Case Studies in Microeconomic Evaluation

Data and methods for learning what works

Matching

Competence Centre on Microeconomic Evaluation (CC-ME)
Joint Research Centre
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A Brief Introduction to Matching

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European Commission

Counterfactual impact evaluation (CIE)

- Evaluating the causal impact of a policy/programme/intervention (**treatment T**)
- Comparing the outcomes (**Y**) of beneficiaries/participants (**treated**) and non-participants (**controls**)

Conterfactual scenario:
What would have happened to treated units in absence of the treatment?

Fundamental problem of causal inference:
Counterfactuals are never observable.

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CIE

- All CIE methods try to mimic the unobserved (**counterfactual**) quantities with appropriate observed (**factual**) ones.
- For example, in case of an intervention targeted at individuals, the perfect counterfactual for a person subject to the intervention would be a twin, equal in all respects to her/him, but not subject to it.
- Given the absence of a natural single counterfactual, causal effects for single units (individuals, firms, regions, etc.) are impossible to estimate.
- Need to compare the results of those participating in the intervention (**treated group**) to those of a comparable group (**control group**) that was not subject to the intervention.
- **CIE objective**: identify a good comparison group to calculate a summary measure of the treatment effect.

Matching

Idea

- **Match** participants to non-participants units who are as similar as possible with respect to observable characteristics.
- The **difference** in the outcome variable between the two groups should only be due to the **treatment status**.

Types

1. **Exact** matching
2. **Propensity score** matching
3. **Optimal** matching

Assumptions

Conditional Independence Assumption (CIA)

- There are **no systematic differences** between participants and non-participants in unobserved characteristics that influence the outcome Y.
- All the variables that affect simultaneously the treatment T and the outcome Y are observed.

CIA also referred to as: *selection on observables, unconfoundedness, ignorable treatment assignment*.

CIA validity depends on the amount of this type of variables which can be observed in the data, i.e. on the richness of the data used in the matching procedures.

Estimated parameter

Treatment effect:

- average treatment effect (**ATE**)
- average treatment effect on the treated (**ATT**)

1) Exact matching

Idea

- **Matching** participants to non-participants units with the **same** observed characteristics.
- **Coarsened exact matching (CEM)**: matching participants to non-participants units on broader **ranges** of the variables, by first coarsening observable characteristics into groups or classes; for example, using income categories rather than a continuous measure (Iacus, King and Porro, 2008).

Treated units			
Age	Gender	Months unemployed	Secondary diploma
19	1	3	0
35	1	12	1
41	0	17	1
23	1	6	0
55	0	21	1
27	0	4	1
24	1	8	1
46	0	3	0
33	0	12	1
40	1	2	0

Untreated units			
Age	Gender	Months unemployed	Secondary diploma
24	1	8	1
38	0	1	0
58	1	7	1
21	0	2	1
34	1	20	0
41	0	17	1
46	0	9	0
41	0	11	1
19	1	3	0
27	0	4	0

Exact matching on 4 dimensions

1) Exact matching

Drawback of exact matching

- As the number of characteristics determining selection increases, it is more and more difficult to find comparable individuals (curse of dimensionality).

Matching on Propensity Score

- Matching on a **single index**, **Propensity Score**, reflecting the probability of participation, could achieve consistent estimates of the treatment effect in the same way as matching on all covariates.
- This single index **summarises** all the relevant information contained in the covariates.

2) Propensity Score Matching (PSM)

- **Propensity Score**: probability of participating in the intervention, conditional on the characteristics (Rosenbaum and Rubin, 1983).
- **Matching**: finding participants and non-participants with equal/similar propensity score.

Assumptions

1) CIA
2) Common support:
   - If there are individuals with **similar propensity scores** in both groups, **matching is feasible**.
3) Propensity Score balances the covariates
   - Similar propensity scores are based on similar observed characteristics.

Propensity Score Matching step by step

In order to check the assumptions, it is advisable to frame the implementation of the PSM in the following steps:

1. Estimate the **propensity score**;
2. Check the assumptions: **common support**;
3. **Match** participants with non-participants;
4. Check the assumptions: **covariates' balance**;
5. Compute the **average treatment effect**;
6. Compute the **standard error** of the treatment effect (not covered).

Step 1 - Estimation of the Propensity Score

- Estimate a binary response model for the probability of being exposed to the policy, such as a logit/probit.
- Use the model to compute predicted probabilities for each unit.

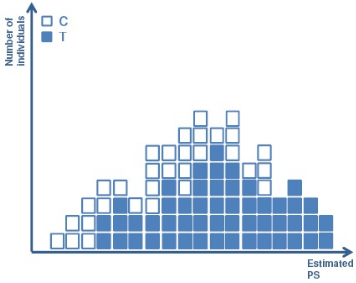
Tip:

Include variables that are measured **prior to the treatment** and that may affect both D_i and Y_i.

Step 2 - Check the assumptions

Common support

Example: Hypothetical situation

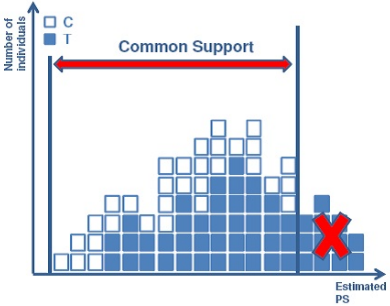


- Compare only similar individuals, that is with similar PS.
- **Drop** treated units that have no units with similar PS in the control group.

Step 2 - Check the assumptions

Common support

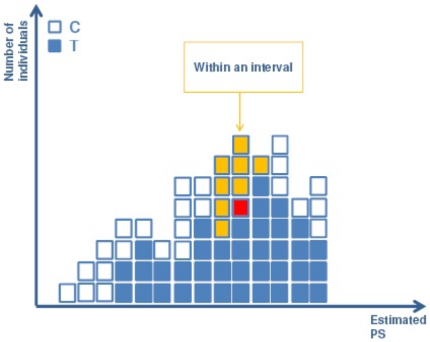
Example: Hypothetical situation



- Compare only similar individuals, that is with similar PS.
- **Drop** treated units for which cannot find control units with similar PS.

Attention: If too many observations are dropped a bias may occur and the remaining treated may not be representative of the treated population. The characteristics of those dropped should be investigated.

Step 3 - Matching



- Matching done individually
- Nearest Neighbors Matching
- Radius Matching
- Kernel Matching

Step 4 - Check covariates’ balance

- The main PSM argument is that units with similar PS are similar in all characteristics.
  This is a **pre-condition** for the success of PSM.
- This **property** of PS can be **assessed**, for instance, by checking if the distribution of all covariates is the same for participants and matched non-participants.
- If **covariate balance is unsatisfactory**, it may indicate lack of comparability between the two groups, therefore**alternative evaluation approaches** should be considered.

Step 5 - Compute the average treatment effect

- Take the mean value of each group's outcome.

$$ATT_i = \overline{T} - \overline{C}$$

- The choice of the matching algorithm affects:
  - the number of units matched from the control group;
  - the weights attributed to each of them.

Pros

- PSM allows more focus on the selection process and on the underlying assumptions.
- Imposition of the **common support** ensures comparability.
- **Versatility**: PSM
  - allows to estimate **heterogeneous** effects (by sub-group);
  - allows to put more emphasis on specific variables, on which exact matching can be done (e.g. region, gender);
  - allows the estimation of **multiple treatments**: different treatment levels or types of participation can be compared.

Cons

- PSM is a ‘data-hungry’ method.
  More efficient methods under CIA exist.
- PSM requires strong robustness and sensitivity analyses.
- CIA is a strong assumption:
  - it is impossible to verify, so bias stemming from unobservables can never be ruled out.
  - Matching is only as good as the characteristics used to match observations.

3) Optimal Matching Algorithm (OMA)

- **OMA**: used to measure the dissimilarity between two different sequences.
- **Individual sequence**: string containing a finite number of characters, each representing the 'state' of an individual in a given moment in time.
- **Sequence analysis**: a stream of the sociological literature dealing with life-course studies in which the sequence, conceived as the representation of a longitudinal process by a series of states, is the object of primary interest.

Sequence defined on the basis of two main elements:

- length and spacing (for instance, a 24-month monthly sequence);
- the so-called state-space, i.e. a full list of states of the world mutually exclusive in time.

Distance between two sequences: **cost** associated to the edit operations required to transform the original sequences and make them identical.

Types of edit operations:

- **insertion/deletion**: a state is inserted or deleted in a specific portion of the sequence;
- **substitution**: a state is replaced by another.

In order to derive a distance metric, specific costs must be assigned to each type of operation. This choice is generally justified on theoretical and empirical grounds and heavily depends on the object of study.

OMA:

- originally developed in the field of information theory;
- introduced in sequence analysis by Abbott (1995): the distance is commonly used to group sequences into clusters based on their **similarity**, and identify patterns of life-course trajectories;
- used combining sequence analysis techniques with **causal inference** for the first time by Barban et al. (2017) in an observational study: OM-computed distances between pre-retirement health trajectories are used to investigate the effect of the age at retirement on subsequent health outcomes.

Matching using sequences: the evaluation of the Irish JobsPlus wage subsidy scheme

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Irish Department of Employment Affairs and Social Protection (DEASP)
European Commission, Joint Research Centre (JRC) Ispra

European Commission

Based on a collaboration between:

- European Commission, Joint Research Centre - Centre for Research on Impact Evaluation (CRIE), Competence Centre on Microeconomic Evaluation (CC-ME)
- Irish Department of Employment Affairs and Social Protection (DEASP)

Aim:

- Counterfactual Impact Evaluation (CIE) of the ‘JobPlus’ scheme within the ‘Data Fitness Initiative for CIE’

JobsPlus scheme

- **Incentive scheme**
- **Type**: wage subsidy to employers
- **Target group**: long-term unemployed jobseekers
- **Objective**: to encourage employers and businesses to focus their recruitment efforts on those who have been out of work for long periods
- **Duration**: 2 years
- **Financing source**: European Social Fund + National budget
- **Budget**: 28m overall in 2016
- **Participants**: since mid 2013 more than 15,000 positions filled by long-term unemployed through the scheme

JobsPlus scheme

Created within the Irish **'Government's Action Plan** for Jobs 2013'

- Part of a range of measures aimed at employers
- More specifically *'Incentivising employers to provide more jobs for those who are unemployed'*

Timeline

- July 2013: pilot phase, 2500 places cap in annual budget
- 2014: expansion to 3000 places cap
- 2015: expansion to 6000 places cap
- 2015: 'JobsPlus Youth' added under EU Youth Guarantee scheme

JobsPlus scheme

Eligibility criteria

Jobseekers: recipience of a jobseeker's payment for at least

- 12 of the previous 18 months for the 7,500 incentive, or
- 24 of the previous 30 months for the 10000 incentive

Employers: recipience of a jobseeker's payment for at least

- private, community, voluntary and not-for-profit sectors;
- full-time work offer, paid at least the national minimum wage (9.55 per hour);
- new positions or positions arising from natural turnover;
- being tax compliant;
- having paid the incentive monthly in arrears.

Related literature

- Wage subsidies, both employee-side and employer-side, have been widely used as ALMP in European and non-European countries
- Concerning employer-side hiring incentives:
  - Card et al. (2010, 2018) meta-analyses: public sector employment programmes tend to have small or even negative average impacts both in the short and the long run, and are relatively ineffective, with respect to other types of policies, such as job search assistance and training programmes
  - Neumark and Grijalva (2013): similar evidence for the US
  - Cahuc et al. (2014): hiring incentives targeted at small firms supported job-growth in France
- Focusing on incentives for long-term unemployed:

Authors	Country	Pub. Year	Interv. Year	Outcomes	Data	Method
Forslund, Johansson, Lindqvist	Sweden	2004	1998-2002	empl./wages	admin	PSM, DID
Sianesi	Sweden	2008	1994	empl.	admin	PSM
Rodríguez-Planas, Jacob	Romania	2009	1999	empl./wages	survey	PSM
Hujer, Thomsen	Germany	2010	2000-2001	empl.	admin	PSM
Mihaylov	Bulgaria	2011	2005	empl.	admin	PSM
Schunemann, Lechner, Wunsch	Germany	2016	2000-2001	empl.	admin	DID, RDD
Sjogren and Vikstrom	Sweden	2015	2007-2011	empl	admin	DID

Related literature

Double selection issue (Schunemann, Wunsch and Lechner, 2015):

- Differently from training or job search assistance programs, wage subsidies cannot be mandated: they require the willingness of an employer to hire a subsidised worker.
- Policy-makers can only provide the option of granting a subsidy, while actual take-up is the outcome of decisions that can only be influenced to some degree.

Selection into:

- subsidy receipt (treatment);
- employment.

Among eligible individuals: **receiving the subsidy is conditional on being employed**

- separating the effect of gaining a job from the effect of gaining the subsidy is rather difficult;
- individuals who find a job are not a random sample of the pool of unemployed individuals;
- selection issue: individual A finds a job and gets the subsidy while individual B either does not find a job (A is positively selected?) or finds a job without the subsidy (A is negatively selected?)

Related literature

Intention- to-treat (ITT) estimation focusing on eligibility for the subsidy rather than on actual take-up of subsidies:

- Being eligible for the subsidy does not require finding employment. Therefore the double-selection problem into both employment and subsidy receipt is absent when the treatment is defined as subsidy eligibility.
- Schunemann, Wunsch and Lechner, (2015): Combination of Regression Discontinuity Design (RDD) with a difference-in-differences (DiD) approach
- Sjögren and Vikström, (2015): Cox-proportional hazard (CPH) model for daily exits to employment

Challenges and limitations:

- Statistical power issue: low take-up rate of the subsidy in the sample;
- Eligibility is defined by unemployment benefit recipiency and differs from unemployment: difficulty in defining exits to employment.

Empirical strategy

Investigate the effect of actual receipt of the subsidy

- Restricting the sample of controls to unemployed individuals who reach eligibility in the period when JobsPlus is in place (from July 2013).

Outcome of interest: probability of receiving unemployment-related benefit *t*-months after the beginning of JobsPlus

- Employment spells are imprecisely recorded in the original database:
  - Start/End dates do not provide an accurate representation of the ”true” spell;
  - Spells might be not recorded.
- Only annual labour earnings and the number of weeks worked in a year are available.

Match treated and control units using their benefit trajectories in the 48 months before JobsPlus (inflow in eligibility):

- Matching is performed within relatively small cells using Optimal Matching.

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Data

Jobseekers Longitudinal Dataset (JLD)

- Rich analytical database consisting of 14 million individual episodes of welfare and work since 2004: welfare claims, activation and training, employment histories

Linkage of records from:

- Department of Employment Affairs and Social Protection: working histories;
- Revenue Commissioners: earnings;
- Monitoring data: JobsPlus information.

Panel structure:

- Each entry is an episode referring to individual *i*;
- Each episode has a start and end date;
- Each episode is categorized according to operational criteria.

From JLD to the eligibility panel database

1. Divide episodes in eligibility VS non-eligibility according to their codes
   - Where eligible stands for: ‘counting towards eligibility for JobsPlus’
   - The eligible VS non-eligible dichotomy reflects the LiveRegister vs non-LiveRegister one
2. Clean episodes of the same type overlapping in time
3. From “wide” to “long”
   - Count the number of days individual *i* spent in eligibility episodes in each month from January 2004 to April 2018
4. Compute, each month, the eligiblity condition according to the two criteria
   - Each month count backward 18 (30) months, and check if *i* accrued 12 (24) months on LiveRegister

view

Sample selection

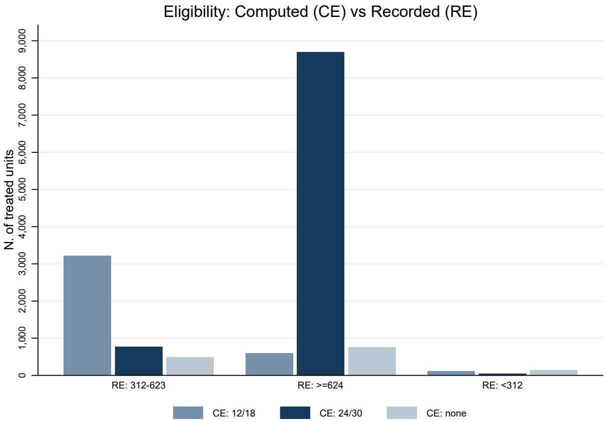
JobsPlus participants: 11763 participants

- Intervention start date: 1 July 2013
- Activity start date: individual (July 2013 - August 2017)
- Standard duration: 24 months
- Data: updated up to April 2018

1. Keep only the treated units for which the computed eligibility (CE) is equal to the recorded eligibility (RE)
2. Identify the month in which treated units become eligible for the subsidy
3. Keep only control units who are ever-eligible (separately for the two criteria) in the “post-JobsPlus” period
4. Identify the month in which control units become eligible
5. Keep only control units who enter the eligibility condition in a month that matches at least one of the treated units

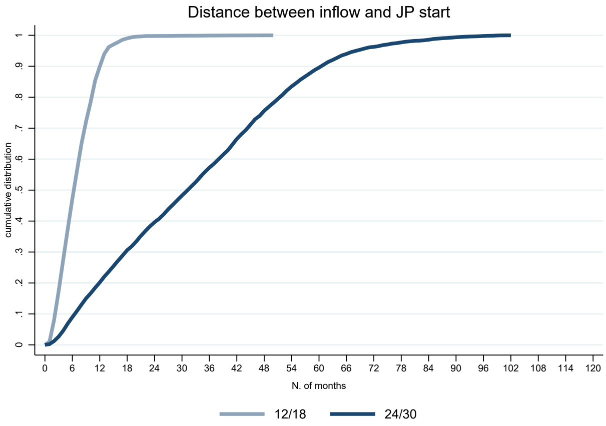
view

Treated sample: eligibility



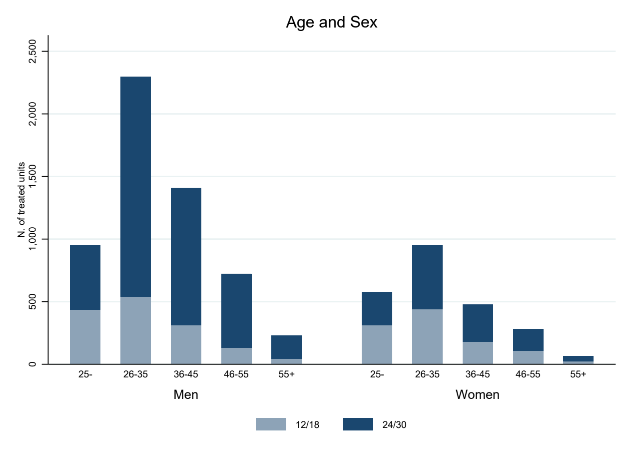
Note: The computed eligibility (CE) is obtained using only information from the JLD database, counting backward the time spent in eligibility episodes in the 18 (30) months before the time of transition into JobsPlus. Recorded eligibility (RE) is the information provided in the monitoring database

Treated sample: time in eligibility

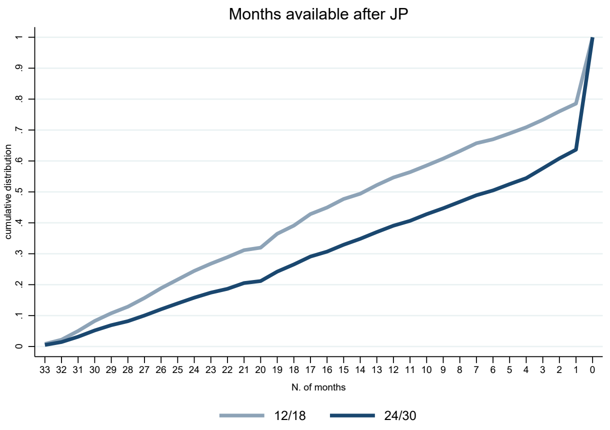


Note: Cumulative distribution for the two treatment groups

Treated sample: age and sex



Treated sample: observable months



Note: Number of months observable after the end of the full subsidy (24 months) - cumulative distribution for the two treatment groups

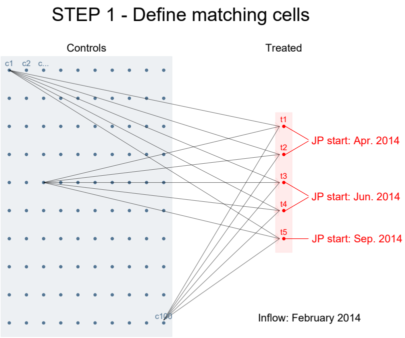
Matching approach

Objective: match treated and control units using their 'history'

- **What we need:**
  - A well-defined time-span
  - A way of classifying the experience of individual *i* in this time-span
- **What we do:**
  - The time span is defined by the 48 months before the beginning of JobsPlus
  - Each month individual *i* can be in only one 'state of the world'
- **Problems:**
  - Control units never start JobsPlus: we only know when they become eligible
  - We need precise monthly information to have a mutually exclusive classification of states...start/end dates of employment spells, as well as annual income or weeks worked won't do!
- **Solutions:**
  - Each control units is used multiple times with different JobsPlus-start dates
  - The same information used to compute eligibility is used to define states: each month *i* can either receive or not receive unemployment related benefits (LiveRegister vs non-LiveRegister)

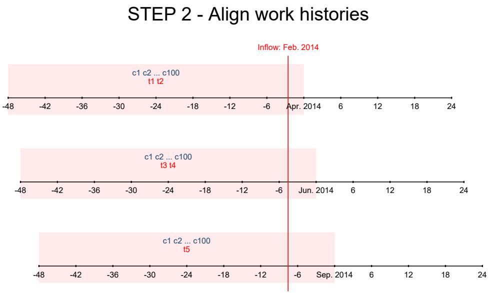
Matching approach: Step 1

- Group all individuals in the sample (of treated and controls) in cells according to the month in which they become eligible
- In each cell we might have more than one treated unit, with potentially different JobsPlus-start dates
- If in cell *c* there are, say, 3 possible dates, create 3 different ‘copies’ of each control unit, and assign to each of these copies the 3 different JobsPlus-start dates.



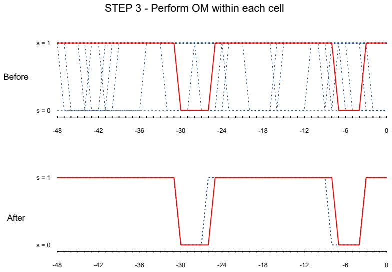
Matching approach: Step 2

- Align individual trajectories in the 48 months before the beginning of JobsPlus
- JobsPlus starting month = true for treated units
- JobsPlus starting month(S) = fake for control units
- Different bits of the full trajectory of *c* will be used when matching with different treated units



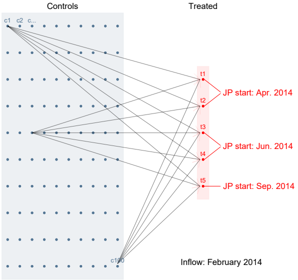
Matching approach: Step 3

- Optimal Matching (OM) is performed within each cell defined by eligibility inflow month and JobsPlus-start
- OM is an algorithm used in sequence analysis to define the ‘distance’ between different sequences
- In a binary world each sequence looks like ‘000001110101’
- The distance between two sequences is computed as the number of ‘operations’ required to convert one sequence into another
- We measure the distance between the sequences of treated and controls
- We select as matched the control(S) with the minimum distance within each cell

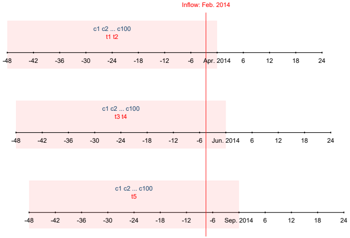


Matching approach: recap

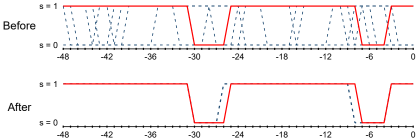
STEP 1 - Define matching cells



STEP 2 - Align work histories

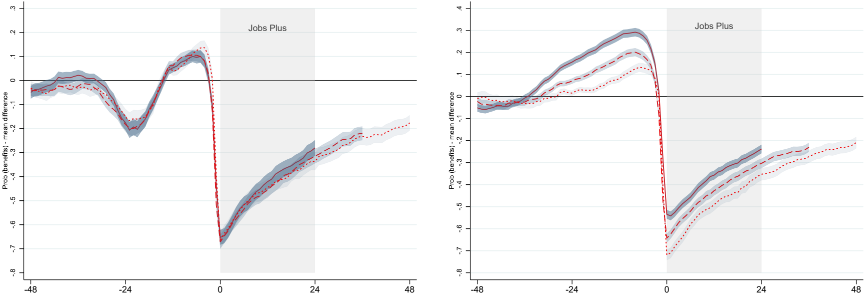


STEP 3 - Perform OM within each cell



Unmatched sequences

Average difference between treated and controls in the probability of receiving unemployment benefits.



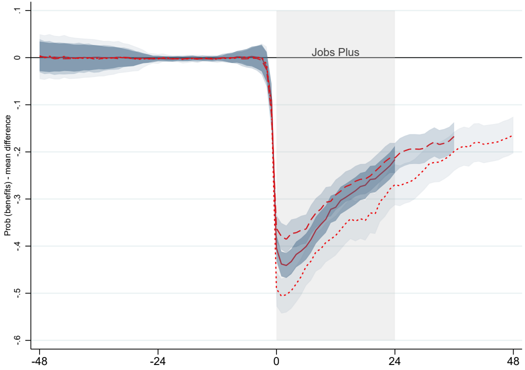
The x axis represents the monthly timeline centered on the beginning of JobsPlus. The left panel refers to the treatment 12/18, the right panel to the treatment 24/30. The solid, dashed, and dotted lines refer to individuals observable for, respectively, 24-35, 36-47, and more than 48 months after the beginning of JobsPlus

Results: Probability of receiving unemployment benefits (12/18)

The x axis represents the monthly timeline centered on the beginning of JobsPlus.The solid, dashed, and dotted lines refer to individuals observable for, respectively, 24-35, 36-47, and more than 48 months after the beginning of JobsPlus.

Results: Probability of receiving unemployment benefits (24/30)

Average difference between treated and controls



The x axis represents the monthly timeline centered on the beginning of JobsPlus.The solid, dashed, and dotted lines refer to individuals observable for, respectively, 24-35, 36-47, and more than 48 months after the beginning of JobsPlus.

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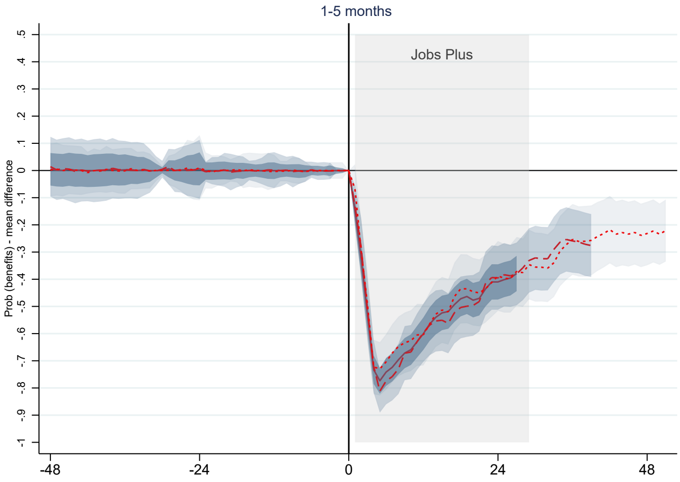
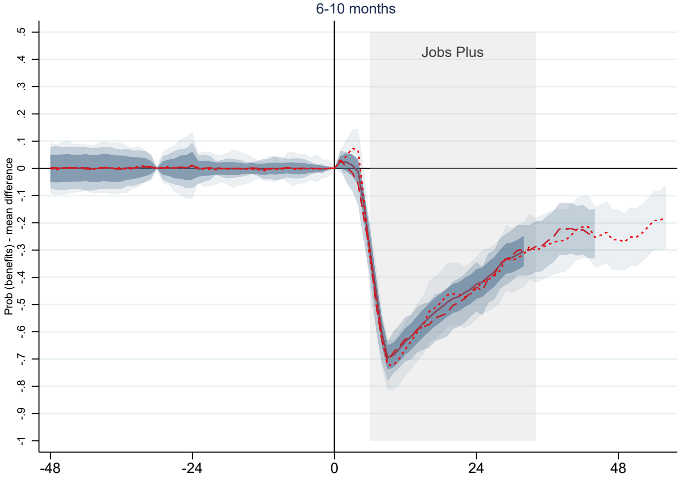
What if we use the inflow month into eligibility, instead of the JobsPlus start date, to align and match?

Results: Matching using inflow (24/30)



Results: Matching using inflow (24/30)



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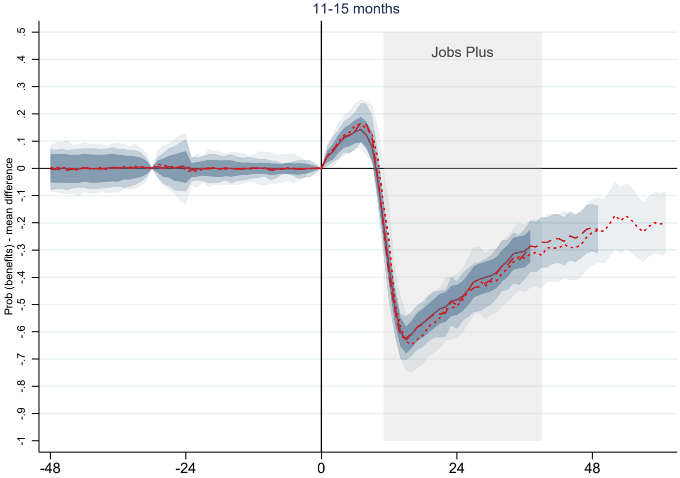
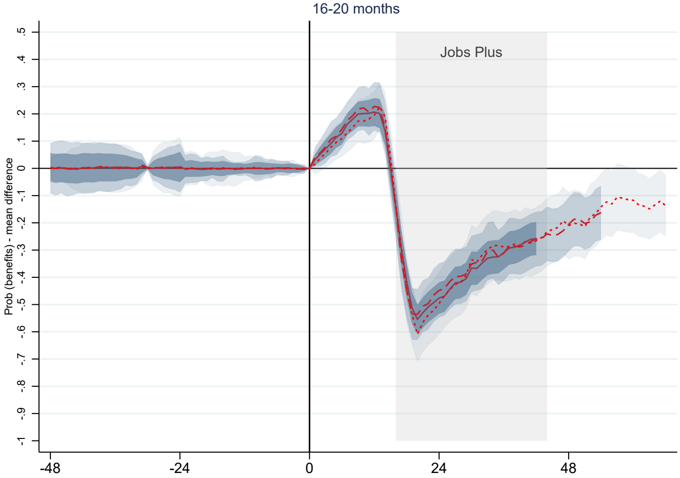
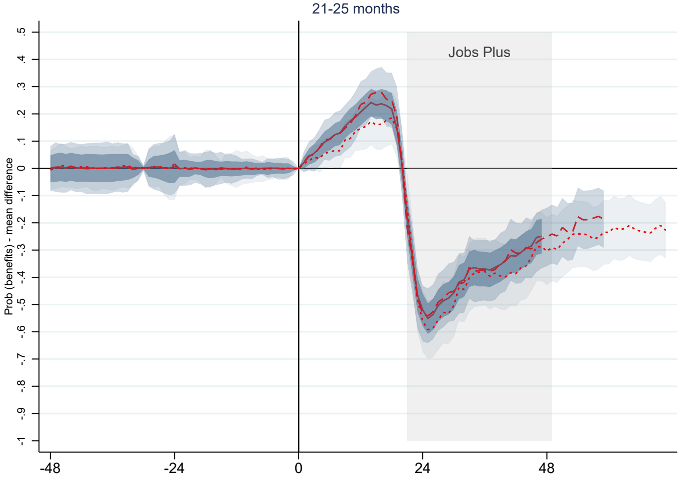
Results: Matching using inflow (24/30)



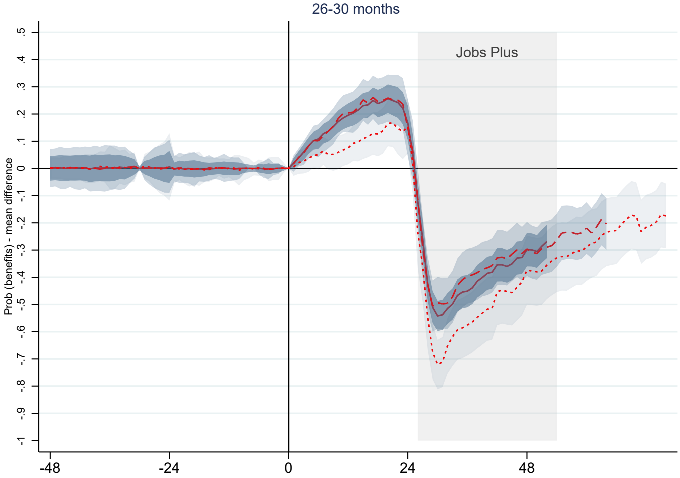
Results: Matching using inflow (24/30)



Results: Matching using inflow (24/30)

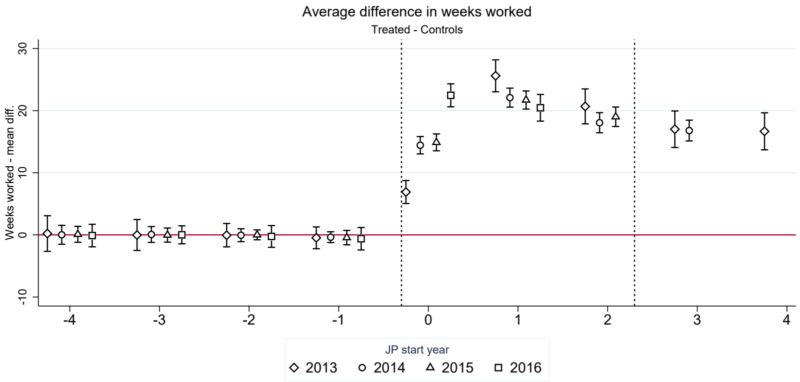


Results: Matching using inflow (24/30)



Results: Number of annual weeks worked (24/30)

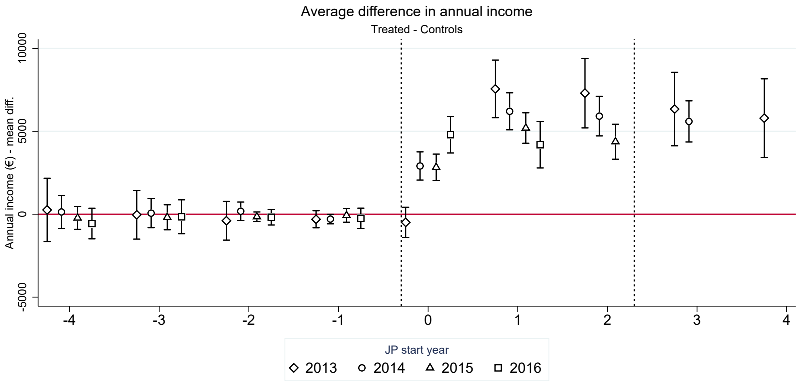
Average difference between treated and controls



Note: The x axis represents the yearly timeline centered on the beginning of JobsPlus.

Results: Annual earnings (24/30)

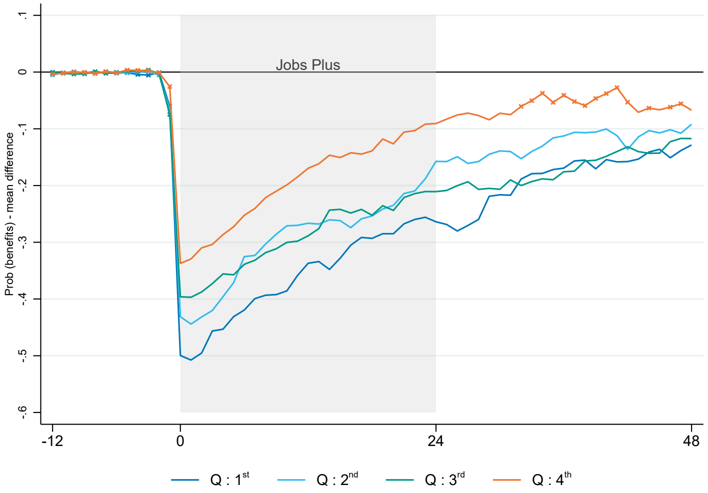
Average difference between treated and controls



Note: The x axis represents the yearly timeline centered on the beginning of JobsPlus.

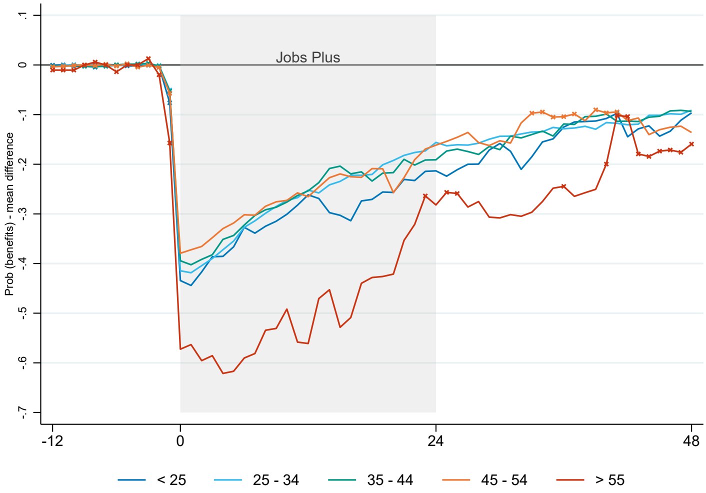
Does the effect vary with previous earnings?

Heterogeneity by previous earnings (24/30)



Does the effect vary with age?

Heterogeneity by age, 24/30



Conclusion

- Positive impact JobsPlus on the the probability of receiving unemployment benefits.
  - It decrease over time, however... still statistically significant after 48 months.
- Impact on the number of weeks in employment:
  - Three and four years after starting JobsPlus, participants work an average of 14.3 weeks more than the matched group of eligible non-participants.
- Impact on earnings:
  - Four years after the start of JobsPlus, participantes have annual earnings from employment approx 6,000 higher than the matched group of eligible non-participants.
- The effect of JobsPlus is strongest for those with the lowest earnings before the beginning of the programme.
- The positive impact of JobsPlus is visible across all age categories.
- Results indicate that JobsPlus is a valuable and effective labour market intervention to help long-term unemployed to secure employment.

newid	ep_start	ep_end	lastlls	lr_flag	lm_code	dob	female	county_code	hh_cat	occ_cat	nat_code	ind_cat
2	20aug2004	10sep2008	EMPL	0	Employment	01nov1982	1	.	.	.	Irish	4
2	11oct2007	01jul2015	OFP	0	One_Parent_Family	01nov1982	1	Sligo	3	7	Irish	.
2	01jan2009	13may2010	EMPL	0	Employment	01nov1982	1	.	.	.	Irish	4
2	14may2010	30jun2010	UB	1	Unemp_Benefit_Assistance	01nov1982	1	Sligo	3	7	Irish	.
2	02jun2010	16jul2011	EMPL	0	Employment	01nov1982	1	.	.	.	Irish	5
2	18jul2011	09nov2011	UB	1	Unemp_Benefit_Assistance	01nov1982	1	Sligo	3	8	Irish	.
2	02jul2015	28jun2017	BTWFD	0	Activation_and_Emp_Subs	01nov1982	1	Sligo	3	6	Irish	.
3	19aug2004	17jan2005	UA	1	Unemp_Benefit_Assistance	01apr1969	0	Louth	2	.	Irish	.
3	02nov2004	17jul2009	EMPL	0	Employment	01apr1969	0	.	.	.	Irish	9
3	20jul2009	23dec2009	UB	1	Unemp_Benefit_Assistance	01apr1969	0	Cavan	2	1	Irish	.
3	24dec2009	31dec2009	EMPL	0	Employment	01apr1969	0	.	.	.	Irish	9
3	05feb2010	17jul2012	UA	1	Unemp_Benefit_Assistance	01apr1969	0	Cavan	2	.	Irish	.
3	18jul2012	06jan2014	EMPL	0	Employment	01apr1969	0	.	.	.	Irish	7
3	24mar2015	01jan2016	EMPL	0	Employment	01apr1969	0	.	.	.	Irish	5
4	31aug2004	22oct2004	FAS	0	Education_and_Training	01mar1983	0	.	.	.	.	.
5	10jun2013	15nov2013	EMPL	0	Employment	01sep1993	1	.	.	.	Irish	.
5	01jan2014	04apr2016	EMPL	0	Employment	01sep1993	1	.	.	.	Irish	7
5	04jan2014	05jan2014	EMPL	0	Employment	01sep1993	1	.	.	.	Irish	.
5	05apr2014	17dec2017	EMPL	0	Employment	01sep1993	1	.	.	.	Irish	7
5	25apr2016	11jan2017	EMPL	0	Employment	01sep1993	1	.	.	.	Irish	6
5	18dec2017	25jan2018	EMPL	0	Employment	01sep1993	1	.	.	.	Irish	7
5	19dec2017	24feb2018	UB	1	Unemp_Benefit_Assistance	01sep1993	1	Cork	3	8	Irish	.
6	01mar2011	29feb2012	EMPL	0	Employment	01jan1960	1	.	.	.	Irish	8
6	24apr2012	10aug2013	UA	1	Unemp_Benefit_Assistance	01jan1960	1	Dublin	5	9	Irish	.
6	12aug2013	31may2014	EMPL	0	Employment	01jan1960	1	.	.	.	Irish	6
6	03jun2014	14oct2014	UA	1	Unemp_Benefit_Assistance	01jan1960	1	Dublin	5	9	Irish	.
6	15oct2014	26feb2016	EMPL	0	Employment	01jan1960	1	.	.	.	Irish	7
6	01jan2016	05jan2018	EMPL	0	Employment	01jan1960	1	.	.	.	Irish	8
7	02jan2008	01jan2009	EMPL	0	Employment	01may1969	0	.	.	.	Irish	5
7	09oct2008	10jan2009	UA	1	Unemp_Benefit_Assistance	01may1969	0	Galway	1	6	Irish	.
7	12jan2009	22jul2009	FAS	0	Education_and_Training	01may1969	0	.	.	.	Irish	.
7	23jul2009	10nov2009	UA	1	Unemp_Benefit_Assistance	01may1969	0	Galway	1	1	Irish	.
7	08dec2009	01mar2010	UA	1	Unemp_Benefit_Assistance	01may1969	0	Clare	1	7	Irish	.

back

Elegibility 12/18:

newid	ym	days	elig_18_m	elig_30_m
6	2010m7	0	0	0
6	2010m8	0	0	0
6	2010m9	0	0	0
6	2010m10	0	0	0
6	2010m11	0	0	0
6	2010m12	0	0	0
6	2011m1	0	0	0
6	2011m2	0	0	0
6	2011m3	0	0	0
6	2011m4	0	0	0
6	2011m5	0	0	0
6	2011m6	0	0	0
6	2011m7	0	0	0
6	2011m8	0	0	0
6	2011m9	0	0	0
6	2011m10	0	0	0
6	2011m11	0	0	0
6	2011m12	0	0	0
6	2012m1	0	0	0
6	2012m2	0	0	0
6	2012m3	0	0	0
6	2012m4	7	0	0
6	2012m5	31	1	1
6	2012m6	30	2	2
6	2012m7	31	3	3
6	2012m8	31	4	4
6	2012m9	30	5	5
6	2012m10	31	6	6
6	2012m11	30	7	7
6	2012m12	31	8	8
6	2013m1	31	9	9
6	2013m2	28	10	10
6	2013m3	31	11	11
6	2013m4	30	12	12
6	2013m5	31	13	13
6	2013m6	30	14	14
6	2013m7	31	15	15
6	2013m8	10	15	15
6	2013m9	0	15	15
6	2013m10	0	15	15
6	2013m11	0	14	15
6	2013m12	0	13	15

Elegibility 24/30:

newid	ym	days	elig_18_m	elig_30_m
134643	2011m1	10	4	5
134643	2011m2	0	3	5
134643	2011m3	0	2	5
134643	2011m4	0	2	5
134643	2011m5	23	3	6
134643	2011m6	30	4	7
134643	2011m7	31	5	8
134643	2011m8	31	6	9
134643	2011m9	30	7	10
134643	2011m10	31	8	11
134643	2011m11	30	9	12
134643	2011m12	31	10	13
134643	2012m1	31	11	13
134643	2012m2	29	11	13
134643	2012m3	31	11	13
134643	2012m4	30	12	14
134643	2012m5	31	13	15
134643	2012m6	30	14	16
134643	2012m7	31	15	17
134643	2012m8	31	16	18
134643	2012m9	30	17	19
134643	2012m10	31	18	20
134643	2012m11	30	18	21
134643	2012m12	31	18	22
134643	2013m1	31	18	23
134643	2013m2	28	18	23
134643	2013m3	31	18	23
134643	2013m4	30	18	24
134643	2013m5	31	18	25
134643	2013m6	30	18	26
134643	2013m7	31	18	27
134643	2013m8	31	18	28
134643	2013m9	30	18	29
134643	2013m10	31	18	30
134643	2013m11	30	18	30
134643	2013m12	31	18	30
134643	2014m1	6	17	29
134643	2014m2	0	16	28
134643	2014m3	0	15	27
134643	2014m4	0	14	26
134643	2014m5	0	13	25
134643	2014m6	0	12	24

back

Sample selection

N episodes	11.185.001	
N individuals	1.850.084	
	12/18	24/30
N eligible post-2013	738.648	549.872
N eligible matching IM	434.640	509.449

N treated	14.838	
N treated RE=CE	11.914	
	12/18	24/30
N treated pre-match	3.222	8.541

back

Thank you