (Le Barbanchon, 2020)

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The literature only examines active and passive policies <u>one conditional on the other</u>:

- Activation programs on receivers of social protection have positive but uncertain effect (Card et al., 2018)
- Cash transfers to receivers of active policies may finance effort (attendance)(Heckman et al., 1999; Aeberhardt et al., 2020)

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Research question

What is the effect of **cash transfers and activation policies (active+passive) <u>combined</u>?**

- In Boone et al. (2007) , increase benefit (cash), sanctions (conditionality), but also monitoring (activation)

This paper

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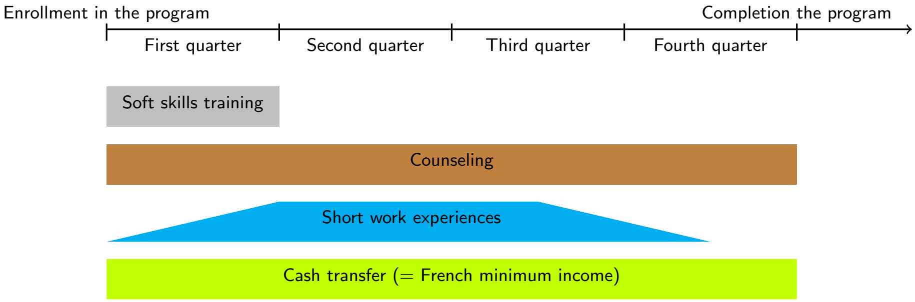
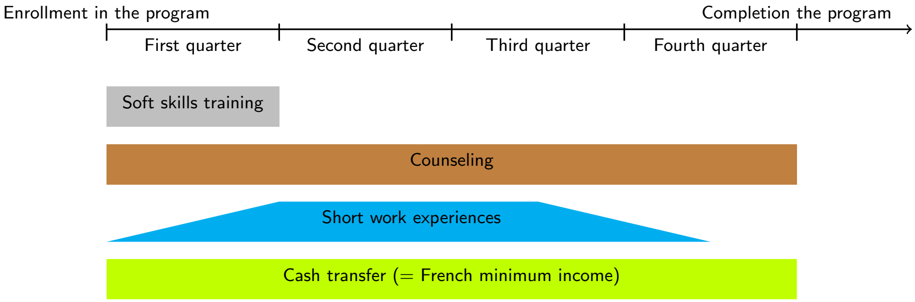


Topics of the soft-skill training
Data about the implementation

This paper

I evaluate an innovative French program for NEETs, *Garantie Jeunes*, combining intensive activation ad cash transfers



Topics of the soft-skill training | Data about the implementation

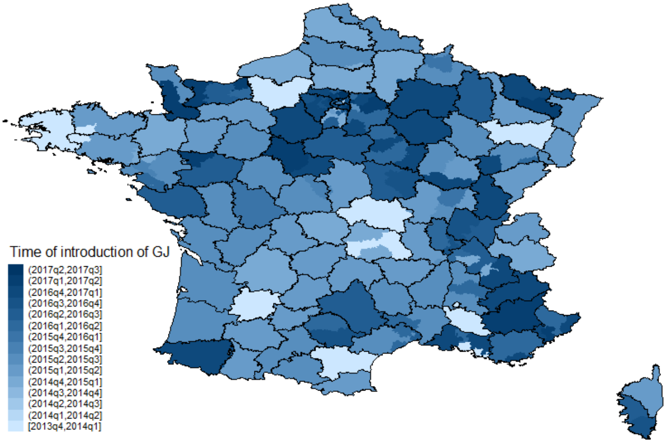
- Politically on the headlines. Currently debated for potential extension. Newspapers on the program

Overview of the results

- Find **strong positive effect** on employment and hours worked, **only when stop receiving cash**
  - In the second year since exposure +1.6 p.p. in employment and +4.3 in hours worked quarterly.
  - In terms of LATE on takers, +26 p.p. in employment, +71 hours worked quarterly.
  - Large LATEs driven by youths completing the program
- **Disentangling the zero effect during enrollment**:
  - Negative lock in effect and reaction to implicit taxation
  - Compensated by large effect of activation
    $\Rightarrow$ significant role of search frictions, labor supply elasticity and time constraints
    $\Rightarrow$ possible complementarities (monitoring/improved search)?
- **I extend innovations to diff-in-diff estimators "rolling" over a third dimension.**
  This applies to staggered adoption settings where potential outcomes depend on three dimensions (e.g. when units are exposed to treatment at different times since registration, school grade, tenure,...)

Program Adoption and Enrollment

- The program is administered by Youth Employment Centers (YECs) Standard program at YECs
- Pilot in Oct. 2013, expanded progressively after evaluation (Gaini et al., 2018)



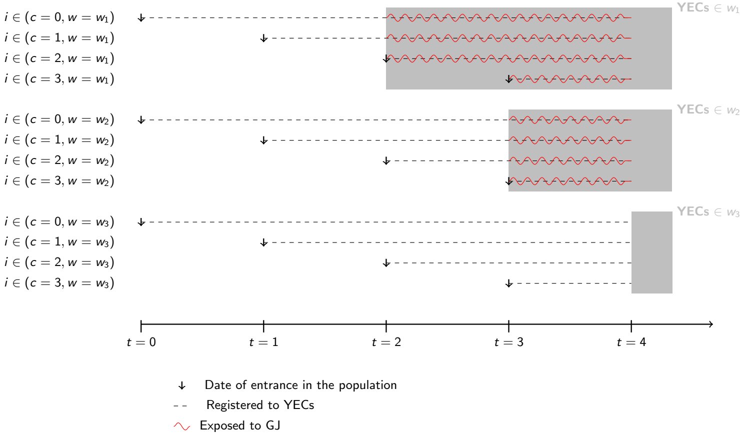
DOM: Guadeloupe - 2015q2; Martinique - 2015q2; Guyane- 2015q4; La Réunion - 2013q4; Mayotte - 2017q1.

Data, Population of Interest, and Take-up

- **Novel dataset**, using two different administrative sources:
  - Administrative dataset of youth employment centers (YEC) administering the program
  - Information on any contract signed by any of the youths that were registered at YECs in 2013-2016, over 2013-2017.
- **Large sample**, all youths registering in YECs:
  - 2 million individuals over 2013-2017
  - Low-educated, more likely to report in "adulthood" characteristics Descriptives
- Once registered to YECs, there is a **selection process** for enrollment in *Garantie Jeunes*:
  - Earning less than minimum income + selection on "fragility" and "motivation" ($\sim$ 50% of eligibles)
  - Youths enrolling report higher housing/health/mobility problems (*freins à l'emploi*)

An illustration of the setting

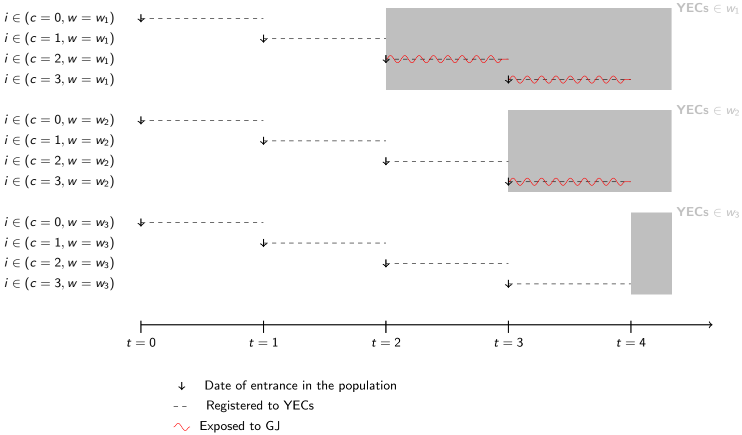
- Individuals enter in cohort c and in a YEC belonging to treatment wave w
- I follow individuals over time t, or equivalently time since registration $h = t - c + 1$



Intuition for identification

I propose $DID^{h}_{w,c}$, were w is the wave, h is time since registration and c is cohort of registration Formal definition

- Focus on $h = 1$



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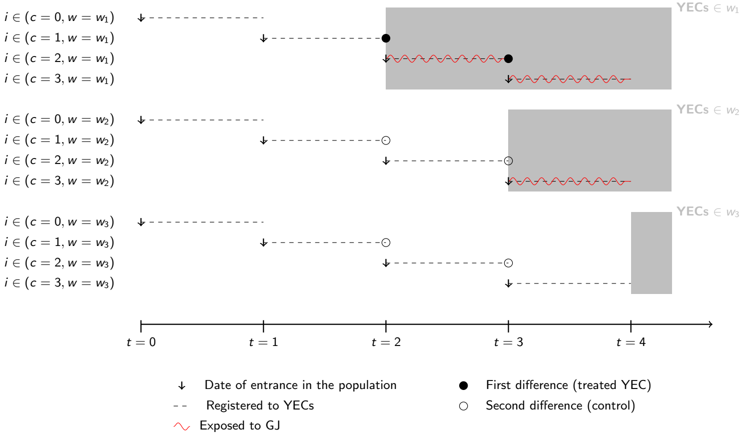
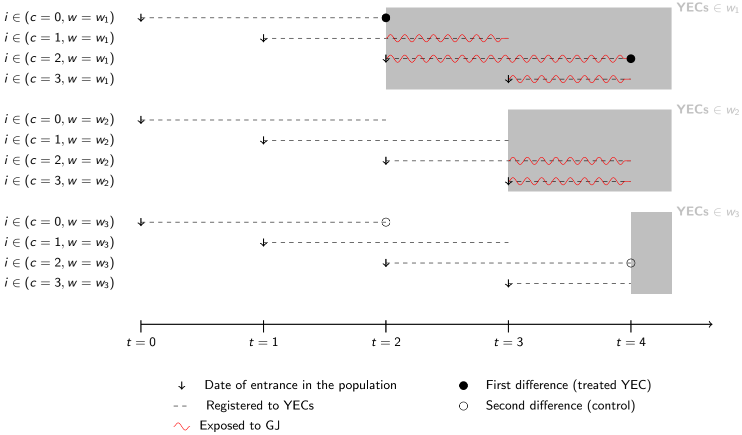
- Example: $DID^{h=1}_{w_1,c=2}$



Intuition for identification

I propose $DID^{h}_{w,c}$, were w is the wave, h is time since registration and c is cohort of registration Formal definition

- Focus on $h = 2$
- Example: $DID^{h=2}_{w_1,c=2}$



Aggregation of ITT: effect since exposure

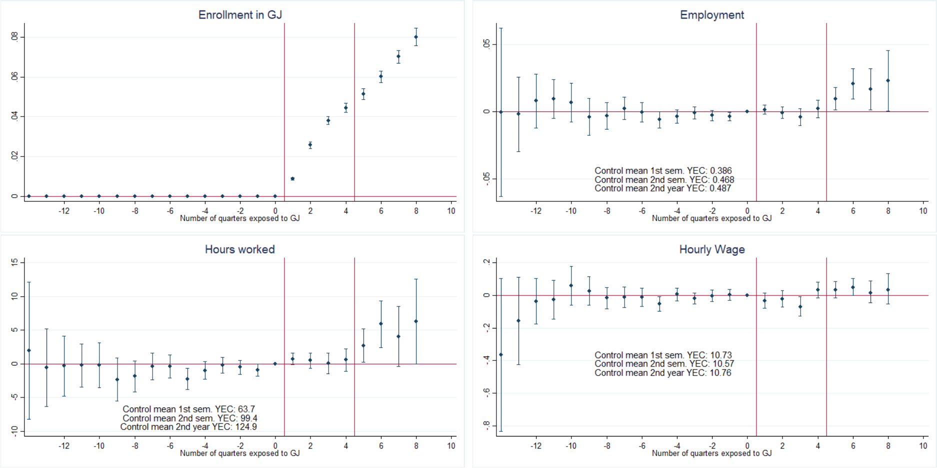
I have many $DID^h_{w,c}$!

- Let $G^h_{w,c}$ be the number of quarter youths in (h, w, c) are exposed to treatment
- **Unbiased estimator of ITT since exposure** using an aggregation:

$$DID^g := \sum_{(w,c|h):G^h_{w,c}=g} \frac{n_{w,c}}{\sum_{(w,c|h):G^h_{w,c}=g} n_{w,c}} DID^h_{w,c}$$

- This generalizes De Chaisemartin and D'Haultfœuille (2020a), who estimate $DID^h_{w,t}$, effect since *adoption*
  In my context, effect since *adoption* can be misleading! Why?

Results: ITTs



- The effect in the second year of exposure is mostly made of **temporary contracts** (+0.7 pp.) and **agency jobs** (+0.5 pp.) Heterogeneity

Getting LATEs

LATE since exposure: ITT rescaled, gives an avarage effect on <u>all</u> takers

LATE since enrollment:

- Let D_i be the number of quarters elapsed since enrollment of each individual
- Unbiased estimators δ_d using the Minimum Distance regression:

$$\begin{aligned} DID^h_{w,c} = &\delta_1 Pr(0 < D_i \leq 2 | i \in h, w, c) + \\ &\delta_2 Pr(2 < D_i \leq 4 | i \in h, w, c) + \\ &\delta_3 Pr(D_i > 4 | i \in h, w, c) + \varepsilon_{h,w,c} \end{aligned}$$

Results: LATEs

	Employment (1)	Hours (2)	Wages (3)
LATE 1st semester of exposure	0.0246	35.1	-1.76
	(0.104)	(27.1)	(1.14)
LATE 2nd semester of exposure	-0.0322	6.63	-0.695
	(0.0680)	(17)	(0.573)
LATE 2nd year of exposure	0.259***	70.7***	0.550
	(0.0837)	(24.5)	(0.340)
LATE 1st semester of enrollm.	-0.0504	15.1	-0.193
	(0.0566)	(14.6)	(0.635)
LATE 2nd semester of enrollm.	-0.00801	14.1	-0.0241
	(0.0758)	(24.3)	(0.707)
LATE after completion	0.326***	72.0**	1.00
	(0.104)	(34.2)	(0.659)

Notes. The table reports the estimates of LATE of GJ on employment, earnings and hours worked, obtained according to Proposition 3. Standard errors are bootstrapped and reported in parenthesis.

- LATE confirms no effect on employment for youths while enrolled, strong (but noisy) effect after completion
- Surprisingly similar to pilot evidence Gaini et al. (2018)

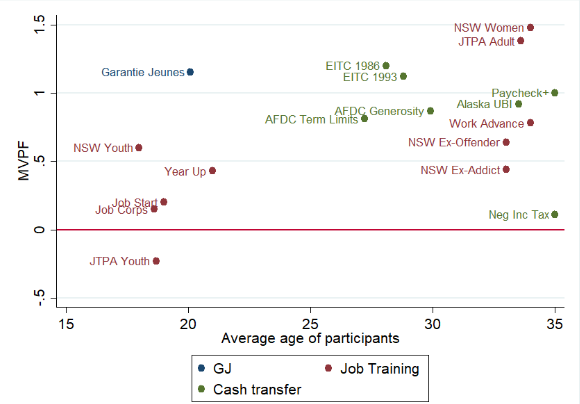
Cost-benefit analysis

Marginal Value of Public Funds (Hendren and Sprung-Keyser, 2020) for *Garantie Jeunes*:

$$MVPF = \frac{WTP}{NetCost} = 1.15$$

Where

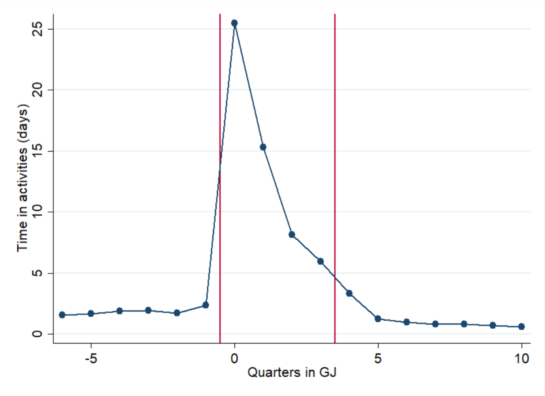
- WTP is the cumulated effect on after-tax income+ cash transfer
- $NetCost$ is the additional cost for each youth in GJ (€1546) plus transfer and rental cost



Disentangling the Mechanisms

2 sources of identification: #1 timing of the activation program

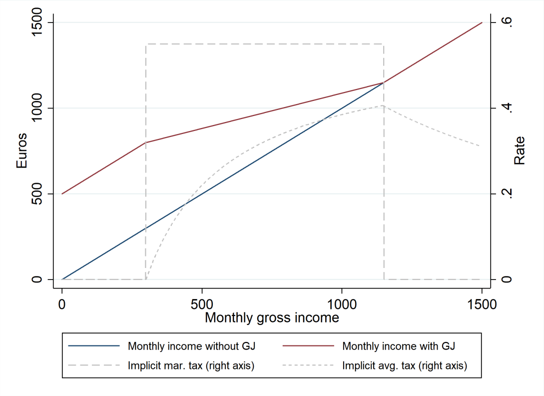
- Activities are mostly concentrated in the first semester, where soft-skill training and most of the job immersions occur



Disentangling the Mechanisms

2 sources of identification: #2 phase-out of the cash transfer with job earnings

- The cash transfer of GJ is fully cumulative with job earnings only up to €300, then decreases linearly until 80% French gross minimum wage ($\sim$ €1100 on average in the period)
- The implicit marginal tax rate on earnings between €300 and €1100 is 55%



Results: Mechanisms

- We can estimate the LATE effect for youths at different stages of the program on the probability of having job earnings below 300, between 300 and 1100 and over 1100.

	Monthly income 1-300 (1)	Monthly income 300-1100 (2)	Monthly income over 1100 (3)
LATE 1st semester of enrollm.	-0.0674*	-0.0482*	0.0221
	(0.0359)	(0.0290)	(0.0361)
LATE 2nd semester of enrollm.	0.0846**	-0.146***	0.129**
	(0.0431)	(0.0544)	(0.0577)
LATE after completion	-0.0863	0.188***	0.197**
	(0.0618)	(0.0700)	(0.0793)

Notes. The table reports estimates of LATE effects obtained using Proposition 3b in the paper, using as outcome the probability of earning in different brackets.

- Descriptives suggest differences in earning distributions in different stages of the program (but no bunching at €300) Graph

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- Descriptives suggest differences in earning distributions in different stages of the program (but no bunching at €300) Graph
- **Lock-in from intensive training** lowers employment (especially part-time) in the first semester
- Youths react to **implicit taxation from cash transfer phase-out** in the second semester
- When out of the program – **when they stop receiving cash – youths increase further employment** in better jobs

WIP: more precise interpretation

A More Formal Interpretation

- Assume employment in income bracket z_0, z_1, z_2, z_3 is a product of labor supply Φ and search frictions P

$$\underbrace{Pr(z_{j*} = z_j)}_{\Phi_j(F,\mathrm{T(z)},b)} \cdot \quad P(active, time)$$

  - F is the cdf of skills, extreme value dist., T(z) is implicit taxation (rate τ), b is the cash transfer
  - $tech, time$ are dummies

- Then $\Phi_j(treat) = \frac{e^{\alpha_j(1-\tau)+\beta+\gamma_j}}{K_{treat}}$ (McFadden et al., 1973), with $\alpha_j, \beta, \gamma_j$ utility of work, cash tr. and leisure

Treatment group

	Monthly income 1-300	Monthly income 350-1100	Monthly income over 1100
LATE 1st semester of enrollm.	$\Phi_1(0)\frac{K_0}{K_1}e^{\beta} \cdot P(1,0)$	$\Phi_2(0)\frac{K_0}{K_1}e^{\beta-\alpha_2\tau} \cdot P(1,0)$	$\Phi_3(0)\frac{K_0}{K_1} \cdot P(1,0)$
LATE 2nd semester of enrollm.	$\Phi_1(0)\frac{K_0}{K_1}e^{\beta} \cdot P(1,1)$	$\Phi_2(0)\frac{K_0}{K_1}e^{\beta-\alpha_2\tau} \cdot P(1,1)$	$\Phi_3(0)\frac{K_0}{K_1} \cdot P(1,1)$
LATE after completion	$\Phi_1(0) \cdot P(1,1)$	$\Phi_2(0) \cdot P(1,1)$	$\Phi_3(0) \cdot P(1,1)$

Control group

	Monthly income 1-300	Monthly income 350-1100	Monthly income over 1100
LATE 1st semester of enrollm.	$\Phi_1(0) \cdot P(0,1)$	$\Phi_2(0) \cdot P(0,1)$	$\Phi_3(0) \cdot P(0,1)$
LATE 2nd semester of enrollm.	$\Phi_1(0) \cdot P(0,1)$	$\Phi_2(0) \cdot P(0,1)$	$\Phi_3(0) \cdot P(0,1)$
LATE after completion	$\Phi_1(0) \cdot P(0,1)$	$\Phi_2(0) \cdot P(0,1)$	$\Phi_3(0) \cdot P(0,1)$

Results: Estimated Parameters

- Obtain a system of 10 unknowns and 18 equations, but only 8 are linearly independent
- Minimal assumption: fix either $\frac{K_1}{K_0}$ or $P(1,1)$, and don't estimate K_1, K_0

Estimated structural parameters based on $P(1,1)$

$\frac{K_1}{K_0}$	$\Phi_1(0)$	$\Phi_2(0)$	$\Phi_3(0)$	$\Phi_1(1)$	$\Phi_2(1)$	$\Phi_3(1)$	$P(1,1)$	$P(1,0)$	$P(0,1)$	$P(1,1)-P(1,0)$	$P(1,1)-P(0,1)$	e^{β}	$e^{-\alpha_2\tau}$
.937	.111	.197	.197	.161	.071	.21	.8	.63	.536	.17	.264	1.355	.251
.996	.111	.197	.197	.151	.067	.198	.85	.669	.536	.181	.314	1.355	.251
1.054	.111	.197	.197	.143	.064	.187	.9	.709	.536	.191	.364	1.355	.251
1.113	.111	.197	.197	.135	.06	.177	.95	.748	.536	.202	.414	1.355	.251
1.172	.111	.197	.197	.128	.057	.168	1	.787	.536	.213	.464	1.355	.251

The table reports the estimated structural parameters as a function of $P(1,1)$. The estimates are obtained by equating the structural interpretation in Table **??** to the average outcomes of compliers in treatment (estimated from the data) and of compliers in the control group (obtained by subtracting the effect in Table 19 to average outcomes of compliers in treatment). This provides 8 linearly independent equations and 10 unknowns. Fixing $P(1,1)$ and avoiding to solve for K_1, K_0 separately the system can be estimated with Equally Weighted Minimum Distance.

Discussion

	Δ Conditional cash transfer=0	Δ Conditional cash transfer>0
Δ Activation=0		
Δ Activation>0		This paper • Strong effect, but only after completion • Activation effect larger the larger disincentives from cash

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Δ Activation>0	Card et al. (2018) • Effect of "work first" programs positive in the short and medium run • Effect smaller on UI receivers	This paper • Strong effect, but only after completion • Activation effect larger the larger disincentives from cash $\Rightarrow$ Complementarities? ▸ Activation=monitoring (Boone et al., 2007) ▸ Activation+cash=escape poverty trap $\Rightarrow$ Success rate $\uparrow \perp$ search intensity, just enough to compensate reduced labor supply?

Conclusions

Search technology and cash jointly increase young NEETs employability only after completion

- Search technology of *Garantie Jeunes* very effective (32-45pp increase in search efficacy)
  $\Rightarrow$ Large role of search frictions/poverty trap for disadvantaged European NEETs?
- Youths reduce employment due to lock-in and implicit taxation
  $\Rightarrow$ Positive labor supply elasticity, significant time-constraints

Policy implications for programs involving active and passive measures

- A success case, but how much externally valid? GJ to be extended!
- Policies for NEETs should combine activation programs and cash incentives
- Cash transfer should be short in time and fully cumulable with job earnings

Apply methodological innovations on Diff-in-Diff

Rolling diff-in-diff estimator $\Rightarrow$ Applicable e.g. to schools (Martorell et al., 2016), firms, hospitals, ...

Thank you!

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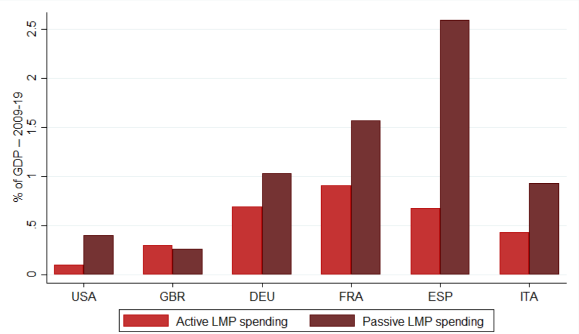
Appendix

Spending in passive and active LMPs in Europe



Source: OECD

Back to Research Question

Example of content in workshops

Source: YECs Thiers

Back to This paper

Garantie Jeunes in the news

Le Monde

Consulter le journal

Se connecter

ACTUALITÉS ÉCONOMIE VIDÉOS OPINIONS CULTURE M LE MAG SERVICE

EMPLOI

Partage

La garantie jeunes, « boulot tout de suite » et suivi renforcé

A Bondy (Seine-Saint-Denis), la mission locale expérimente le nouveau dispositif, qui propose aux jeunes les plus en difficulté un suivi étroit et individualisé.

Par Pascale Krémer

Publié le 23 janvier 2014 à 12h17 - Mis à jour le 23 janvier 2014 à 12h17 · Lecture 4 min.

Le Monde

Consulter le journal

Se connecte

ACTUALITÉS ÉCONOMIE VIDÉOS OPINIONS CULTURE M LE MAG SERV

ÉCONOMIE · EMPLOI

Partage

Emploi : vers la mise en place d'une « garantie jeunes universelle »

Selon l'entourage de la ministre du travail, Elisabeth Borne, l'un des objectifs est d'« unifier » plusieurs dispositifs, en veillant à ce qu'ils assurent un accompagnement vers un métier et le versement d'un pécule, en cas de besoin.

Par Bertrand Bissuel

Publié le 09 janvier 2021 à 10h05 · Lecture 2 min.

Back to This paper Back to Conclusions

Gaini et al. (2018)

- Use only survey evidence on employment of the first wave
- Find remarkably similar ATTs, even larger relatively to control (more disadvantaged territories)
- Find effect also during the program, but their survey question can include "job immersions"

Tableau 3 : Impact de la Garantie jeunes sur le fait d'avoir travaillé au moins heure dans le mois, sur différentes périodes après leur entrée dans le programme

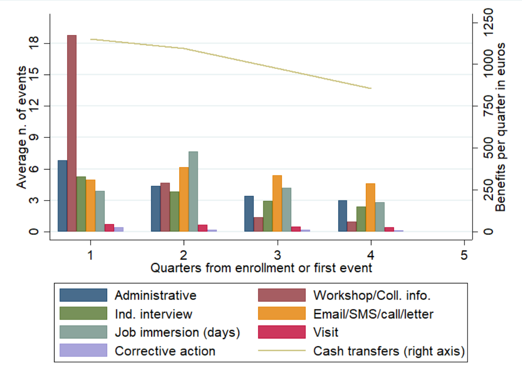
Nombre de mois depuis l'entrée en GJ	Taux observé parmi les bénéficiaires *(en %)*	Effet sur les bénéficiaires
3 mois ou moins	36	26,1*** (7,3)
De 4 à 9 mois	45	18,4*** (5,4)
De 10 à 12 mois	46	– 6,6 (8,3)
De 13 à 16 mois	47	22,2*** (7,6)
17 mois et plus	51	6,6 (4,8)

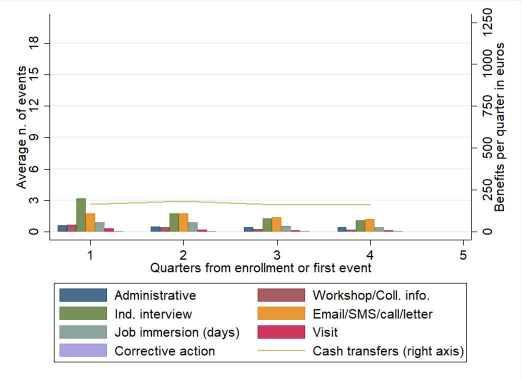
*** : significatif au seuil de 1 %, ** : significatif au seuil de 5 %, * : significatif au seuil de 10 %.
Lecture : entre le 4e et le 9e mois après leur entrée en Garantie jeunes, 45 % des jeunes ont travaillé au moins une heure dans le mois. L'impact de la Garantie jeunes sur la proportion moyenne de jeunes bénéficiaires à avoir travaillé au moins une heure est de + 18,4 points. Il est significatif.
Champ : répondants aux trois interrogations, repérés comme éligibles ou non éligibles entre juin et décembre 2014 sur les territoires pilotes (territoires de la vague 1 d'expérimentation) et sur des territoires témoins.
— *Source* : enquêtes de suivi Garantie jeunes, traitement Dares.

Back to Results

Competing programs at YECs

Garantie Jeunes (left) and standard program offered at YECs (CIVIS, right)





Back to This paper
Back to Setting

Descriptives of the sample

Population of interest is low-educated, gender-balanced, and tends engage more in "adulthood" activities

Characteristics of the overall population, of youths in YECs (sample observed), and of youths registering in YECs standard program CIVIS and in GJ

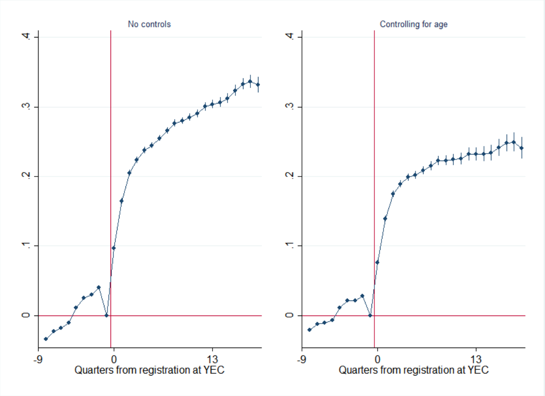
	All youths 16-25 (Census) (1)	Youths in YECs (2)	Youths in std. prog. (3)	Youths in GJ (4)
Number of youths (stock)	9327476	1967000	444309	113085
Number of youths (quarter inflow)		125689	41471	14899
Lower than secondary educ.	0.394	0.373	0.424	0.467
Upp. secondary edu. diploma	0.434	0.519	0.541	0.507
Avg. age	20.3	20.1	19.7	18.8
Female	0.491	0.491	0.511	0.463
French nat.	0.915	0.912	0.919	0.929
Empl. last quarter	0.297	0.349	0.335	0.212
Lives independently	0.230	0.365	0.369	0.354
Has kids	0.0390	0.0838	0.0878	0.0496

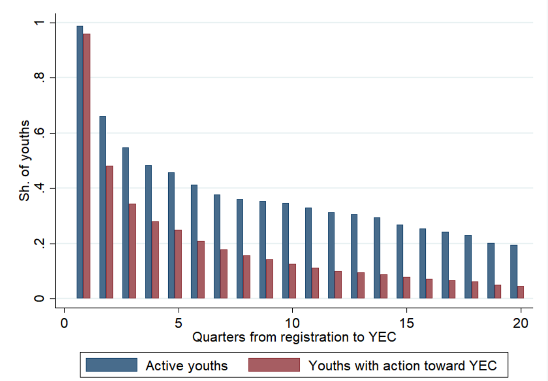
Notes. The table compare the characteristics of youths in different population. The first column concerns all youths aged 16-25 in France, as reported by the Census in years 2013-2016. The second column reports all youths in the sample, namely all youths who registered at YECs in the 2013-2016 period. The third and fourth column reports respectively information on youths enrolling in the standard program offered at YECs, CIVIS, and enrolling in *Garantie Jeunes*. All lines report the characteristics of youths in the sample, except the second line which reports the inflow of youths, on average over 2013-2016 for column 2, in the first quarter of 2014 for column 3 and in the first quarter of 2017 for the last column.

Back to Data

Time since registration matters

Average employment rates in the quarters precedent/following registration at YEC, controlling or not for age (left). Share of youths considered active at the YEC and youths who actually undertake action toward YEC over time from registration (right).





Back to Data

Rolling Diff-in-Diff: cell-level ITT

Unbiased estimator of group-cohort-time since registration ITT:

$$DID^h_{w,c} = Y^h_{w,c} - Y^h_{w,c'} - \sum_{w' \in \Omega_w} \frac{n_{w',c}}{N_{\Omega_{w,c}}} (Y^h_{w',c} - Y^h_{w',c'})$$

$$\forall \, given \, (w, c, h) : G^h_{w,c} > 0$$

Where

- w are waves of treatment by date of adoption, c are cohorts of entrance in the population, h is time since registration in the YEC (time from first registration)
- $Y^h_{w,c} = \mathbb{E}(Y^h_i | w, c)$ is the average outcome of interest (take-up, employment, earnings, hours) in cell h, w, c
- c' is s.t. $G^h_{w,c'} = 0$ but $G^h_{w,c'+1} = 1$
- $\Omega_{w,c}$ is the set of waves such that $G^h_{w',c} = G^h_{w',c'} = 0$, for each $w' \neq w$ and $c' \neq c$. $n_{w'}$ is the number of individuals of cohort c in wave w' while $N_{\Omega_{w,c}}$ is the total number of individuals of cohort c in all waves $w' \in \Omega_{w,c}$

Under assumptions of independent groups, strong exogeneity, no anticipation and common trends (Balance checks), $DID^h_{w,c}$ is an unbiased estimator of

$$\Delta^{ITT}(h, w, c) = Y^h_{w,c}(g) - Y^h_{w,c}(0) \qquad \forall \, given \, (w, c, h) : G^h_{w,c} > 0$$

Example of results
Back to Intuition for identification

Balance checks

	(Check 1) GJ adopt.	(Check 2) GJ adopt.*quart. adopt.	GJ adopt.	(Check 3) GJ adopt.*quart. adopt.	(Mean)
Share of female	-0.00115	-0.00148	-0.000295	-0.000358	0.491
	(0.00179)	(0.00177)	(0.000391)	(0.000388)	
Age at registration	0.0135	0.0133	-0.000154	0.000599	20.1
	(0.0121)	(0.0127)	(0.00322)	(0.00333)	
No diploma	0.00376	0.00337	-0.000326	-0.000118	0.373
	(0.00244)	(0.00236)	(0.000489)	(0.000478)	
CAP or BAC	-0.00212	-0.00153	0.000521	0.000403	0.519
	(0.00227)	(0.00230)	(0.00056)	(0.000566)	
French nationality	-0.00208	-0.00154	0.000473	0.000357	0.912
	(0.00217)	(0.00230)	(0.00051)	(0.000538)	
Housing problems	0.00591***	0.00634***	0.000376	0.000704	0.0500
	(0.00157)	(0.00175)	(0.000431)	(0.00046)	
Resident in Urban Sensitive Area	0.000625	0.00407	0.003	0.00303	0.105
	(0.00355)	(0.0052)	(0.00211)	(0.00220)	
Distance residency-YEC	-4.67	-3.47	1.01	0.759	715
	(3.47)	(3.74)	(1.43)	(1.43)	
Resources declared	1.07	1.54	0.411	0.470	155
	(2.26)	(2.59)	(0.779)	(0.814)	
Has a motor vehicle	-0.00389*	-0.00373	0.000135	-0.0000778	0.410
	(0.00233)	(0.00239)	(0.000499)	(0.000516)	
Lives alone	0.000507	0.000805	0.000259	0.000287	0.899
	(0.00217)	(0.00223)	(0.000472)	(0.000485)	
Kids	0.00154	0.00230*	0.000652*	0.000738*	0.0837
	(0.00119)	(0.00125)	(0.000382)	(0.000381)	
Problems with childcare	0.00614	0.00474	-0.00119	-0.000841	0.348
	(0.00620)	(0.00609)	(0.00145)	(0.00140)	

Notes. The table reports the coefficients of a regression of average characteristics of registering cohorts on a dummy for GJ introduction (named "instrument"), on a linear trend (named "l_trend"), and on both. Column (4) reports the mean and standard deviations of the variable before GJ introduction.

Back to Intuition for identification

Why effect since adoption can be misleading?

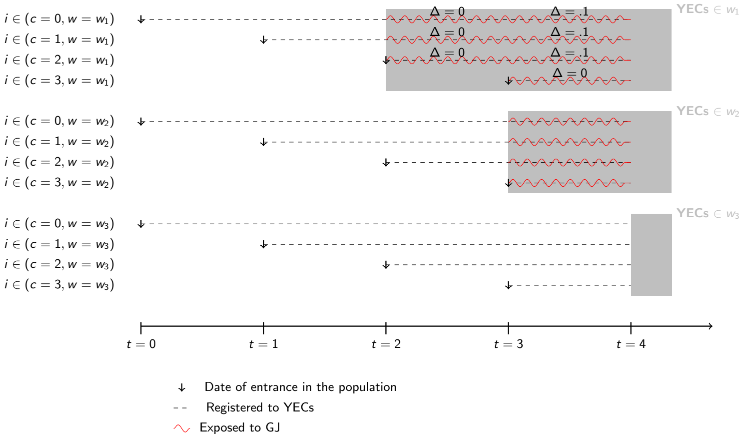
- De Chaisemartin and D'Haultfœuille (2020b): 2WFE, building block is $DID_{w,t}$ (effect since *adoption*)
- Two problematic features of my setting:
  1. Dynamic effects of the program with cohorts registering after introduction
  2. Time since registration is a source of unobserved selection into treatment Visual evidence, hence of potential heterogeneity

In these two cases, effect since adoption can be misleading!

Why effect since adoption is misleading?

Case #1: Dynamic effects over exposure to the program with cohorts registering after introduction

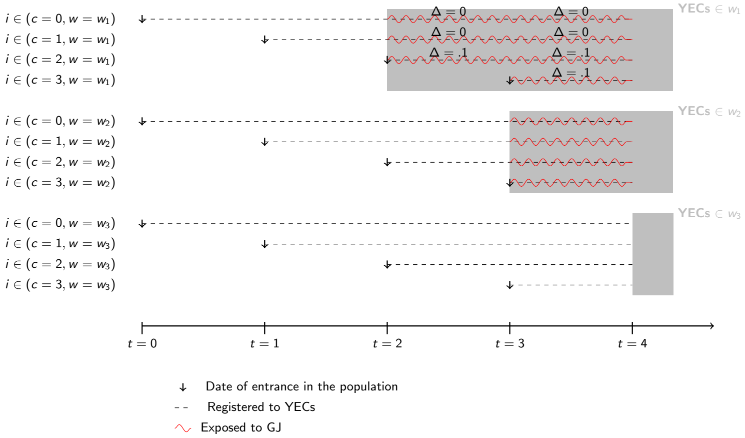
- Suppose the true effect is $\Delta = 0$ when exposed $G = 1$ quarters, $\Delta = .1$ when $G = 2$. Avg. effect when $G = 2$ is .1
- Effect two quarters since adoption: $DID_{w_1, t=2} = 0.075$



Why effect since adoption is misleading?

Case #2: Time since registration is a source of unobserved selection into treatment, hence of heterogeneity

- Suppose true effect is $\Delta = 0$ if $G^h_{w,c} > 0$, $h > G$, and $\Delta = .1$ if $G^h_{w,c} > 0$, $h = G$. Average effect when $G^h_{w,c} = 2$ is .03
- Effect two quarters since adoption: $DID_{w_1,t=2} = 0.05$



Back to Identification

Example of results for cell-specific ITT

Coefficients of reduced form and first stage for every wave (each line corresponds to one wave) and cohort (each column corresponds to one cohort of registration). YEC time since registration is 4 quarters after registration. Colors represent the scale of the value in the cell relative to the table, red for positive green for negative. $h = 5$

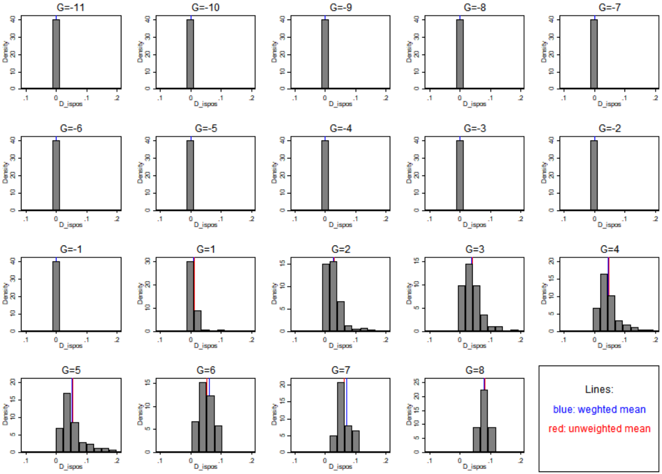
$DID^4_{w,c}$	2013q1	2013q2	2013q3	2013q4	2014q1	2014q2	2014q3	2014q4	2015q1	2015q2	2015q3	2015q4	2016q1	2016q2
2014q2	0.0000	-0.0135	-0.0390	-0.0328	-0.0093	-0.0245	-0.0446	-0.0091	0.0516	-0.0270	-0.0003	0.0243	0.0273	0.0476
2014q4	0.0735	-0.1579	0.0000	-0.0004	0.0262	-0.1778	-0.0210	-0.0547	-0.0406	-0.1604	-0.0950	-0.0645	-0.0807	-0.1722
2015q1	-0.0440	-0.0193	-0.0096	0.0000	0.0023	0.0064	0.0144	0.0177	0.0073	-0.0101	0.0155	0.0097	-0.0063	-0.0016
2015q2	-0.0171	-0.0162	-0.0096	-0.0299	0.0000	0.0138	0.0185	0.0073	0.0071	-0.0008	0.0273	0.0163	0.0046	0.0082
2015q3	-0.0113	-0.0026	0.0098	0.0077	-0.0040	0.0000	-0.0052	-0.0081	-0.0055	-0.0055	0.0187	0.0066	-0.0072	-0.0028
2015q4	0.0711	0.0548	0.0613	0.0556	0.0593	0.0099	0.0000	0.0261	0.0269	0.0060	-0.0141	0.0428	0.0780	0.0460
2016q1	-0.0788	-0.1054	-0.1128	-0.1053	-0.0567	0.0001	-0.0033	0.0000	0.0102	-0.0183	-0.0193	-0.0242	-0.0181	-0.0509
2016q2	0.0279	0.0021	0.0249	0.0074	0.0044	-0.0045	0.0096	0.0018	0.0000	-0.0029	-0.0015	-0.0202	-0.0308	-0.0366
2016q3	-0.0380	-0.0188	0.0017	0.0102	-0.0134	-0.0036	0.0093	0.0054	-0.0024	0.0000	-0.0014	-0.0146	-0.0274	-0.0290
2016q4	-0.0027	-0.0257	-0.0156	-0.0418	-0.0099	-0.0046	0.0161	-0.0121	-0.0230	0.0011	0.0000	-0.0110	-0.0234	-0.0184

$Pr(D^4_{w,c} > 1)$	2013q1	2013q2	2013q3	2013q4	2014q1	2014q2	2014q3	2014q4	2015q1	2015q2	2015q3	2015q4	2016q1	2016q2
2014q2	0.0000	0.0055	0.0256	0.0510	0.0529	0.1232	0.1186	0.1641	0.1368	0.1095	0.1559	0.1976	0.1346	0.1234
2014q4	0.0000	0.0000	0.0000	0.0000	0.0056	0.0114	0.0351	0.0388	0.0528	0.0295	0.0474	0.0370	0.0572	0.0316
2015q1	0.0000	0.0000	0.0000	0.0000	0.0061	0.0163	0.0312	0.0421	0.0539	0.0620	0.0796	0.0775	0.0830	0.0935
2015q2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0064	0.0174	0.0276	0.0409	0.0574	0.0702	0.0740	0.0710	0.0783
2015q3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0049	0.0123	0.0217	0.0388	0.0595	0.0649	0.0658	0.0741
2015q4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0064	0.0127	0.0272	0.0383	0.0549	0.0546	0.0550
2016q1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0027	0.0076	0.0165	0.0177	0.0265	0.0482
2016q2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0072	0.0135	0.0208	0.0362	0.0489
2016q3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0048	0.0096	0.0169	0.0352
2016q4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0094	0.0215	0.0275

$n^4_{w,c}$	2013q1	2013q2	2013q3	2013q4	2014q1	2014q2	2014q3	2014q4	2015q1	2015q2	2015q3	2015q4	2016q1	2016q2
2014q2	452	363	430	569	397	357	506	585	468	338	417	663	431	308
2014q4	354	715	369	419	357	703	370	361	341	441	380	378	297	474
2015q1	13423	12015	17831	17003	14335	11912	18571	17106	13759	12571	17632	15659	12875	11361
2015q2	17701	15797	23058	22965	19450	16471	24314	22569	18653	16197	23054	20801	17081	15541
2015q3	25680	22528	31255	32295	27282	22789	32574	32289	26590	21985	30497	29523	24561	21390
2015q4	1591	1402	2028	2261	1735	1502	2428	2184	1738	1399	2038	1657	1466	1145
2016q1	3255	2981	4134	4138	3561	2991	4383	4411	3364	2901	3992	3901	3394	3052
2016q2	6467	5669	8273	8283	7062	6099	8935	8435	6886	6073	8170	7465	6162	5850
2016q3	8248	7679	10590	10901	9289	7868	10935	10911	8900	7649	10329	9896	8065	7038
2016q4	4053	3589	5042	5497	4566	4007	5589	6168	4765	3855	5391	5548	4320	3488

Example of results for cell-specific ITT

Distribution of $DID^h_{w,c} \quad \forall w, c, h : G^h_{w,c} = g$ for employment



Back to identification

Comparison with the Classical Event-Study Design

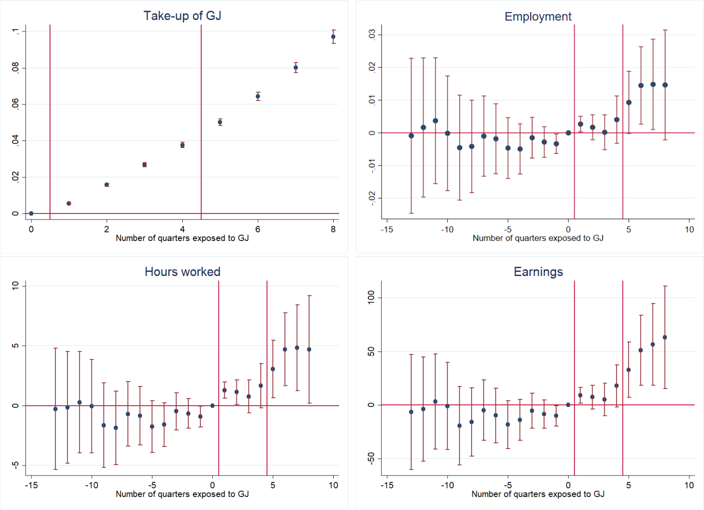
Following Borusyak and Jaravel (2017):

$$y_{i,t} = \sum_{g} \beta^{g} \mathbb{1}(G^{h}_{w,c} = g) + \gamma_{c,h} + \mu_{m,h} + \epsilon_{i,t} \tag{1}$$

Where:

- $\gamma_{c,h}$ are cohort-time since registration fixed effects
- $\mu_{m,h}$ are YEC fixed effects (with each YEC belonging to one wave)

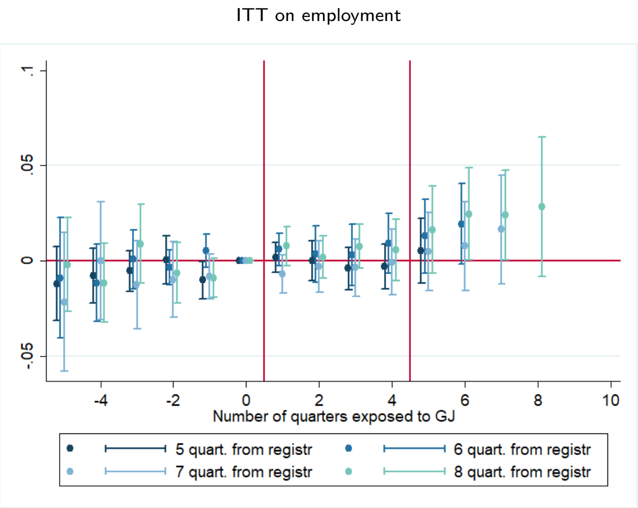
Results: Event-Study Design



Notes. The upper right panel of the figure reports coefficients and 95% confidence intervals for the first stage regression, where the dependent variable is a dummy equal to one from the quarter of enrollment in GJ onward, and the independent variable is a dummy for exposure to GJ, as in Regression **??**. The other three panels report reduced-form regressions where the outcomes are a dummy equal to one if the individual has been employed at least once in the quarter, the total amount of earnings, and the total amount of hours.

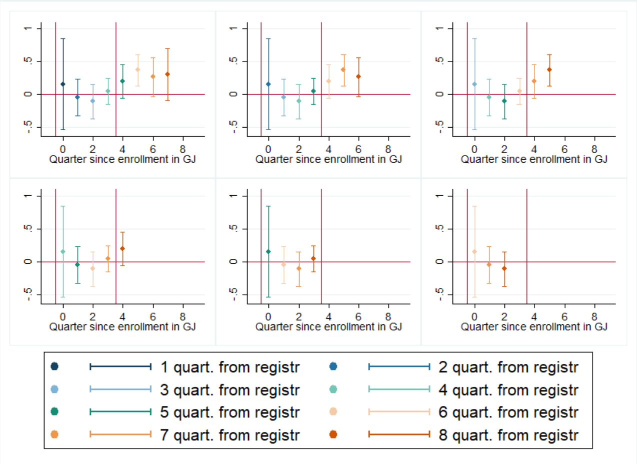
Back to Results

Results: by time-since-registration



Results: by time-since-registration

LATE on employment, grouping together cells containing the same individuals



Back to Results

Results: ITTs heterogeneity

By kind of contract Table

- The effect in the second year of exposure is mostly made of **temporary contracts** (+0.7 pp.) and **agency jobs** (+0.5 pp.).
- Lower and insignificant effect considering only open-ended (+0.3 pp.).
- Apprenticeships increase of .1 p.p. since the first year of exposure.

By youth characteristic Table

- The effect is lower for aged 16-18 vs. others
- The effect is slightly larger but noisy for youths with less than upper secondary education

By regional labor market tightness (Crépon et al., 2013) Table

- The effect is driven by tight markets (but pre-trends problematic)

Heterogeneity by kind of contract

	Open-ended (1)	Temporary (2)	Agency jobs (3)	Apprenticeships (3)
ITT effect 1st semester of exposure	0.000224	0.000858	0.00147	0.000971
	(0.00133)	(0.00205)	(0.00136)	(0.00113)
Total n.obs	3194961	3194961	3194961	3194961
ITT effect 2nd semester of exposure	0.000224	0.000858	0.00147	0.000971
	(0.00208)	(0.00258)	(0.00217)	(0.00115)
Total n.obs	2379924	2379924	2379924	2379924
ITT effect 2nd year of exposure	0.00218	0.00674	0.00389	0.00115
	(0.00437)	(0.00438)	(0.00246)	(0.00189)
Total n.obs	2665714	2665714	2665714	2665714
Mean for control 1st semester of registration in ML	0.084	0.155	0.078	0.031
Mean for control 2nd semester of registration in ML	0.109	0.184	0.081	0.034
Mean for control 2nd year of registration in ML	0.138	0.191	0.086	0.037
LATE 1st semester of exposure	0.00947	0.0363	0.0623*	0.0412
	(0.0348)	(0.0550)	(0.0362)	(0.0296)
LATE 2nd semester of exposure	0.00947	0.0363	0.0623***	0.0412***
	(0.0225)	(0.0278)	(0.0234)	(0.0126)
LATE 2nd year of exposure	0.0403	0.124***	0.0718***	0.0211
	(0.0326)	(0.0328)	(0.0179)	(0.0142)
LATE 1st semester after enrollm.	0.0264	0.0107	-0.00615	-0.00492
	(0.0192)	(0.0193)	(0.0137)	(0.0109)
LATE 2nd semester after enrollm.	0.0601	0.0405	0.0954**	-0.0144
	(0.0819)	(0.0640)	(0.0423)	(0.0630)
LATE 2nd year after enrollm.	0.0403	0.124***	0.0718***	0.0211
	(0.0326)	(0.0328)	(0.0179)	(0.0142)

Back

Heterogeneity by gender

	Men				Women			
	Enrollment in GJ (1)	Employment (2)	Hours (3)	Wages (4)	Enrollment in GJ (5)	Employment (6)	Hours (7)	Wages (8)
ITT 1st semester of exposure	0.0173***	0.000722	0.357	-0.679	0.0164***	0.000223	0.816	1.18
	(0.00068)	(0.00233)	(0.503)	(1.31)	(0.000647)	(0.00260)	(0.569)	(1.75)
Total n.obs		2024678	1997745	740992		1952910	1934617	773620
ITT 2nd semester of exposure	0.0420***	-0.000997	0.453	-2.62	0.0392***	-0.00137	0.0819	2.63
	(0.00145)	(0.00435)	(1.22)	(1.67)	(0.0014)	(0.00505)	(1.44)	(3.10)
Total n.obs		1980704	1946295	780753		1909974	1886860	801193
ITT 2nd year of exposure	0.0641***	0.0163*	4.27	-2.22	0.0577***	0.0151	4.29	0.876
	(0.00226)	(0.00942)	(2.75)	(1.43)	(0.00220)	(0.00987)	(3.03)	(3.05)
Total n.obs		2840870	2778796	1177636		2734015	2693958	1188740
Control mean 1st semester in YEC			61	10.9			67	11.2
Control mean 2nd semester in YEC			98	10.8			101	10.9
Control mean 2nd year in YEC			124	11.0			126	10.9

Heterogeneity by education

	Less than upper secondary education				At least upper secondary education			
	Enrollment in GJ (1)	Employment (2)	Hours (3)	Wages (4)	Enrollment in GJ (5)	Employment (6)	Hours (7)	Wages (8)
ITT 1st semester of exposure	0.0150***	0.00118	0.770	1.77	0.0199***	-0.000668	0.336	-2.75
	(0.000656)	(0.00296)	(0.579)	(1.10)	(0.000682)	(0.00199)	(0.508)	(3.76)
Total n.obs		2523492	2493070	1002782		1454096	1439292	511830
ITT 2nd semester of exposure	0.0354***	-0.000223	0.608	0.832	0.0499***	-0.00298	-0.159	-1.87
	(0.00140)	(0.0055)	(1.51)	(2.18)	(0.00151)	(0.00361)	(1.03)	(2.54)
Total n.obs		2468647	2429875	1037911		1422031	1403280	544035
ITT 2nd year of exposure	0.0510***	0.0168	4.86	0.343	0.0784***	0.0138*	3.47	-2.09
	(0.00205)	(0.0112)	(3.41)	(1.09)	(0.00266)	(0.00743)	(2.12)	(3.97)
Total n.obs		3516911	3448890	1532286		2057974	2023864	834090
Control mean 1st semster in YEC			69	11.3			55	10.4
Control mean 2nd semster in YEC			107	11.1			87	10.4
Control mean 2nd year in YEC			130	11.0			115	10.8

Heterogeneity by age

	Aged 16-18				Aged 19-21				Aged 22-25			
	Enrollment in GJ (1)	Employment (2)	Hours (3)	Wages (4)	Enrollment in GJ (5)	Employment (6)	Hours (7)	Wages (8)	Enrollment in GJ (9)	Employment (10)	Hours (11)	W (
									s			
ITT 1st semester of exposure	0.0177***	0.00301	0.612	2.23	0.0203***	0.00134	1.05**	-2.15	0.0110***	-0.000103	0.444	3.
	(0.00062)	(0.00206)	(0.5)	(1.52)	(0.00083)	(0.00238)	(0.480)	(2.12)	(0.000511)	(0.00473)	(0.861)	(1
Total n.obs		1160694	1152974	373832		1632664	1612033	705471		1180716	1163848	43
ITT 2nd semester of exposure	0.0491***	-0.00177	-0.197	-1.18	0.0467***	0.00137	1.42	-3.68	0.0235***	0.0000201	0.323	6
	(0.00151)	(0.00294)	(0.840)	(0.902)	(0.00171)	(0.00380)	(1.19)	(3.09)	(0.000993)	(0.00899)	(2.36)	(3
Total n.obs		1138145	1127245	414957		1596649	1570190	727114		1152411	1132254	43
ITT 2nd year of exposure	0.0821***	0.00902	1.64	-1.83	0.0659***	0.0236***	7.48***	-1.37	0.0319***	0.0189	4.75	1
	(0.00258)	(0.00588)	(1.62)	(1.33)	(0.00257)	(0.00877)	(2.59)	(3)	(0.00142)	(0.0159)	(4.85)	(1
Total n.obs		1635336	1614145	656997		2289327	2242361	1078119		1645214	1611256	63
Control mean 1st semester in YEC		00.276	40	8.8		00.440	71	11.4		00.421	78	1
Control mean 2nd semester in YEC		00.276	40	8.8		00.440	71	11.4		00.421	78	1
Control mean 2nd year in YEC			72	9.5			110	11.2			112	1

Back

Heterogeneity by market tightness

	Loose markets				Tight markets			
	Enrollment in GJ (1)	Employment (2)	Hours (3)	Wages (4)	(5)	(6)	(7)	(8)
ITT 1st semester of exposure	0.0252***	0.00342	1.35	-0.0249	0.0297***	-0.00420	-1.31	-0.0584**
	(0.00118)	(0.00324)	(0.891)	(0.0266)	(0.00105)	(0.00435)	(1.33)	(0.0274)
Total n.obs		1941294	1915424	763253		2036294	2016938	751359
ITT 2nd semester of exposure	0.0252***	0.00342	1.35	-0.0249	0.0297***	-0.00420	-1.31	-0.0584**
	(0.00118)	(0.00324)	(0.891)	(0.0266)	(0.00105)	(0.00435)	(1.33)	(0.0274)
Total n.obs		1882431	1850644	781056		2008247	1982511	800890
ITT 2nd year of exposure	0.0563***	0.0494***	14.4***	0.0074	0.0661***	-0.0287*	-8.65*	0.0099
	(0.00233)	(0.0104)	(3.26)	(0.0330)	(0.0018)	(0.0166)	(5.17)	(0.0383)
Total n.obs		2467191	2419328	1061110		3107694	3053426	1305266
Control mean 1st semester in YEC		0.412	68.2	11.26		0.363	59.7	10.75
Control mean 2nd semester in YEC		0.493	127.7	11.09		0.479	121.4	10.79
Control mean 2nd year in YEC		0.493	127.7	11.09		0.479	121.4	10.79

Back

Descriptives of the sample

Population of interest is low-educated, gender-balanced, and tends to be premature in "adulthood" activities

Characteristics of the overall population, of youths in YECs (sample observed), and of youths registering in YECs standard program CIVIS and in GJ

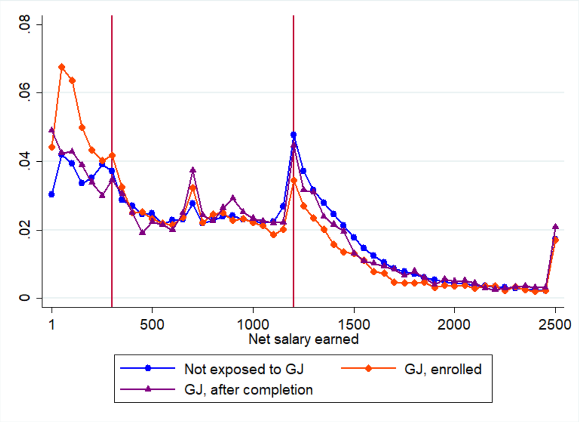
	All youths 16-25 (Census) (1)	Youths in YECs (2)	Youths in std. prog. (3)	Youths in GJ (4)
Number of youths (stock)	9327476	1967000	444309	113085
Number of youths (quarter inflow)		125689	41471	14899
Lower than secondary educ.	0.394	0.373	0.424	0.467
Upp. secondary edu. diploma	0.434	0.519	0.541	0.507
Avg. age	20.3	20.1	19.7	18.8
Female	0.491	0.491	0.511	0.463
French nat.	0.915	0.912	0.919	0.929
Empl. last quarter	0.297	0.349	0.335	0.212
Lives independently	0.230	0.365	0.369	0.354
Has kids	0.0390	0.0838	0.0878	0.0496

Notes. The table compare the characteristics of youths in different population. The first column concerns all youths aged 16-25 in France, as reported by the Census in years 2013-2016. The second column reports all youths in the sample, namely all youths who registered at YECs in the 2013-2016 period. The third and fourth column reports respectively information on youths enrolling in the standard program offered at YECs, CIVIS, and enrolling in *Garantie Jeunes*. All lines report the characteristics of youths in the sample, except the second line which reports the inflow of youths, on average over 2013-2016 for column 2, in the first quarter of 2014 for column 3 and in the first quarter of 2017 for the last column.

Back to Data

Earning distributions for youths in GJ

Distribution of net earnings for takers by enrollment in *Garantie Jeunes*



Back to Mechanisms