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What Works for Whom? Youth Labour Market Policy in Poland*

Co skutecznie wspiera osoby bezrobotne? Aktywne polityki rynku pracy dla osób młodych w Polsce

Abstract

We compare the relative effectiveness of selected active labour market policies (ALMPs) available to young unemployed people in Poland in 2015 and 2016. We find sizeable negative employment effects of participating in public works programmes, particularly among disadvantaged individuals. The second-least effective ALMP was standard on-the-job training, even though it was the most popular among young unemployed people. We also show that on-the-job training vouchers (where the unemployed find the training provider) were more effective than standard on-the-job training schemes (where the public employment service finds the training provider) for all subgroups of participants. However, we find no support for the greater effectiveness of vouchers in the case of classroom training. Moreover, the most effective alternative for participants in public works programmes and on-the-job training depended on gender. Women would have benefited the most if they had been offered an on-the-job training voucher, while men would have benefited the most if they had participated in classroom training (standard or financed with a voucher). Finally, we find that the offer of public employment services does not match the needs of tertiary-educated women, who constitute a significant part of the young unemployed in Poland.

Keywords:
ALMP, youth unemployment, wage subsidies, public works, training vouchers

JEL classification codes:
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Streszczenie

W niniejszym artykule porównujemy względną efektywność wybranych aktywnych polityk rynku pracy (*active labour market policies*, ALMP) skierowanych do młodych osób bezrobotnych w Polsce w latach 2015–2016. Stwierdzamy, że uczestnictwo w robotach publicznych ma istotny negatywny wpływ na prawdopodobieństwo zatrudnienia w porównaniu z innymi formami wsparcia. Drugą najmniej skuteczną ALMP są staże, choć były najbardziej popularne. Stwierdzamy również, że bony, które umożliwiają osobom bezrobotnym samodzielne znalezienie organizatorów stażu, są bardziej efektywne niż zwykłe staże, na które bezrobotni są kierowani przez pracowników powiatowych urzędów pracy. Wpływ uczestnictwa w robotach

Słowa kluczowe:
ALMP, bezrobocie osób młodych, subsydiowane zatrudnienie, roboty publiczne, bony stażowe

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publicznych i staży zależał od płci. Kobiety korzystały w większym stopniu z bonów na staż, a mężczyźni ze szkoleń – niezależnie od źródła ich finansowania. Stwierdzamy także, że oferta ALMP nie odpowiada na potrzeby zarejestrowanych w urzędach pracy wykształconych kobiet, które stanowią istotną część osób bezrobotnych.

Introduction

In 2013, the European Commission announced the Youth Guarantee (YG) Programme, which offered EU member states substantial financial support to improve the labour market integration of young unemployed individuals through active labour market policies (ALMPs), such as training, public works, business start-up support, and wage subsidies. The objective was to tackle high unemployment among young people, which became particularly persistent after the economic crisis of 2007/2008. Were any of the policies offered more effective than others? Did the effectiveness of these policies vary depending on the participants' demographic characteristics, gender in particular? Did the policy design and implementation matter for their effectiveness? These are the key questions we aim to answer in this paper. Studies have shown that extended unemployment spells at a young age may negatively affect a person's career prospects and earning potential in the future [**Caliendo, Schmidl, 2016**]. Therefore, knowing which ALMPs work is crucial for the design of effective policies [**Cabasés Piqué et al., 2016**], especially since there have been very few evaluations investigating the effects of the YG programme.

Overall, meta-analysis studies have shown that, among the various ALMPs, wage subsidies and classroom training have a positive impact on the employment of young people, while on-the-job training and public works programmes have no or negative effects [**Caliendo, Schmidl, 2016**]. Similar findings hold for the general population of unemployed individuals [**Card et al., 2018**; **Crépon, Van den Berg, 2016**]. Studies have also shown that ALMPs have heterogeneous effects for different groups of participants, depending on their gender, age, education, literacy level, place or residence, or having children [**Nordlund, 2011**; **Van Vugt 2022**]. In particular, the effects are greater for women than men [**Dengler, 2019**; **Kruppe, Lang, 2018**], especially in regions with low labour force participation among women [**Bergemann, Van den Berg, 2008**; **Crépon, Van den Berg, 2016**; **Card et al., 2018**]. Little is known about the heterogeneity in the case of young people, as most studies did not focus particularly on this group.

The main objective of our study is to compare the relative effectiveness of selected active labour market policies available to young unemployed individuals in Poland during the 2015–2016 period: i.e., on-the-job training (OJT), classroom training (CT), public works programmes (PW), wage subsidies (WS), on-the-job training vouchers (OJTV), and classroom training vouchers (CTV). We aim to assess if matching specific groups to different programmes might improve their effectiveness. We use administrative data and propensity score matching (PSM) techniques to control for the non-random selection of unemployed individuals into various ALMPs.

This study contributes to the literature in several areas. First, we analyse the heterogeneity of the relative effectiveness of ALMPs, considering supply-side (participants' gender and education) and demand-side factors (distance to the county seat and the local unemployment rate), which have not been assessed for young people so far. Second, we provide evidence on the effectiveness of the ALMP demand-side financing measures (vouchers), which were introduced to increase participants' flexibility in choosing training providers. We compare these vouchers to standard ALMPs in which the unemployed have little control over the training provider. Previous studies have shown a positive selection of unemployed people to vouchers: little effect in the short run due to the longer lock-in effect, but positive effects in the long run [**Doerr et al., 2017**; **Huber et al., 2018**; **Rinne et al., 2013**; **Schwerdt et al., 2012**]. Some studies have found vouchers to be more effective for highly skilled individuals [**Rinne et al., 2013**], while others for low-skilled individuals [**Doerr et al., 2017**; **Stefanik, 2021**]. We thus add to the still modest literature on the institutional design of labour market policies. Third, we contribute to the limited literature on the ALMPs in Central and Eastern Europe [Burger et al., 2022; Madoń et al., 2023; Stefanik, 2021; Wiśniewski, 2022], in particular ALMPs targeted at youth [Bratti et al., 2021; Hora, Sirovátka, 2020].

We find that PW were the least effective policy, and OJT measures were the second-least effective policy among those evaluated. These were, at the same time, the two most expensive programmes. The most effective alternative support measure for participants depended on their gender. Women would have gained the most if offered an OJTV, while men would have gained the most if they had participated in CT or CTV. The large negative employment effects of participating in PW were particularly acute for disadvantaged individuals living in regions with high unemployment. The differences between the effectiveness of other ALMPs were relatively small, and most turned insignificant over time. We also find that OJTV schemes were more effective than standard OJT in which public employment services (PES) directed the unemployed to the training providers. However, we observe no such differences for CT, which suggests that the details of the institutional design and the market for training influenced the relative effectiveness of these measures.

The study is structured as follows. The next section discusses the institutional background of ALMPs in Poland. Then, we describe the data and the methods used. We investigate the relative effectiveness of selected ALMPs in the Results section. The last section concludes.

ALMPs for the young unemployed in Poland

EU countries spend a total of EUR 50–60 billion on ALMPs every year. An additional EUR 9 billion was offered by the European Commission to EU member states to fight youth unemployment as part of the YG Programme in 2014–2020. This study analyses the relative effectiveness of selected ALMPs available to young unemployed people in Poland in 2015–2016: OJT, CT, PW, WS, OJTV, and CTV. These measures are described below, and their summary statistics are presented in Table 1.

On-the-job training – OJT

OJT is provided at the workplace to support the process of gaining skills and work experience. Under the supervision of an experienced employee, trainees learn how to use the machines, tools, and equipment required to perform the work. The most popular training areas in 2015–2016 were secretarial and office work, sales, and marketing [MRPiPS, 2019].

Classroom training – CT

CT is designed to help people acquire skills or qualifications. In 2015–2016, the most popular were the skills needed to obtain a driving licence, technical skills (welding or operating a forklift), management and administration, and accounting [MRPiPS, 2019]. Most CTs end with the trainee receiving a certificate validating the qualifications acquired.

Wage subsidy – WS

WS is a type of subsidised employment: an employer creates a position for an unemployed individual, bears all of the employment-related costs, and is then reimbursed for part of these costs.

Public works – PW

PW is a subsidised employment programme where employers must be local governments or NGOs. There is a bifurcation in the types of individuals who participate in these programmes: most are engaged in public tasks carried out by the local government, such as road maintenance or cleaning public places. These are often seasonal, ad hoc jobs. Yet, some public works are office jobs, often in local government[1]. Thus, these programmes attract relatively high shares of both tertiary- and primary-educated individuals but few medium-educated individuals.

On-the-job training vouchers – OJTV and classroom training vouchers – CTV

PES have been criticised for offering unemployed individuals a narrow range of courses and leaving them with no real choice of training. Vouchers were introduced in 2014 to motivate unemployed people to look for training on their own and to give them more flexibility in choosing their course content and training providers.

The selection process, financial issues, and retaining employees after ALMP ends

Selecting unemployed individuals for ALMPs is similar for OJT, WS and PW. The employer must answer a call opened by PES and indicate what types of employees the firm needs in terms of education and qualifications. A caseworker then directs suitable candidates to a job interview with a potential employer, and the employer decides whom to employ. For CT, the local PES usually prepare a plan with a list of courses for each year. The content of the courses is usually related to the demand in the region. Training providers are selected through a public procurement procedure. A caseworker then directs suitable candidates to the course. To receive a voucher (for both OJT and CT), an unemployed individual must first find a training provider and then obtain the approval of a caseworker.

In 2015 and 2016, OJT, CT, OJTV, and CTV beneficiaries received a monthly scholarship of around EUR 230 net. For WS, the subsidy rate was up to 50% of the minimum wage (around EUR 210) plus social security contributions. At the same time, for PW, it was up to 50% of the average wage (EUR 460) plus social security contributions.

Employers taking part in OJT and PW are not obliged to retain employees after the ALMP ends. By contrast, employers taking part in WS and OJTV must retain employees for three to six months depending on the programme.

Data and methods

Polish PES administrative data

We use an administrative dataset that covers the entire population of young unemployed individuals registered with PES. The data include a person's entire history of unemployment spells and participation in ALMPs. Socio-demographic variables include age, gender, level of education, place of residence (urban/rural), disability status, presence of young children in the household, lack of qualifications, and recent graduation. The data also include information on total work experience and dummies for having had any job before, having been dismissed for the employer's reasons, eligibility for unemployment benefits, farm ownership, and declaring an interest in migrating to other EU countries (see Table A1 in Appendix A).

We also use data collected by the Statistics Poland agency at the NUTS-4 level: the local unemployment rate, the local average wage as a percentage of the country average, and the distance to the county seat from the municipality of residence (NUTS-5 level).

Finally, we draw on qualitative data based on semi-structured interviews with 10 PES representatives who were caseworkers, career counsellors, data managers, or directors at five PES offices in different regions. The interviews, which were conducted in person and via telephone, gave us a better understanding of the institutional setting of ALMPs and the design and implementation details.

Our sample consists of individuals who started participating in ALMPs between 1 January 2015 and 30 April 2016. As we aim to follow the participants for three consecutive years, we censor our sample at the

1 Based on a review of public works contracts from several PES.

end of April 2016 (we have data until the end of April 2019). We further restrict the sample to participants between 18 and 29 years old when the ALMP started and focus on the first support measure granted[2]. We end up with a total sample of 247,116 individuals.

The outcome of interest is each individual's labour market status after they complete the ALMP. The outcome variable indicates whether the beneficiary was out of the unemployment register and was not enrolled in another ALMP[3]. For each individual, we measure this outcome every 30 days for 36 consecutive periods since the start of the ALMP.

Summary statistics

Of the ALMPs taken up by young unemployed people in Poland during the analysed period, OJT was the most popular, with over 170,000 participants (Table 1).

The characteristics of the participants varied significantly depending on the type of ALMP. Women were over-represented in OJT/OJTV and under-represented in CT/CTV. CTs correspond to the local demand reported by employers to the PES, and these vacancies are more likely to be low and medium-skilled jobs that are often perceived as "male." Thus, these training courses tend to be less suitable for women, especially as women are twice as likely as men to be tertiary educated among the registered unemployed, meaning they seek high-skilled jobs (as Table 1 shows, tertiary-educated unemployed are under-represented among CT participants).

We see a positive selection in the case of the voucher schemes (on-the-job and classroom). Those using OJTV and CTV had better qualifications, more job experience and shorter unemployment spells than those who participated in standard OJT and CT schemes.

Participants in OJT and OJTV had the shortest work experience (10–13 months). CT, CTV, and WS participants were the most experienced (19–21 months). Cumulative unemployment until the beginning of the current unemployment spell varied significantly among the ALMPs, ranging from seven months (OJTV) to 16 months (PW).

The time between registration and the start of the ALMP varied between four months (CTV) to six months (CT). Only a fraction of the participants started the ALMP more than 12 months after the beginning of the current unemployment spell (8% – 13%).

The duration of the ALMP differed significantly. The OJT schemes (standard and vouchers) and the WS lasted five to seven months. The CT courses (standard and vouchers) lasted one to two months. Most of the PW lasted up to six months.

Table 1. Summary statistics and ALMP characteristics

	OJT	OJTV	CT	CTV	WS	PW	All
Pre-treatment variables							
Personal characteristics							
Female	0.67	0.63	0.29	0.18	0.55	0.59	0.60
Age	22.5	22.8	23.2	23.2	23.3	23.8	22.7
Secondary education	0.61	0.60	0.67	0.70	0.64	0.51	0.62
Tertiary education	0.30	0.32	0.17	0.15	0.25	0.34	0.28
No qualifications	0.34	0.29	0.34	0.28	0.30	0.34	0.34
Less than 12 months since graduation	0.43	0.43	0.24	0.23	0.23	0.20	0.38
Child under 6 years old	0.10	0.09	0.11	0.09	0.13	0.14	0.10

2 Any subsequent ALMP participation is considered a consequence of the first treatment. More than 90% of participants receive only one support measure. It could be argued that for the proper identification of the effect of a particular ALMP, observations treated with different ALMPs should be excluded, as they could confound the effect. However, excluding individuals who received support more than once would lead to selection based on future successful outcomes [Sianesi, 2008].

3 A person in an ALMP is removed from the unemployment register.

	OJT	OJTV	CT	CTV	WS	PW	All
Information about the current unemployment spell							
Time to treatment (days)	173	162	180	125	173	156	172
Short time to treatment (less than 14 days)	0.09	0.12	0.04	0.14	0.12	0.17	0.09
Long time to treatment (more than 12 months)	0.12	0.11	0.12	0.08	0.13	0.10	0.12
Pre-treatment outcomes & labour market histories							
No work experience	0.64	0.58	0.45	0.40	0.42	0.46	0.59
Work experience (days)	321	388	594	632	577	448	389
Cumulated unemployment (days)	250	212	296	272	357	491	272
Cumulated number of registrations	1.45	1.34	1.83	1.89	2.25	3.21	1.62
Eligible for unemployment benefits	0.06	0.08	0.15	0.15	0.14	0.12	0.08
Reason for the last separation: dismissal	0.01	0.01	0.03	0.03	0.02	0.01	0.01
Motivation & potential obstacles							
Disability	0.02	0.01	0.02	0.01	0.02	0.03	0.02
Farm ownership	0.02	0.01	0.02	0.01	0.02	0.02	0.02
Interest in any job	0.88	0.90	0.87	0.87	0.86	0.88	0.88
Interest in work in another EU country	0.10	0.09	0.14	0.17	0.10	0.09	0.10
Regional characteristics							
Rural area	0.51	0.49	0.50	0.48	0.57	0.56	0.51
Unemployment rate (NUTS-4, %)	7.36	6.72	7.08	7.25	7.80	8.53	7.37
Income related to country average (NUTS-4, %)	85.20	88.10	86.30	87.50	83.50	83.40	85.20
Average distance to city (NUTS-5, km)	10.40	10.68	10.38	10.20	11.41	12.77	10.56
ALMP characteristics							
Average duration of the ALMP (days)[1]	156	212	28	49	150	197	140
Maximum potential duration (months)	365	183	730	Not specified	548	365	–
Scholarship/reimbursement (2015–2016)	EUR[2] 230	EUR 230	EUR 230	EUR 230	Up to 50% of the minimum wage (~210 EUR)	Up to 50% of the average wage (~460 EUR)	–
Average total cost per participant[3]	EUR 1447	EUR 987	EUR 195	EUR 819	EUR 1268	EUR 3075	
Obligation to retain a worker after the ALMP	No	Yes, 6 months	–	–	Yes, 3 to 6 months	No	–
Outcome variables							
Not in register and not in ALMP (18 months)	0.74	0.83	0.82	0.83	0.79	0.63	0.75
Not in register and not in ALMP (24 months)	0.77	0.84	0.83	0.85	0.80	0.67	0.78
Not in register and not in ALMP (36 months)	0.83	0.86	0.87	0.88	0.84	0.77	0.84
Observations	176 308	6 493	33 405	2 722	21 355	6 833	247 116

Notes: The table reports the average values of variables among the participants of selected ALMPs. The variables are described in Table A.1. [1]The duration of OJTV and WS includes the period after the programme when an employer is obliged to retain a worker. [2]2016 average exchange rate[3] The average cost per participant is calculated as the product of the monthly cost per participant (the average value from MPiPS-02 forms for January, June, and December 2016) and the average duration in our sample.

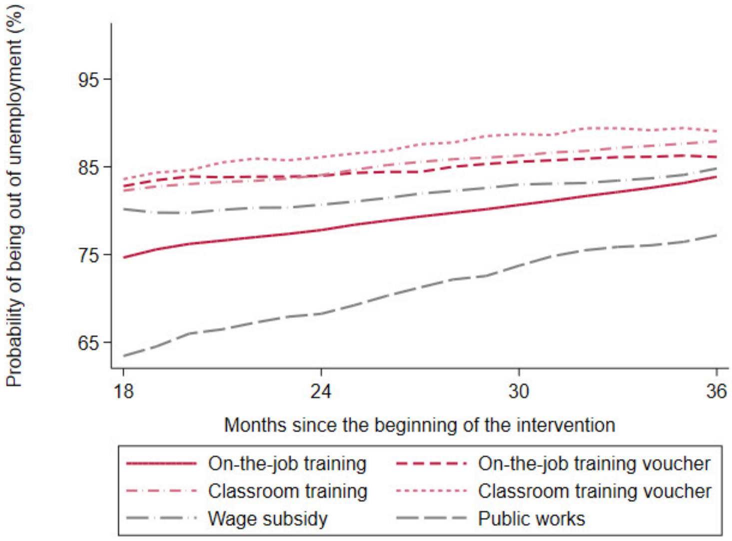
Source: Authors' calculations based on PES data.

Figure 1 shows the average likelihood of being outside the unemployment register and not in ALMP depending on the type of ALMP[4]. Neither the order nor the differences between the ALMP types changed

[4] Our outcome variable may overestimate the successful outcomes, as some individuals who did not register with PES were not employed but withdrew from the labour market. However, we expect that the size of this effect was small and similar among the interventions we compared, so it should not impact our results.

significantly during the studied period: the "raw" success rate was always the lowest for PW and consistently the highest for CTV. However, these "raw" outcomes were likely driven by substantial differences in the characteristics of participants, as shown above. The following subsection describes how we deal with this potential selection into a particular ALMP.

Figure 1. Probability of being out of the unemployment register: average values of the outcome variable



Source: Authors' calculations based on PES data.

Method

Ideally, to accurately estimate the causal average treatment effect on the treated population, we would conduct a field experiment. In this experiment, we would randomly select unemployed individuals and assign some of them to receive ALMPs while others would not. Subsequently, we could compare their labour market outcomes. The difference between those two groups would identify the effects of ALPMs on unemployed. However, such a scenario is not feasible in our case. Therefore, we use PSM, one of the established methods for analysing causal relationships in the absence of counterfactual observations [**Angrist, Pischke, 2008**].

However, PSM has its limitations. First, it does not adjust for the selection bias. If unobservable confounders affect treatment assignment and the outcome, the ATT estimate (average treatment effect on the treated) will be biased. Second, the identification of the parameters in PSM relies on the conditional independence assumption (CIA). We assume that we observe all factors determining participation in the treatment. Third, it relies on the common support assumption. The distribution of propensity scores between the treated and control groups must overlap. Otherwise, lacking common support may lead to difficulty in finding suitable matches. Moreover, matching reduces the sample size by discarding observations that cannot be matched. Hence, both the treated and control groups should be appropriately large.

To account for the likely non-random selection of participants into different ALMPs, we do not compare participants in ALMP with non-participants as they represent a distinct group. Using this group as a control group could lead to a substantial bias in the estimation of ALMP effects on employment prospects. Most non-participants are long-term unemployed and register for health insurance and social benefits. They are probably less motivated to work and face various barriers to employment (e.g., care obligations, health issues) that negatively affect their employment chances.

We also do not compare individuals participating in WS, PW, OJT, OJTV, CT and CTV with individuals participating in other ALMPs which have strict eligibility criteria or the take-up of these ALMPs is very low (e.g. start-up subsidies, wage subsidy vouchers, mobility allowances). These ALMPs are targeted at individuals with very specific characteristics, or the sample size is too small for statistical analysis.

We compare the effectiveness of an ALMP that a person received (treatment group) with five other ALMPs one by one (control groups). A pairwise comparison of ALMPs using PSM is well established in the ALMP evaluation literature (see **Dorsett** [**2006**]; **Lechner** [**2001**]; **Lechner et al.** [**2011**]; **Wunsch, Lechner** [**2008**]).

The causal identification of parameters in PSM relies on the conditional independence assumption (CIA). It means that we assume we can observe all factors that determine whether an individual took part in a particular ALMP (compared to a different ALMP) if we control for a comprehensive set of variables [**Caliendo et al., 2017**]. These factors include personal characteristics (age, gender, presence of a child under six years old), skills (level of education, vocational qualifications, recent graduate status), data on the current unemployment spell (entry timing, time to treatment), regional characteristics (unemployment rate, average income, distance to the county seat, rural area). Unobserved heterogeneity in motivation and employability is captured indirectly. First, we include pre-treatment outcomes such as work experience, cumulated unemployment, and eligibility for unemployment benefits. Second, we know whether the job seeker is fully mobile within the EU and whether there are potential health obstacles to employment.

A similar set of variables is used by, among others, **Doerr et al.** [**2017**] and **Lechner et al.** [**2011**]. Meeting the CIA assumption may be more difficult in the case of young people with shorter employment histories. However, as we compare the effectiveness of different ALMPs only among the participants, we believe that the control variables suffice to account for selection into different ALMPs.

Under the CIA assumption, the mean effect of treatment m relative to treatment n for those receiving treatment m is given by the following equation:

$$\alpha_{ATET}^{m,n} = \mathrm{E}\left[Y^m - Y^n \mid D = m, \boldsymbol{X}\right] = \mathrm{E}\left[Y^m \mid D = m, \boldsymbol{X}\right] - \mathrm{E}\left[Y^n \mid D = m, \boldsymbol{X}\right]$$

where m denotes the participants in ALMP m as the "treated" group, and n denotes the participants in ALMP n as the "control" group. Y^m (Y^n) denotes the potential outcome when the individual is treated (not treated), and $D = m$ ($D = n$) indicates (not) obtaining treatment. $\mathrm{E}\left[Y^n \mid D = m, \boldsymbol{X}\right]$ cannot be observed in the data but can be replaced by $\mathrm{E}\left[Y^n \mid D = n, \boldsymbol{X}\right]$ (expected value for the control group), under the assumption of null self-selection bias conditional on the observables X ($\mathrm{E}\left[Y^n \mid D = m, \boldsymbol{X}\right] - \mathrm{E}\left[Y^n \mid D = n, \boldsymbol{X}\right] = 0$). The latter is true thanks to the CIA assumption, and $\alpha_{ATET}^{m,n}$ is identified.

More specifically, we conduct nearest-neighbour PSM. First, we use a probit regression model to estimate the propensity scores for participants in each pair of the analysed ALMP. The model includes a comprehensive set of socio-economic and regional characteristics described above. Second, we match observations from the treated and control groups so that the distributions of the propensity scores are comparable. The parameter of interest – ATT, or average treatment on the treated – is the mean difference between the groups.

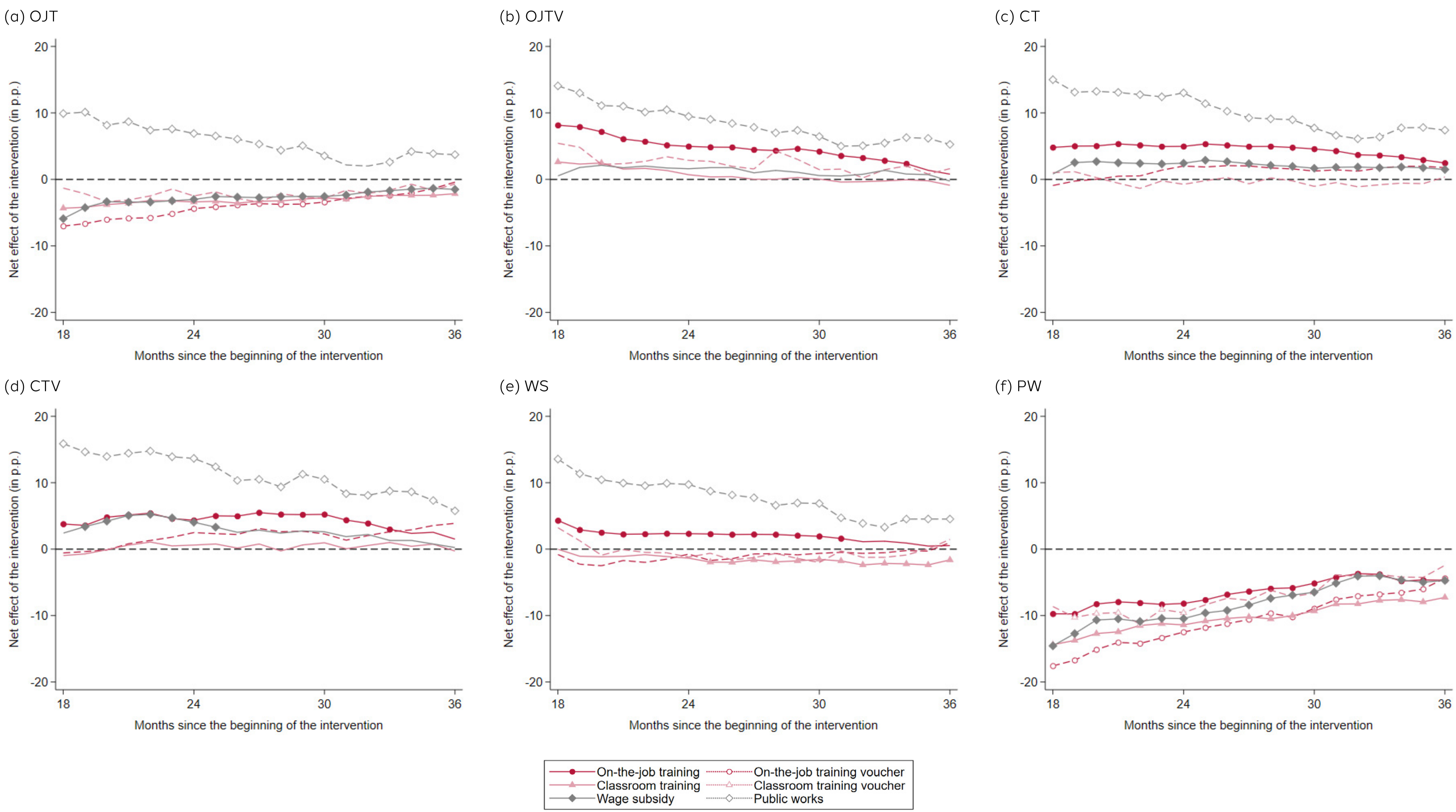
The quality of matching is sufficiently good: the mean standardised bias (MSB) – defined as the difference in the covariates means before and after matching, divided by the square root of the average sample variance [**Rosenbaum, Rubin, 1983**] – does not exceed 5%. The balance tables are presented in Appendix B. Additionally, all coefficients are inside the "Lechner bounds," which suggests that the common support assumption is easily met (see **Lechner** [**2008**]).

Results

Main results

Figure 2 shows the differences in the relative effectiveness of the six ALMPs we analysed. Each graph presents the impact of participating in ALMP m, named above the graph, on the probability of being out of the unemployment register and not in ALMP, compared to the counterfactual outcomes of this group of participants if they were offered a different treatment n (named in the legend). A line above zero indicates that ALMP m has a positive effect relative to policy n, associated with that line. The marker on the line at each point in time indicates if the difference between the compared ALMPs is statistically significant at the 5% significance level.

Figure 2. Dynamics of ALMP effects



Notes: Figure shows the average treatment effect on the treated of participating in programme m instead of programme n. Subfigures titles indicate m programme, while the lines on the figures indicate the programme n to which m is compared. The marker on the line at a particular point in time indicates whether the difference in effectiveness is statistically significant at the 5% significance level. Subfigure (a) reads as follows: 18 months after the beginning of the ALMP, the participants in OJT were more likely to be out of unemployment (by 10 p.p.) than they would have been if they had participated in the PW (the counterfactual), and the effect is statistically significant. Estimated with PSM, the balancing scores can be found in Appendix B, and the variables used in the matching procedure are summarised in Table 1. Additionally, the year and quarter of the beginning of the ALMP are controlled for.

Source: Authors' calculations based on PES data.

For instance, in Figure 2a, we can see that 18 months[5] after the beginning of the ALMP, participants in the OJT were more likely to be out of unemployment (by 8 p.p.) than they would have been if they had participated in PW (the counterfactual).

A few key findings emerge. First, the PW were the least effective ALMP among those we evaluated. This means that the participants in any other ALMP would have fared worse if they had instead been in PW (Figure 2f), and the participants in PW would have fared better if they had participated in any other ALMP (Figures 2a–2e). These effects decreased with time but stayed statistically significant throughout the 36-month observation period. Second, OJT is the second-least effective ALMP (Figure 2a). The participants in OJT would have benefited more from participating in WS, CT, CTV, or OJTV. The participants in any other ALMP except for PW would have fared worse if they had instead been in OJT. The negative effects of participation in OJT were smaller than those of participation in PW. The differences in the effectiveness of other policies were smaller, and virtually disappeared by the end of our 36-month observation period.

Finally, the OJTV were more effective than standard OJT in which PES directed the unemployed person to the training provider (Figure 2b). The difference was significant: OJTV participants were 9 p.p. less likely to return to unemployment 18 months after the start of the ALMP than they would have been if they had been offered OJT. This effectiveness gap narrowed with time but remained significant until the end of the 36-month observation period. There was no difference in effectiveness between standard and voucher schemes in the case of CT, even though the institutional setting was similar to that of OJT (Figures 2c and 2d).

Next, we explore heterogeneity in the effectiveness gaps between the ALMPs depending on the selected supply– and demand-side factors.

Heterogeneity of the effects

To investigate the heterogeneity in ALMP effectiveness, we stratify our sample along the supply-side (gender, education) and demand-side dimensions (urban/rural area, distance to county seat[6] and local unemployment rate).

The detailed results of the heterogeneity analysis for all pairwise comparisons for which MSB after matching is smaller than 5%, are presented in Appendix C.

We find large gender differences in effectiveness. CT (both standard and vouchers) was more effective than any other ALMP among men (Figure C1 in supplementary material) but not among women. Women who participated in CT would have fared better if offered a WS or an OJTV. However, for women who participated in a standard OJT, CT would have been a better alternative (Figure C2 in supplementary material).

As PW and OJT were the two ALMPs with the lowest relative effectiveness, the question arises which ALMP would have been the most effective alternative for the participants depending on their personal and regional characteristics.

Among both the PW and OJT participants, men would have benefited the most if offered a CTV (Figure C1), while women would have benefited the most if offered an OJTV (Figure C2). The potential benefits of the other ALMP were smaller for the OJT participants.

Regarding the education level, participating in PW had a much smaller relative negative effect for participants with a tertiary education than those with a primary and secondary education (Figures C7 and C8). Participating in WS, CT or OJTV would have been more beneficial for tertiary-educated participants, but the effect disappeared with time. Participating in any other ALMP would have been more beneficial for primary- and secondary-educated participants, with OJT providing the smallest advantage and OJTV providing the biggest advantage in the medium run. Among the OJT participants, participating in an OJTV, CT or WS would

5 We are interested in medium-term employment outcomes and present results from the 18th month after the ALMP started. Full results are available upon request.

6 Proximity to the county seat means that the distance (in km) from the municipality of residence to the county seat is below the median.

have been more beneficial, regardless of the educational level of the participants. Still, the relative advantage of participating in these ALMPs was greater for participants with a tertiary education (Figures C7 and C8).

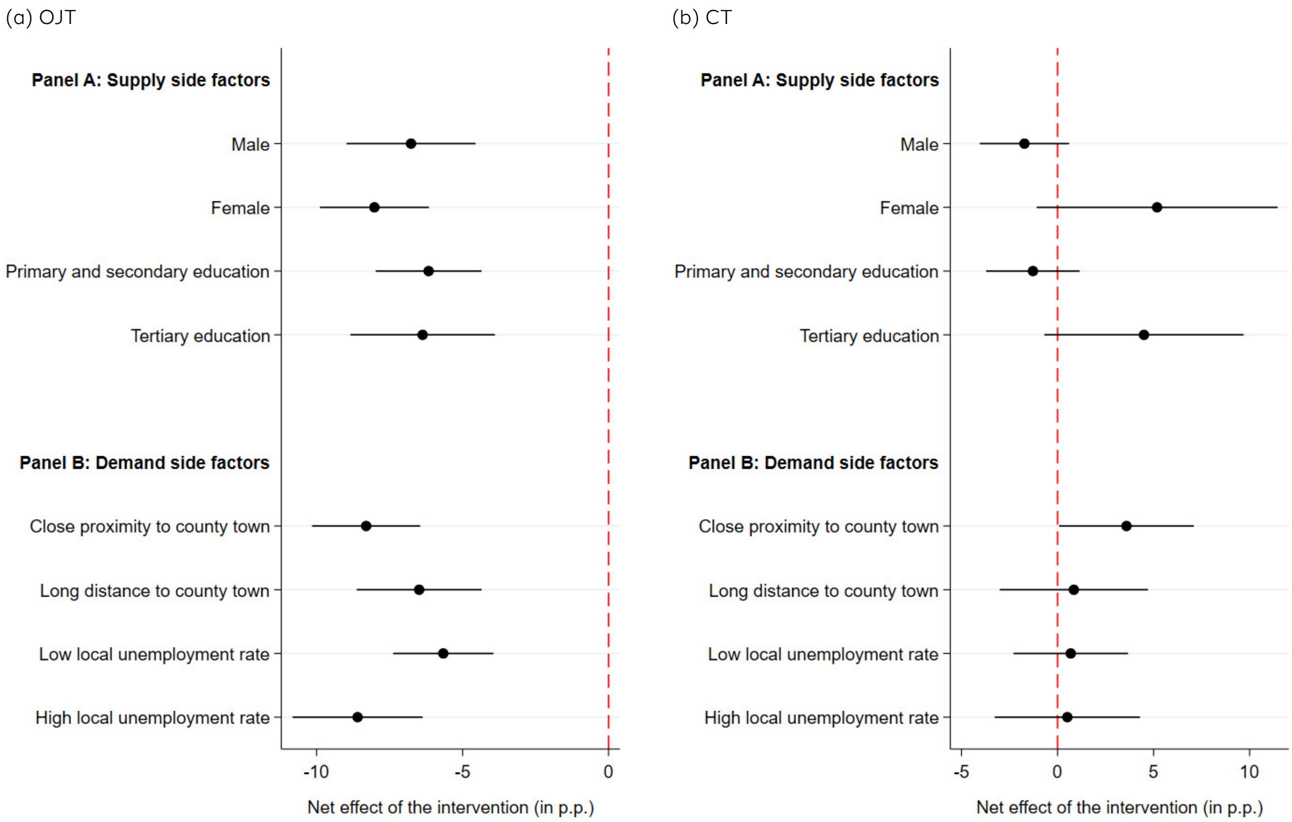
For the other subpopulations of PW and OJT participants (stratified by urban/rural area, distance to the county seat, and local unemployment rate), there were either small differences between the more effective alternative ALMP or the OJTV scheme was the most effective (rural areas, high unemployment – Figures C3 and C5).

Training vouchers and standard training interventions

In this subsection, we focus on the heterogeneity of the effects between pairs of ALMPs that were similar in form but had different implementation procedures: i.e., between training vouchers and standard training and between two types of subsidised employment (PW and WS).

The OJTV schemes were more effective than the standard OJT for all the subgroups of OJT participants. There was no difference between these groups, as the standard error intervals for point estimates overlapped (Figure 3a). The CTV were slightly less effective than CT among the tertiary educated, women, and unemployed living nearby the county seat, but these differences were not statistically significant.

Figure 3. Heterogeneity: vouchers vs. standard interventions, 18 months after the beginning of the intervention



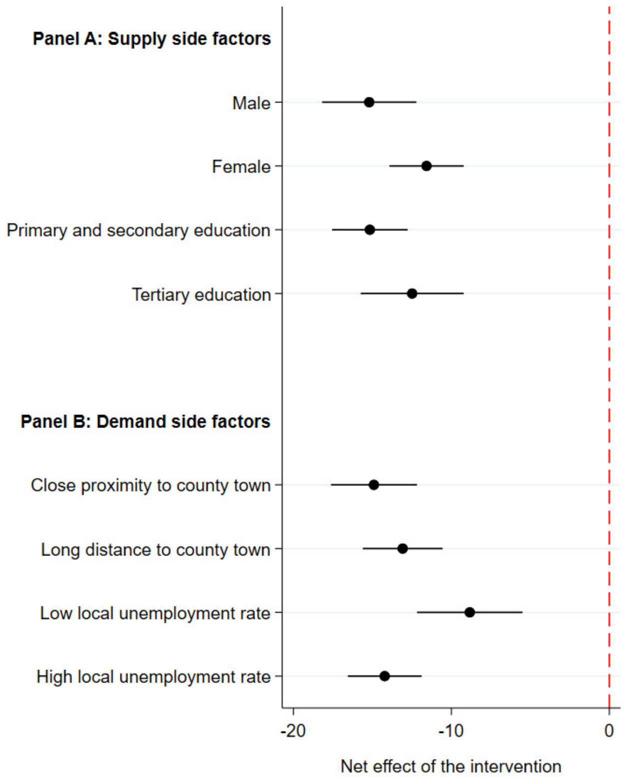
Notes: Figure shows the average treatment effect on the treated of participation in the standard intervention instead of the intervention financed with a voucher for standard intervention participants. The point estimates on the left-hand side of the dashed red zero line indicate by how much the standard interventions were less effective than the voucher schemes in the given group. For example, compared to participation in standard OJT, participation in OJTV increased the probability of success by about 8 p.p. among females. We present 95% confidence intervals. The standard errors are computed with an estimator derived by Abadie and Imbens [2016].

Source: Authors' calculations based on PES data.

Subsidised employment

PWs were less effective than WS for all the subgroups of PW participants, particularly for individuals from areas with high unemployment (Figure 4). The scarring effect of participating in PW [Nilsen, Reiso, 2014] is one of the potential explanations for this result. Another is that the employers in PW are not obliged to continue to employ the participants after the subsidy expired. Most did not as local governments often do not have vacancies available and usually draw on subsidised workers participating in PW to meet their labour demand.

Figure 4. Heterogeneity: PW vs. WS, 18 months after the beginning of the intervention



Notes: Figure shows the average treatment effect on the treated of participation in a public works programme instead of a wage subsidy scheme for public works programme participants. The point estimates on the left-hand side of the dashed red zero line indicate by how much participation in a PW instead of a WS decreased the probability of success for the public works programme participants. For example, for tertiary-educated individuals, participation in PW rather than WS decreased their probability of success by about 13 p.p. We use 95% confidence intervals. The standard errors are computed with an estimator derived by Abadie and Imbens [2016].

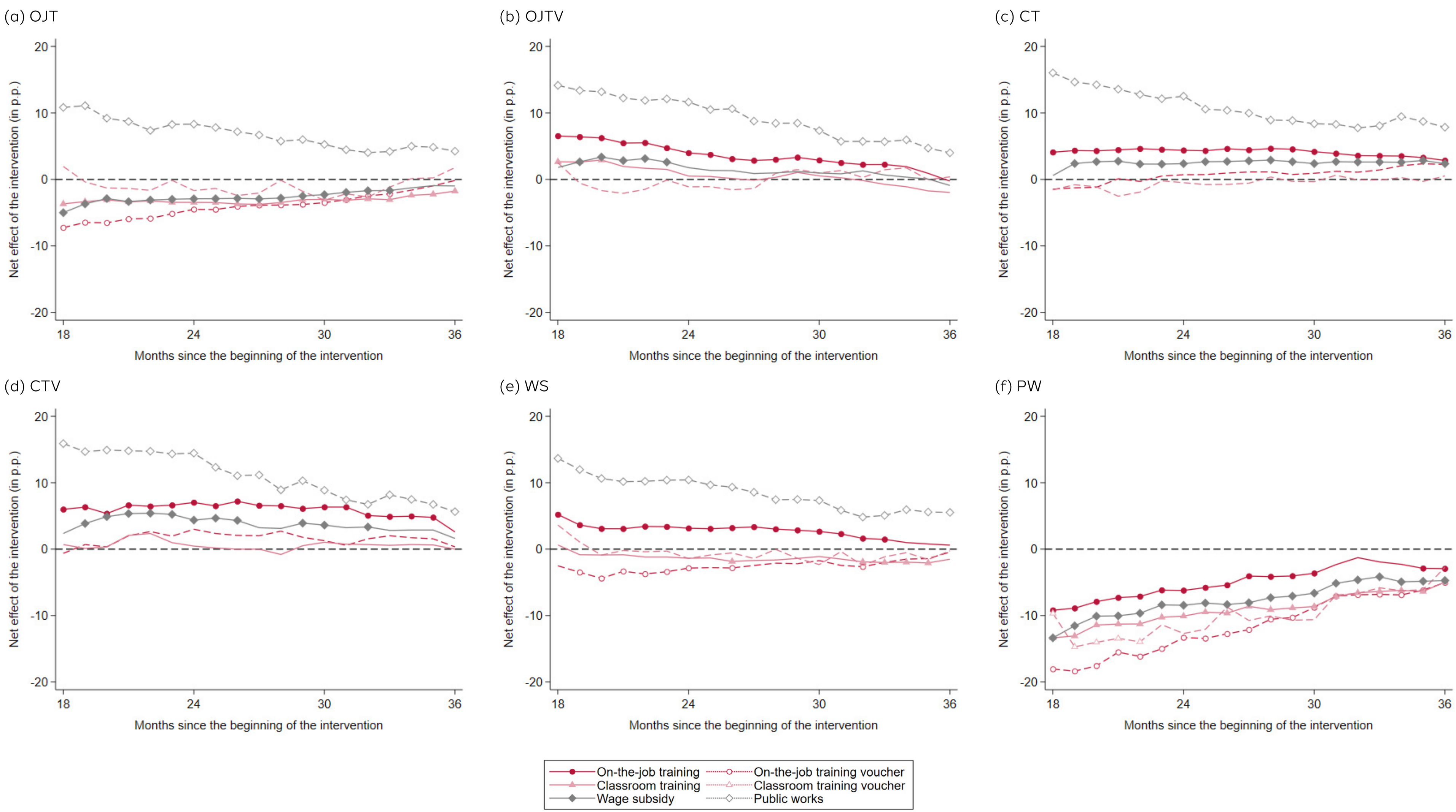
Source: Authors' calculations based on PES data.

Robustness checks

We perform a few robustness checks to test our results. Firstly, we restrict our sample only to 2015, the first full year of YG in Poland (Figure 5). Secondly, we use a different matching algorithm and let treated individuals be matched with four rather than one non-treated individual (Figure 6)[7]. Our main results are robust to these tests. Some of them are even more pronounced.

[7] Similarly, changing the matching algorithm to a caliper instead of the nearest neighbour does not change the main findings. The results are available upon request.

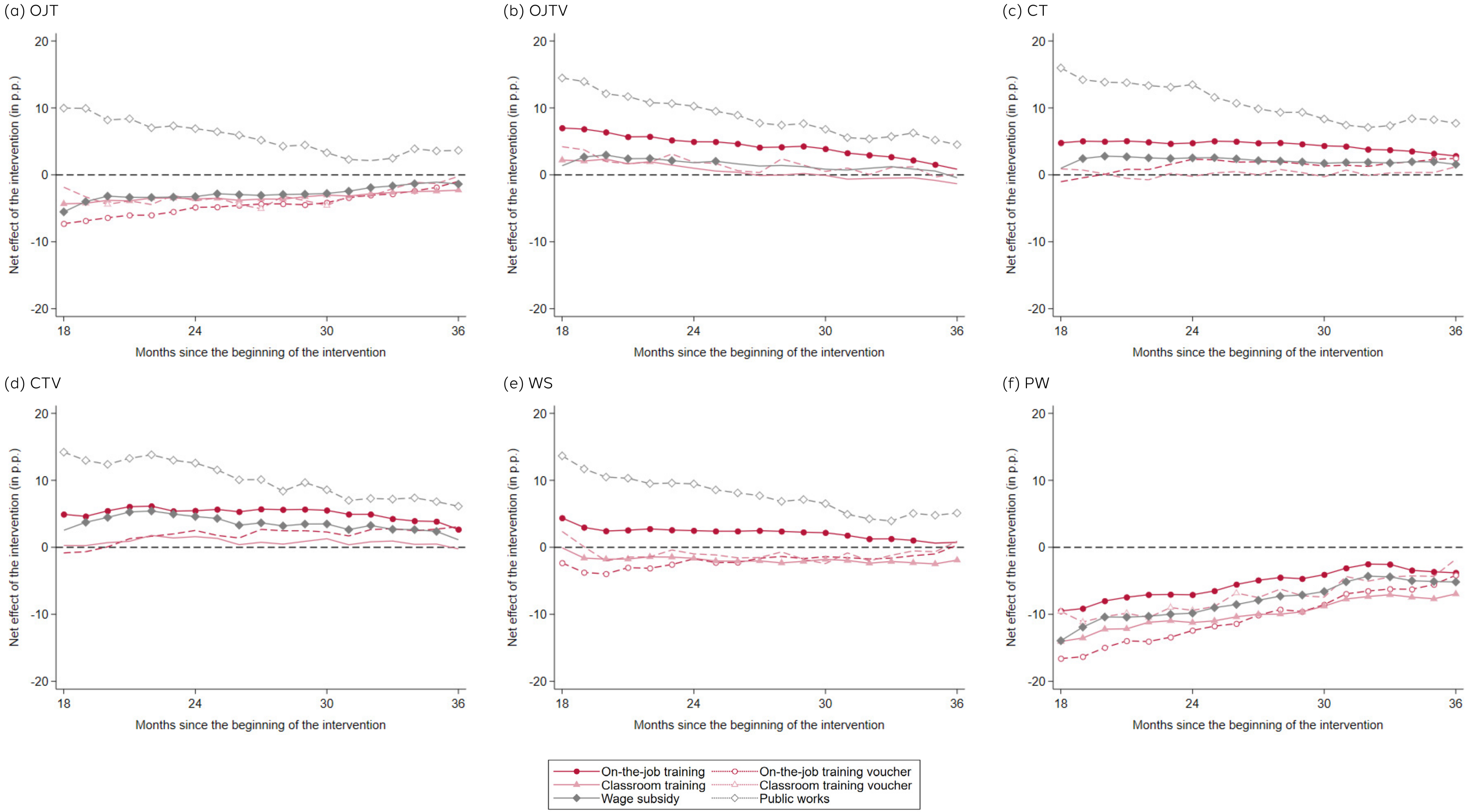
Figure 5. Dynamics of ALMP effects – sample restricted to ALMPs started in 2015



Notes: Figure shows the average treatment effect on the treated of participating in programme m instead of programme n. Subfigure titles indicate programme m, while the lines in the figures indicate programme n to which m is compared. The marker on the line at a particular point in time indicates whether the difference in effectiveness is statistically significant at the 5% significance level. Subfigure (a) reads as follows: 18 months after the beginning of the intervention, the participants in the OJT were more likely to be out of unemployment (by about 10 p.p.) than they would have been if they had participated in the PW (the counterfactual), and the effect is statistically significant. Estimated with PSM, the balancing scores can be found in Appendix B, and the variables used in the matching procedure are summarised in Table 1. Additionally, the year and quarter of the beginning of the ALMP are controlled for.

Source: Authors' calculations based on PES data.

Figure 6. Dynamics of ALMP effects – the nearest neighbour matching algorithm with 4 neighbours



Notes: Figure shows the average treatment effect on the treated of participating in programme m instead of programme n. Subfigure titles indicate programme m, while the lines in the figures indicate programme n to which m is compared. The marker on the line at a particular point in time indicates whether the difference in effectiveness is statistically significant at the 5% significance level. Subfigure (a) reads as follows: 18 months after the beginning of the intervention, the participants in the OJT were more likely to be out of unemployment (by 10 p.p.) than they would have been if they had participated in the PW (the counterfactual), and the effect is statistically significant. Estimated with PSM, the balancing scores can be found in Appendix B, and the variables used in the matching procedure are summarised in Table 1. Additionally, the year and quarter of the beginning of the ALMP are controlled for.

Source: Authors' calculations based on PES data.

Conclusions and discussion

We evaluated the medium-term effects of ALMPs offered to young unemployed individuals in Poland between 2015 and 2016. We used administrative data and matching techniques that allowed us to adjust for the selection of unemployed individuals into particular ALMPs. We compared the relative effectiveness of six ALMPs by studying the employment effects, measured as non-return to the unemployment register and not being in ALMP over three years after the beginning of the ALMP.

PW had the lowest relative effectiveness among the interventions we evaluated, with a gap in the success rate of 8 to 17 p.p. at month 18 (after the start of the intervention) to around 4 to 6 p.p. at month 36. These negative effects were particularly large for disadvantaged individuals living in regions with high unemployment. The second-least effective intervention was OJT, the most popular intervention among young unemployed people we studied (accounting for over 70% of the interventions in our sample). The participants in OJT would have benefited more from participating in WS, CT or OJTV.

We also found that women would have benefited the most if they had been offered an OJTV, while men would have benefited more if they had been offered CT, standard or financed with a voucher. Important gender differences were also found in the ALMP take-up rates, which may have been influenced by gender differences in ALMP effectiveness. In addition to women being under-represented in CT, female participants in CT would have benefited more if they had received a WS or an OJTV instead. It remains an open question whether women were aware of this difference in relative effectiveness and therefore opted for interventions other than CT, or whether the low participation of women in CT influenced its effectiveness (by, for instance, curricula not being matched to women's needs). As evaluations of ALMP in Germany indicate that training programs have a more positive impact on the labour market prospects of women than men [**Dengler, 2019**; **Kruppe, Lang, 2018**], we suspect that the PES offer does not match young women's needs.

One of the contributions of our study is the analysis of the institutional setting of training schemes and wage subsidies. We found that in the case of OJT, voucher schemes were more effective than the standard training that the PES selected and paid for. The main reason financing through vouchers was more effective is that it likely allowed a better match between an unemployed person's interests and an employer's needs. Moreover, an employer using a voucher scheme had an obligation to retain the participant after the intervention, whereas an employer using a standard OJT scheme did not. Thus, employers with less potential to retain workers after OJT may have self-selected into the standard training scheme. This institutional difference could also explain, at least partially, the difference in the relative effectiveness of two types of subsidised employment: i.e., an employer using a PW had no obligation to retain the worker after the intervention, while an employer using a WS scheme was obligated to keep employing the participant after the intervention.

We did not find differences in effectiveness between the standard and voucher-based CT schemes, which suggests that choosing the training provider was not the only factor that influenced the effectiveness of these interventions. Most probably, other institutional factors came into play, including the supply structure in the training markets (local firms targeting mainly PES, resulting in a modest range for individual customers). Thus, the design of a policy and its implementation matter a great deal for its effectiveness.

We believe that the results of our study provide evidence for policymakers that changing the allocation of unemployed individuals to interventions might increase the overall effectiveness of the YG programme and youth ALMP in general. PES should award more OJTV to unemployed individuals who typically participate in standard OJT. Second, we argue that PW do not fulfil their role, as they offer no labour market prospects to young people and are particularly disappointing for the disadvantaged ones. It appears that PW are too often used as a way to fill in the gaps in public agencies, which are under financial constraints and have a limited number of vacancies. As such, they cannot offer continuous employment to ALMP participants, but benefit from workers supplied by PES. PW had low relative effectiveness despite having the highest cost per participant among the analysed interventions. Therefore, potential PW participants should be offered alternative ALMPs instead. Third, PES should redesign the CT offerings to make them more attractive to women.

With no differences in CT and CTV effectiveness, and a much higher cost per participant for CTV, the CT might be a better alternative.

This study is not without limitations. Our data did not allow us to control for the employer's characteristics, which could be important when comparing the effectiveness of OJT schemes and other types of subsidised employment. Moreover, data on other types of outcomes that were not available in our data, such as cumulative employment spells or wages, would provide a fuller picture of the relative effectiveness of the analysed interventions. An open question remains whether a substantial increase in the number of OJTV offered – to match the levels of standard OJT – would maintain the difference in their effectiveness.

We have also identified several other questions that call for further, more detailed research. First, researchers should explore to what extent the potentially heterogenous outreach efforts of ALMP to young unemployed people impact the effectiveness of the support offered. Second, given the large regional differences in labour market conditions, more research is needed on the most effective interventions in different labour markets, including those with close to monopsonistic structures, where youth are paid minimum wages. Third, we need to learn more about the gender differences in ALMP take-up and effectiveness and about the factors behind these differences. Related to this issue is the fourth important research strand on the detailed effects of policy design and implementation on policy successes and failures. All in all, there is a continuous need to assess the effectiveness of public policies, ALMP in particular, to address post-crisis economic challenges and improve labour market opportunities for people in vulnerable situations.

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Appendix A. Control variables

Table A1. Varable description

Variable	Description	Categories/Scale
Female		0=Men; 1=Women
Age	Age of an individual	1 year, individuals between 18 and 29 age old
Secondary education	Dummy for secondary education	1 = secondary education 0 = other education
Tertiary education	Dummy for tertiary education	1 = tertiary education 0 = other education
No qualifications	Individual without professional competences	1 = True 0 = False
Less than 12 months since graduation	Individual graduated within last 12 months	1 = True 0 = False
Child under 6 years old	Individual has at least one child under 6 years old	1 = True 0 = False
Time to treatment (days)	Time since last registration to beginning the treatment	1 day
Short time to treatment (less than 14 days)	Dummy for starting the treatment in less than 14 days since registration	1 = True 0 = False
Long time to treatment (more than 12 months)		1 = True 0 = False
Quarter	Dummy for the quarter of beginning the treatment	1 = True 0 = False
Year	Dummy for the year of beginning the treatment	1 = True 0 = False
No work experience		1 = individual without professional experience 0 = individual has professional experience
Work experience (days)		Working experience in days
Cumulated unemployment (days)		Total time spent in unemployed register in days
Cumulated number of registrations		The total number of registered unemployment spells
Eligible to unemployment benefit		1 = True 0 = False
Reason for separation: dismissal		1 = True 0 = False
Disability		1 = person with disabilities 0 = person without disabilities
Farm ownership		1 = True 0 = False
Interest in any job	Individual agrees to take up any job	1 = True 0 = False
Interest in work in another EU country	Individual agrees to take up a job in other EU country	1 = True 0 = False
Rural area		0 = lives in urban area; 1 = lives in rural area
Unemployment rate	Unemployment rate in poviat (NUTS4)	In percentage points
Income related to country average	The ratio of the average income in poviat to the average income in whole country	
Average distance to city	The route distance from municipality of residence to the poviat city	1 km

Source: Authors' elaboration.

Appendix B. Balance tables

Table B1. Balance table: On-the-job training

	OJTV–OJT		OJTV–CT		OJTV–CTV		OJTV–WS		OJTV–PW	
	Raw std. diff.	Matched std. diff.	Raw std. diff.	Matched std. diff.	Raw std. diff.	Matched std. diff.	Raw std. diff.	Matched std. diff.	Raw std. diff.	Matched std. diff.
Gender: Female	0.076	0.01	0.833	−0.002	1.126	0.028	0.248	0.025	0.155	0.059
Age	−0.099	−0.022	−0.23	−0.013	−0.233	−0.103	−0.284	0.00	−0.457	−0.022
Rural area	0.051	−0.004	0.007	0.06	0.051	0.225	−0.127	0.006	−0.118	0.0230
No work experience	0.135	0.019	0.402	−0.007	0.516	0.004	0.474	0.003	0.365	−0.002
Secondary education	0.032	0.012	−0.156	0.04	−0.229	0.085	−0.077	−0.018	0.188	0.003
Tertiary education	−0.037	−0.009	0.316	−0.018	0.354	−0.064	0.12	0.019	−0.079	0.023
Disability	0.063	0.002	0.039	−0.066	0.11	0.065	0.048	−0.018	−0.072	−0.004
Time to treatment (days)	0.04	−0.032	−0.025	−0.074	0.211	−0.063	−0.002	−0.056	0.047	−0.138
Short time to treatment (less than 14 days)	−0.085	−0.002	0.202	0.004	−0.166	−0.03	−0.084	0.016	−0.228	0.046
Long time to treatment (more than 12 months)	0.024	−0.001	−0.01	−0.086	0.151	−0.019	−0.023	−0.046	0.024	−0.097
No qualifications	0.117	0.009	0.023	−0.021	0.161	−0.026	0.088	0.009	0.019	−0.002
Less than 12 months since graduation	0.004	0.005	0.414	0.004	0.433	0.021	0.447	0.002	0.532	0.025
Child under 6 years old	0.018	−0.022	−0.032	−0.016	0.013	−0.011	−0.091	−0.006	−0.135	−0.026
Work experience (days)	−0.124	−0.01	−0.433	0.003	−0.501	−0.009	−0.438	−0.006	−0.238	−0.026
Days in register (total)	0.094	−0.015	−0.115	−0.019	−0.051	−0.099	−0.258	−0.005	−0.497	−0.043
Eligible for unemployment benefits	−0.066	−0.002	−0.288	0.011	−0.315	0.093	−0.269	0.015	−0.238	0.027
No work experience	−0.108	−0.011	−0.319	0.003	−0.447	−0.057	−0.447	−0.016	−0.419	0.012
Reason for last separation: dismissal	−0.016	−0.004	−0.123	−0.007	−0.123	0.053	−0.084	−0.004	0.004	−0.035
Farm ownership	0.058	−0.031	0	0.010	0.033	0.071	−0.033	−0.009	−0.028	0.001
Interest in work in another EU country	0.012	−0.022	−0.130	0.016	−0.238	−0.049	−0.016	0.007	0.052	−0.011
Unemployment rate (NUTS-4, %)	0.231	0.027	0.084	−0.03	0.055	0.04	−0.153	0.016	−0.444	−0.025
Income related to country average (NUTS-4, %)	−0.204	−0.016	−0.061	−0.011	−0.167	−0.079	0.149	−0.032	0.181	0.014
Labour demand	−0.07	−0.015	−0.073	−0.013	0.004	−0.034	−0.129	0.035	−0.163	−0.006
Average distance to city (NUTS-5, km)	−0.032	−0.013	−0.008	0.032	0.018	0.164	−0.095	0.015	−0.233	−0.002
Cumulative number of registrations	0.055	−0.013	−0.191	−0.026	−0.215	−0.061	−0.397	−0.027	−0.729	−0.036
Interest in any job	−0.06	0.017	0.024	−0.027	0.052	−0.058	0.076	−0.003	0.011	0.020
Quarter 1	0.189	−0.006	0.026	−0.024	0.045	−0.062	0.015	0	0.164	0.029
Quarter 2	0.048	−0.05	−0.074	0.006	0.053	0.001	−0.068	0.007	−0.017	−0.050
Quarter 3	−0.138	0.007	−0.047	−0.007	−0.064	0.021	−0.021	0.005	−0.095	0.001
Year	0.139	−0.008	0.211	0.05	−0.13	0.039	0.298	−0.003	0.248	−0.11
Total	0.081	0.014	0.163	0.024	0.209	0.058	0.169	0.014	0.206	0.031

Notes: Table reports standard differences between treated and control groups for raw and matched samples. The quality of matching is considered as sufficient if the matched standard difference does not exceed 5%. OJT – On-the-job training, OJTV – On-the-job training voucher, CT– Classroom training, CTV–Classroom training voucher, WS – Wage subsidy, PW – Public works.

Source: Authors' calculations based on PES data.

Table B2. Balance table: On-the-job training voucher

	OJTV–OJT		OJTV–CT		OJTV–CTV		OJTV–WS		OJTV–PW	
	Raw std. diff.	Matched std. diff.	Raw std. diff.	Matched std. diff.	Raw std. diff.	Matched std. diff.	Raw std. diff.	Matched std. diff.	Raw std. diff.	Matched std. diff.
Gender: Female	−0.076	0.003	0.745	−0.017	1.027	0.026	0.171	0.015	0.079	0.006
Age	0.099	−0.025	−0.137	−0.001	−0.138	−0.027	−0.189	−0.002	−0.363	−0.022
Rural area	−0.051	−0.012	−0.045	0.007	0	0.076	−0.178	0.033	−0.169	0.019
No work experience	−0.135	0.013	0.264	0.005	0.375	−0.025	0.334	0.007	0.228	−0.001
Secondary education	−0.032	−0.009	−0.188	0.018	−0.261	0.032	−0.11	−0.02	0.156	0.008
Tertiary education	0.037	0.002	0.354	−0.006	0.392	−0.023	0.157	0.019	−0.042	0.005
Disability	−0.063	−0.026	−0.024	−0.035	0.049	−0.027	−0.015	−0.026	−0.133	0.007
Time to treatment (days)	−0.04	−0.027	−0.067	−0.016	0.177	−0.066	−0.043	−0.01	0.009	−0.059
Short time to treatment (less than 14 days)	0.085	0.002	0.284	−0.026	−0.082	0.019	0.001	0.02	−0.143	0.041
Long time to treatment (more than 12 months)	−0.024	−0.005	−0.035	−0.022	0.127	0.001	−0.047	−0.002	0	−0.054
No qualifications	−0.117	0.011	−0.094	−0.006	0.044	−0.029	−0.029	−0.011	−0.098	0.021
Less than 12 months since graduation	−0.004	0	0.411	−0.009	0.43	0.02	0.443	−0.003	0.528	−0.016
Child under 6 years old	−0.018	0.007	−0.05	0.009	−0.006	0.015	−0.109	−0.007	−0.154	−0.027
Work experience (days)	0.124	0.003	−0.316	−0.022	−0.382	−0.027	−0.316	0.001	−0.11	−0.038
Days in register (total)	−0.094	−0.012	−0.213	0.001	−0.151	−0.039	−0.358	−0.007	−0.591	−0.017
Eligible for unemployment benefits	0.066	−0.01	−0.224	−0.013	−0.251	0.037	−0.205	−0.002	−0.173	0.028
No work experience	0.108	−0.003	−0.209	0.002	−0.335	0.003	−0.335	0.004	−0.308	−0.043
Reason for last separation: dismissal	0.016	0.003	−0.109	−0.012	−0.108	0.033	−0.069	0.005	0.02	−0.023
Farm ownership	−0.058	−0.011	−0.058	−0.006	−0.025	0.07	−0.09	−0.026	−0.086	0.012
Interest in work in another EU country	−0.012	−0.007	−0.142	−0.008	−0.25	−0.015	−0.028	−0.018	0.04	−0.01
Unemployment rate (NUTS-4, %)	−0.231	−0.002	−0.145	−0.008	−0.187	0.045	−0.394	−0.049	−0.686	0.016
Income related to country average (NUTS-4, %)	0.204	0.005	0.145	0.015	0.037	0.005	0.338	−0.029	0.378	0.025
Labour demand	0.07	−0.023	−0.003	0.031	0.071	−0.015	−0.059	0.019	−0.095	−0.01
Average distance to city (NUTS-5, km)	0.032	0.007	0.024	−0.017	0.049	0.059	−0.06	0.035	−0.194	−0.008
Cumulative number of registrations	−0.055	−0.022	−0.247	−0.006	−0.271	0.003	−0.456	−0.015	−0.784	−0.048
Interest in any job	0.06	−0.002	0.084	0.026	0.112	−0.027	0.136	0.018	0.071	−0.001
Quarter 1	−0.189	−0.007	−0.162	−0.034	−0.143	−0.073	−0.174	−0.004	−0.025	−0.029
Quarter 2	−0.048	−0.012	−0.122	−0.029	0.005	−0.018	−0.116	0.046	−0.065	0.014
Quarter 3	0.138	−0.018	0.091	−0.01	0.074	0.04	0.117	−0.01	0.043	0.014
Year	−0.139	−0.003	0.071	0.023	−0.27	0.033	0.159	0.003	0.108	−0.027
Total	0.081	0.01	0.169	0.015	0.194	0.031	0.175	0.016	0.196	0.022

Notes: Table reports standard differences between treated and control groups for raw and matched samples. The quality of matching is considered as sufficient if the matched standard difference does not exceed 5%. OJT – On-the-job training, OJTV – On-the-job training voucher, CT – Classroom training, CTV–Classroom training voucher, WS – Wage subsidy, PW – Public works.

Source: Authors' calculations based on PES data.

Table B3. Balance table: Classroom training

	OJTV–OJT		OJTV–CT		OJTV–CTV		OJTV–WS		OJTV–PW	
	Raw std. diff.	Matched std. diff.	Raw std. diff.	Matched std. diff.	Raw std. diff.	Matched std. diff.	Raw std. diff.	Matched std. diff.	Raw std. diff.	Matched std. diff.
Gender: Female	−0.833	−0.007	−0.745	−0.005	0.24	0.047	−0.556	0.001	−0.657	0.013
Age	0.23	−0.013	0.137	0.014	0.002	0.006	−0.046	−0.01	−0.211	−0.012
Rural area	−0.007	0.017	0.045	0.031	0.044	0.043	−0.133	0	−0.125	−0.017
No work experience	−0.402	0.006	−0.264	−0.024	0.108	−0.043	0.069	−0.004	−0.035	−0.026
Secondary education	0.156	0.027	0.188	0.015	−0.073	0.008	0.078	0.011	0.346	0.039
Tertiary education	−0.316	−0.005	−0.354	−0.019	0.037	−0.016	−0.196	0.008	−0.397	0.027
Disability	−0.039	−0.02	0.024	−0.043	0.073	−0.055	0.009	−0.011	−0.11	−0.044
Time to treatment (days)	0.025	−0.041	0.067	−0.084	0.246	−0.013	0.024	−0.023	0.073	−0.103
Short time to treatment (less than 14 days)	−0.202	−0.005	−0.284	0.015	−0.362	0.004	−0.283	0.004	−0.421	0.039
Long time to treatment (more than 12 months)	0.01	−0.047	0.035	−0.068	0.161	0.012	−0.012	−0.017	0.035	−0.071
No qualifications	−0.023	−0.024	0.094	−0.04	0.138	−0.021	0.066	0.003	−0.003	−0.024
Less than 12 months since graduation	−0.414	−0.002	−0.411	0.019	0.018	−0.022	0.031	0.015	0.113	0.01
Child under 6 years old	0.032	−0.005	0.05	−0.009	0.044	0.037	−0.059	−0.013	−0.104	−0.012
Work experience (days)	0.433	−0.014	0.316	0.014	−0.061	−0.006	0.011	−0.002	0.218	−0.039
Days in register (total)	0.115	−0.02	0.213	−0.019	0.069	0.02	−0.146	−0.004	−0.398	−0.059
Eligible for unemployment benefits	0.288	0.004	0.224	0.04	−0.027	0.015	0.02	0.022	0.051	0.041
No work experience	0.319	0.002	0.209	0.031	−0.125	0.035	−0.124	0.013	−0.097	0.047
Reason for last separation: dismissal	0.123	0.01	0.109	0.023	0.001	0.038	0.041	−0.004	0.127	−0.009
Farm ownership	0	−0.002	0.058	0.006	0.033	0.044	−0.034	−0.004	−0.029	−0.028
Interest in work in another EU country	0.13	−0.014	0.142	−0.003	−0.108	−0.007	0.114	0.027	0.182	−0.025
Unemployment rate (NUTS-4, %)	−0.084	−0.021	0.145	−0.016	−0.034	−0.012	−0.24	−0.032	−0.529	−0.054
Income related to country average (NUTS-4, %)	0.061	0	−0.145	0.011	−0.108	0.003	0.207	0.013	0.243	0.042
Labour demand	0.073	0.003	0.003	0.007	0.074	−0.048	−0.055	−0.006	−0.091	−0.025
Average distance to city (NUTS-5, km)	0.008	0.003	−0.024	−0.007	0.026	0.037	−0.087	−0.015	−0.223	−0.025
Cumulative number of registrations	0.191	−0.018	0.247	−0.02	−0.027	0.018	−0.204	0.016	−0.556	−0.007
Interest in any job	−0.024	−0.002	−0.084	−0.038	0.028	0.025	0.053	−0.021	−0.013	0.027
Quarter 1	−0.026	0.004	0.162	0.018	0.019	−0.002	−0.012	−0.021	0.137	−0.003
Quarter 2	0.074	−0.005	0.122	−0.008	0.127	0.016	0.006	0.012	0.057	0.002
Quarter 3	0.047	−0.005	−0.091	−0.047	−0.017	−0.029	0.026	0.007	−0.048	−0.002
Year	−0.211	0.015	−0.071	0.003	−0.341	−0.009	0.088	−0.002	0.037	−0.058
Total	0.163	0.012	0.169	0.023	0.092	0.023	0.101	0.011	0.189	0.031

Notes: Table reports standard differences between treated and control groups for raw and matched samples. The quality of matching is considered as sufficient if the matched standard difference does not exceed 5%. OJT – On-the-job training, OJTV – On-the-job training voucher, CT – Classroom training, CTV–Classroom training voucher, WS – Wage subsidy, PW – Public works.

Source: Authors' calculations based on PES data.

Table B4. Balance table: Classroom training voucher

	OJTV–OJT		OJTV–CT		OJTV–CTV		OJTV–WS		OJTV–PW	
	Raw std. diff.	Matched std. diff.	Raw std. diff.	Matched std. diff.	Raw std. diff.	Matched std. diff.	Raw std. diff.	Matched std. diff.	Raw std. diff.	Matched std. diff.
Gender: Female	−1.126	−0.039	−1.027	−0.017	−0.24	−0.007	−0.819	−0.017	−0.929	0.026
Age	0.233	−0.061	0.138	−0.02	−0.002	−0.008	−0.05	−0.01	−0.218	−0.047
Rural area	−0.051	−0.002	0	0.073	−0.044	0.031	−0.178	0.052	−0.169	0.11
No work experience	−0.516	0.043	−0.375	−0.042	−0.108	−0.008	−0.04	0.037	−0.144	−0.004
Secondary education	0.229	0.057	0.261	0.025	0.073	0.002	0.151	0.002	0.421	0.054
Tertiary education	−0.354	−0.043	−0.392	0	−0.037	−0.009	−0.232	0.004	−0.435	0.004
Disability	−0.11	−0.009	−0.049	0.052	−0.073	−0.004	−0.064	0	−0.176	−0.013
Time to treatment (days)	−0.211	−0.038	−0.177	−0.054	−0.246	−0.037	−0.223	0.018	−0.16	−0.002
Short time to treatment (less than 14 days)	0.166	−0.006	0.082	−0.003	0.362	−0.01	0.083	0.034	−0.062	0.008
Long time to treatment (more than 12 months)	−0.151	−0.036	−0.127	−0.014	−0.161	−0.042	−0.173	0.029	−0.127	0.013
No qualifications	−0.161	0.049	−0.044	−0.047	−0.138	−0.015	−0.073	0.007	−0.142	−0.081
Less than 12 months since graduation	−0.433	0.033	−0.43	0.051	−0.018	0.029	0.013	−0.012	0.095	0.034
Child under 6 years old	−0.013	−0.036	0.006	0.036	−0.044	−0.046	−0.103	0	−0.148	0.041
Work experience (days)	0.501	−0.049	0.382	0.033	0.061	−0.001	0.073	−0.033	0.284	−0.03
Days in register (total)	0.051	0.02	0.151	−0.059	−0.069	−0.014	−0.218	−0.026	−0.468	−0.066
Eligible for unemployment benefits	0.315	−0.034	0.251	0.003	0.027	0.007	0.047	0.007	0.079	0.083
No work experience	0.447	−0.033	0.335	−0.005	0.125	−0.027	0.001	−0.049	0.027	0.023
Reason for last separation: dismissal	0.123	−0.034	0.108	−0.041	−0.001	0.021	0.041	−0.01	0.126	0.021
Farm ownership	−0.033	0.022	0.025	−0.012	−0.033	−0.02	−0.066	−0.02	−0.061	0.022
Interest in work in another EU country	0.238	0.01	0.25	−0.038	0.108	0.023	0.222	−0.029	0.289	−0.011
Unemployment rate (NUTS-4, %)	−0.055	0.043	0.187	0.024	0.034	−0.005	−0.217	0.029	−0.52	0.057
Income related to country average (NUTS-4, %)	0.167	0.011	−0.037	0.015	0.108	0.005	0.303	0.018	0.342	−0.042
Labour demand	−0.004	−0.015	−0.071	−0.009	−0.074	−0.022	−0.127	−0.028	−0.159	−0.009
Average distance to city (NUTS-5, km)	−0.018	0.047	−0.049	0.02	−0.026	−0.005	−0.113	0.01	−0.25	0.035
Cumulative number of registrations	0.215	0	0.271	−0.024	0.027	0.001	−0.175	−0.003	−0.527	−0.05
Interest in any job	−0.052	0.012	−0.112	0.011	−0.028	0.021	0.024	0.019	−0.042	0.001
Quarter 1	−0.045	0.002	0.143	−0.062	−0.019	−0.025	−0.03	−0.039	0.118	−0.023
Quarter 2	−0.053	−0.025	−0.005	−0.014	−0.127	0.012	−0.121	0.005	−0.07	0.009
Quarter 3	0.064	−0.011	−0.074	0.011	0.017	−0.018	0.042	0.008	−0.031	0.04
Year	0.13	0.044	0.27	−0.005	0.341	−0.008	0.429	−0.022	0.379	−0.034
Total	0.209	0.029	0.194	0.027	0.092	0.016	0.148	0.019	0.233	0.033

Notes: Table reports standard differences between treated and control groups for raw and matched samples. The quality of matching is considered as sufficient if the matched standard difference does not exceed 5%. OJT – On-the-job training, OJTV – On-the-job training voucher, CT – Classroom training, CTV–Classroom training voucher, WS – Wage subsidy, PW – Public works.

Source: Authors' calculations based on PES data.

Table B5. Balance table: Wage subsidy

	OJTV–OJT		OJTV–CT		OJTV–CTV		OJTV–WS		OJTV–PW	
	Raw std. diff.	Matched std. diff.	Raw std. diff.	Matched std. diff.	Raw std. diff.	Matched std. diff.	Raw std. diff.	Matched std. diff.	Raw std. diff.	Matched std. diff.
Gender: Female	−0.248	0.018	−0.171	0.001	0.556	0.007	0.819	0.018	−0.092	0
Age	0.284	0	0.189	0.015	0.046	0.006	0.05	0.024	−0.168	−0.047
Rural area	0.127	0.003	0.178	0.022	0.133	0.006	0.178	0.093	0.009	0.019
No work experience	−0.474	−0.006	−0.334	0.011	−0.069	−0.004	0.04	−0.095	−0.104	0.002
Secondary education	0.077	−0.008	0.11	−0.003	−0.078	0	−0.151	−0.019	0.267	0.034
Tertiary education	−0.12	0.008	−0.157	0.004	0.196	0.007	0.232	0.056	−0.2	−0.025
Disability	−0.048	0.008	0.015	−0.061	−0.009	0.005	0.064	0.029	−0.118	−0.023
Time to treatment (days)	0.002	−0.003	0.043	−0.065	−0.024	−0.018	0.223	−0.072	0.051	−0.013
Short time to treatment (less than 14 days)	0.084	0.004	−0.001	0.019	0.283	−0.008	−0.083	0.009	−0.144	0.023
Long time to treatment (more than 12 months)	0.023	−0.005	0.047	−0.047	0.012	−0.029	0.173	−0.034	0.047	−0.01
No qualifications	−0.088	−0.004	0.029	−0.004	−0.066	−0.003	0.073	−0.103	−0.069	0.028
Less than 12 months since graduation	−0.447	0.004	−0.443	0.013	−0.031	−0.027	−0.013	−0.055	0.082	0.016
Child under 6 years old	0.091	−0.005	0.109	−0.006	0.059	0.013	0.103	−0.073	−0.045	−0.019
Work experience (days)	0.438	0.002	0.316	−0.012	−0.011	−0.009	−0.073	0.02	0.214	−0.028
Days in register (total)	0.258	−0.006	0.358	−0.015	0.146	−0.007	0.218	−0.045	−0.263	−0.045
Eligible for unemployment benefits	0.269	0.008	0.205	−0.007	−0.02	0.02	−0.047	0.129	0.031	−0.004
No work experience	0.447	0.001	0.335	−0.028	0.124	−0.008	−0.001	0.056	0.027	−0.014
Reason for last separation: dismissal	0.084	0.001	0.069	0.01	−0.041	0.012	−0.041	0.047	0.088	−0.064
Farm ownership	0.033	0.005	0.09	−0.003	0.034	0.011	0.066	0.064	0.005	−0.052
Interest in work in another EU country	0.016	0.002	0.028	0.006	−0.114	0.013	−0.222	0.002	0.068	−0.062
Unemployment rate (NUTS-4, %)	0.153	0.003	0.394	−0.01	0.24	0.007	0.217	0.056	−0.3	−0.03
Income related to country average (NUTS-4, %)	−0.149	−0.01	−0.338	−0.066	−0.207	0.002	−0.303	−0.079	0.017	−0.008
Labour demand	0.129	0.013	0.059	0.002	0.055	−0.022	0.127	−0.098	−0.039	0.02
Average distance to city (NUTS-5, km)	0.095	−0.009	0.06	−0.025	0.087	−0.023	0.113	0.109	−0.14	0.009
Cumulative number of registrations	0.397	−0.004	0.456	−0.022	0.204	−0.005	0.175	0.011	−0.374	−0.014
Interest in any job	−0.076	0.012	−0.136	−0.011	−0.053	−0.017	−0.024	−0.041	−0.066	0.034
Quarter 1	−0.015	−0.01	0.174	0.023	0.012	0.001	0.03	−0.043	0.149	−0.03
Quarter 2	0.068	0.011	0.116	−0.017	−0.006	0.002	0.121	−0.07	0.051	0.038
Quarter 3	0.021	−0.001	−0.117	−0.023	−0.026	−0.015	−0.042	0.026	−0.074	0.023
Year	−0.298	−0.004	−0.159	−0.011	−0.088	−0.009	−0.429	0.014	−0.051	−0.028
Total	0.169	0.006	0.175	0.019	0.101	0.011	0.148	0.053	0.112	0.025

Notes: Table reports standard differences between treated and control groups for raw and matched samples. The quality of matching is considered as sufficient if the matched standard difference does not exceed 5%. OJT – On-the-job training, OJTV – On-the-job training voucher, CT – Classroom training, CTV–Classroom training voucher, WS – Wage subsidy, PW – Public works.

Source: Authors' calculations based on PES data.

Table B6. Balance table: Public works

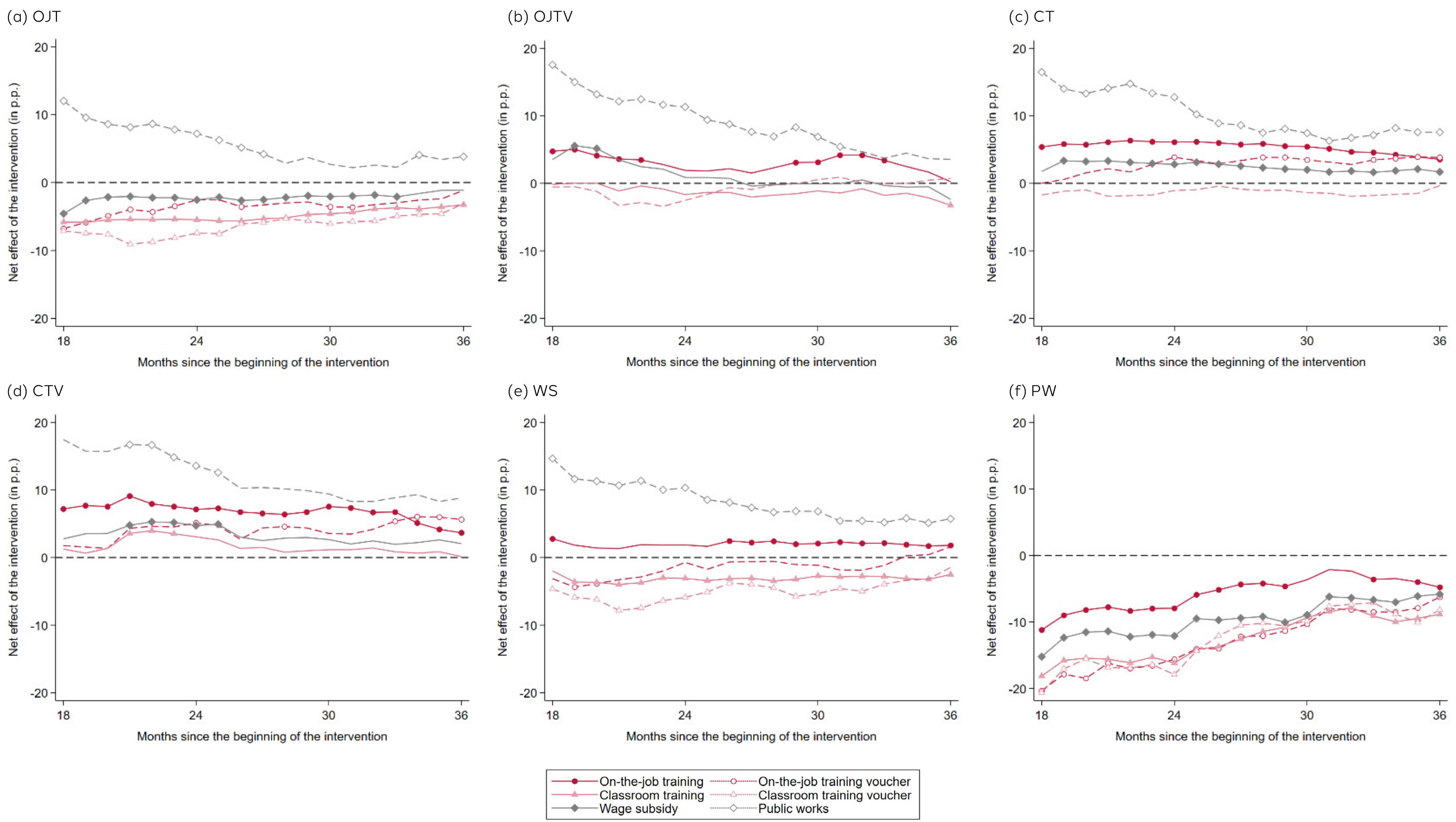
	OJTV–OJT		OJTV–CT		OJTV–CTV		OJTV–WS		OJTV–PW	
	Raw std. diff.	Matched std. diff.	Raw std. diff.	Matched std. diff.	Raw std. diff.	Matched std. diff.	Raw std. diff.	Matched std. diff.	Raw std. diff.	Matched std. diff.
Gender: Female	−0.155	0.027	−0.079	−0.01	0.656	0.031	0.929	−0.012	0.092	−0.024
Age	0.457	−0.022	0.363	0.003	0.211	−0.009	0.218	−0.044	0.168	−0.002
Rural area	0.118	0.007	0.17	−0.005	0.125	0.01	0.169	0.078	−0.009	−0.009
No work experience	−0.365	−0.021	−0.227	−0.015	0.036	−0.007	0.144	−0.16	0.104	0.007
Secondary education	−0.188	−0.005	−0.156	0.013	−0.346	−0.008	−0.421	−0.086	−0.267	−0.008
Tertiary education	0.079	0.015	0.042	−0.006	0.397	0.036	0.435	0.068	0.2	0.011
Disability	0.072	−0.011	0.133	0.035	0.11	−0.052	0.176	0.04	0.118	0.023
Time to treatment (days)	−0.047	−0.034	−0.009	−0.07	−0.073	−0.046	0.16	−0.183	−0.051	−0.009
Short time to treatment (less than 14 days)	0.228	0.037	0.143	0.031	0.42	0.014	0.061	0.01	0.144	0.009
Long time to treatment (more than 12 months)	−0.024	−0.022	0	−0.063	−0.035	−0.058	0.127	−0.066	−0.047	0.004
No qualifications	−0.019	−0.015	0.097	0.025	0.003	−0.011	0.141	−0.034	0.069	−0.012
Less than 12 months since graduation	−0.532	0.003	−0.528	0.049	−0.113	0.053	−0.095	−0.026	−0.082	0.039
Child under 6 years old	0.135	0.01	0.153	0.026	0.103	−0.027	0.147	0.012	0.045	−0.031
Work experience (days)	0.238	0.002	0.111	0.037	−0.218	−0.036	−0.284	0.064	−0.214	−0.009
Days in register (total)	0.497	−0.04	0.59	−0.041	0.397	−0.057	0.467	−0.153	0.263	−0.008
Eligible for unemployment benefits	0.238	−0.013	0.173	0.032	−0.051	0.023	−0.079	0.12	−0.031	−0.004
No work experience	0.419	0.015	0.307	0.005	0.097	0.007	−0.027	0.064	−0.027	−0.008
Reason for last separation: dismissal	−0.004	−0.002	−0.02	−0.036	−0.127	−0.007	−0.126	0.043	−0.088	0.026
Farm ownership	0.028	−0.012	0.086	0.037	0.029	0.023	0.061	0.097	−0.005	−0.003
Interest in work in another EU country	−0.052	0.001	−0.04	−0.039	−0.182	−0.006	−0.289	−0.104	−0.068	−0.039
Unemployment rate (NUTS-4, %)	0.444	0.014	0.686	0.015	0.529	0.008	0.52	0.154	0.3	−0.017
Income related to country average (NUTS-4, %)	−0.181	−0.002	−0.378	0.004	−0.243	0.013	−0.342	−0.056	−0.017	−0.009
Labour demand	0.163	0.007	0.095	−0.009	0.091	0.01	0.159	−0.082	0.039	0.001
Average distance to city (NUTS-5, km)	0.233	0.016	0.194	−0.03	0.224	−0.032	0.25	0.073	0.14	0.015
Cumulative number of registrations	0.729	−0.028	0.791	0.004	0.56	−0.048	0.531	−0.026	0.374	−0.016
Interest in any job	−0.011	0.006	−0.071	−0.021	0.013	−0.013	0.041	0.06	0.066	0.014
Quarter 1	−0.164	−0.006	0.025	0.015	−0.137	0.001	−0.118	−0.056	−0.149	−0.022
Quarter 2	0.017	−0.009	0.065	−0.03	−0.057	−0.023	0.07	−0.004	−0.051	−0.009
Quarter 3	0.095	0.015	−0.043	0.039	0.048	−0.046	0.031	0.026	0.074	0.022
Year	−0.248	−0.011	−0.108	−0.022	−0.037	−0.009	−0.379	−0.086	0.051	−0.021
Total	0.206	0.014	0.196	0.025	0.189	0.024	0.233	0.07	0.112	0.014

Notes: Table reports standard differences between treated and control groups for raw and matched samples. The quality of matching is considered as sufficient if the matched standard difference does not exceed 5%. OJT – On-the-job training, OJTV – On-the-job training voucher, CT – Classroom training, CTV–Classroom training voucher, WS – Wage subsidy, PW – Public works.

Source: Authors' calculations based on PES data.

Appendix C. Heterogeneity of the effects

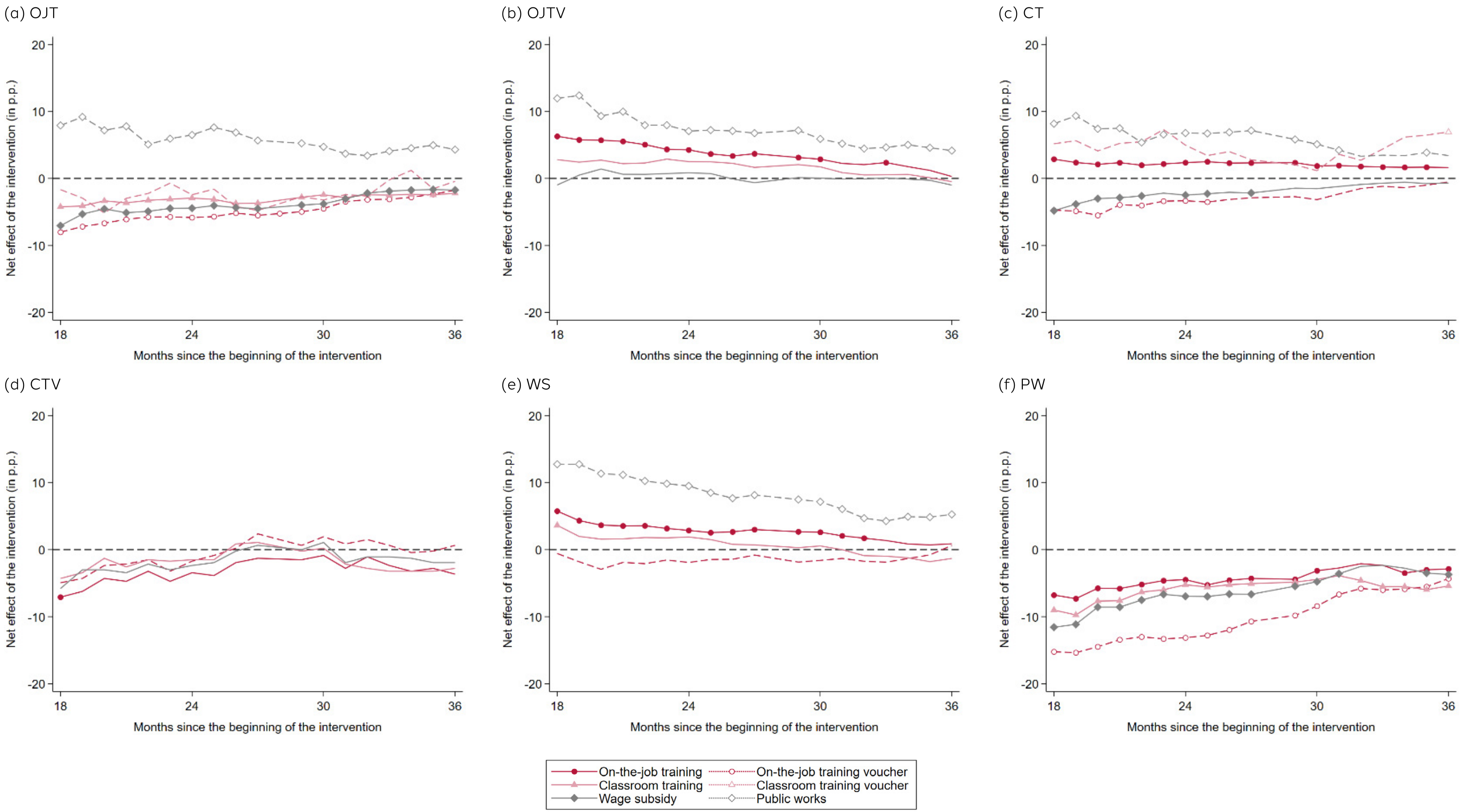
Figure C1. Dynamics of ALMP effects – men



Notes: Figure shows the average treatment effect on the treated of participating in programme m instead of programme n. Subfigures titles indicate m programme, while the lines on the figures indicate the programme n to which m is compared. The marker on the line at a particular point in time indicates whether the difference in effectiveness is statistically significant at the 5% significance level. Subfigure (a) reads as follows: 18 months after the beginning of the ALMP, the participants in OJT were more likely to be out of unemployment (by about 12 p.p.) than they would have been if they had participated in the PW (the counterfactual), and the effect is statistically significant. Estimated with PSM, the balancing scores can be found in Appendix B, and the variables used in the matching procedure are summarised in Table 1. Additionally, the year and quarter of the beginning of the ALMP are controlled for.

Source: Authors' calculations based on PES data.

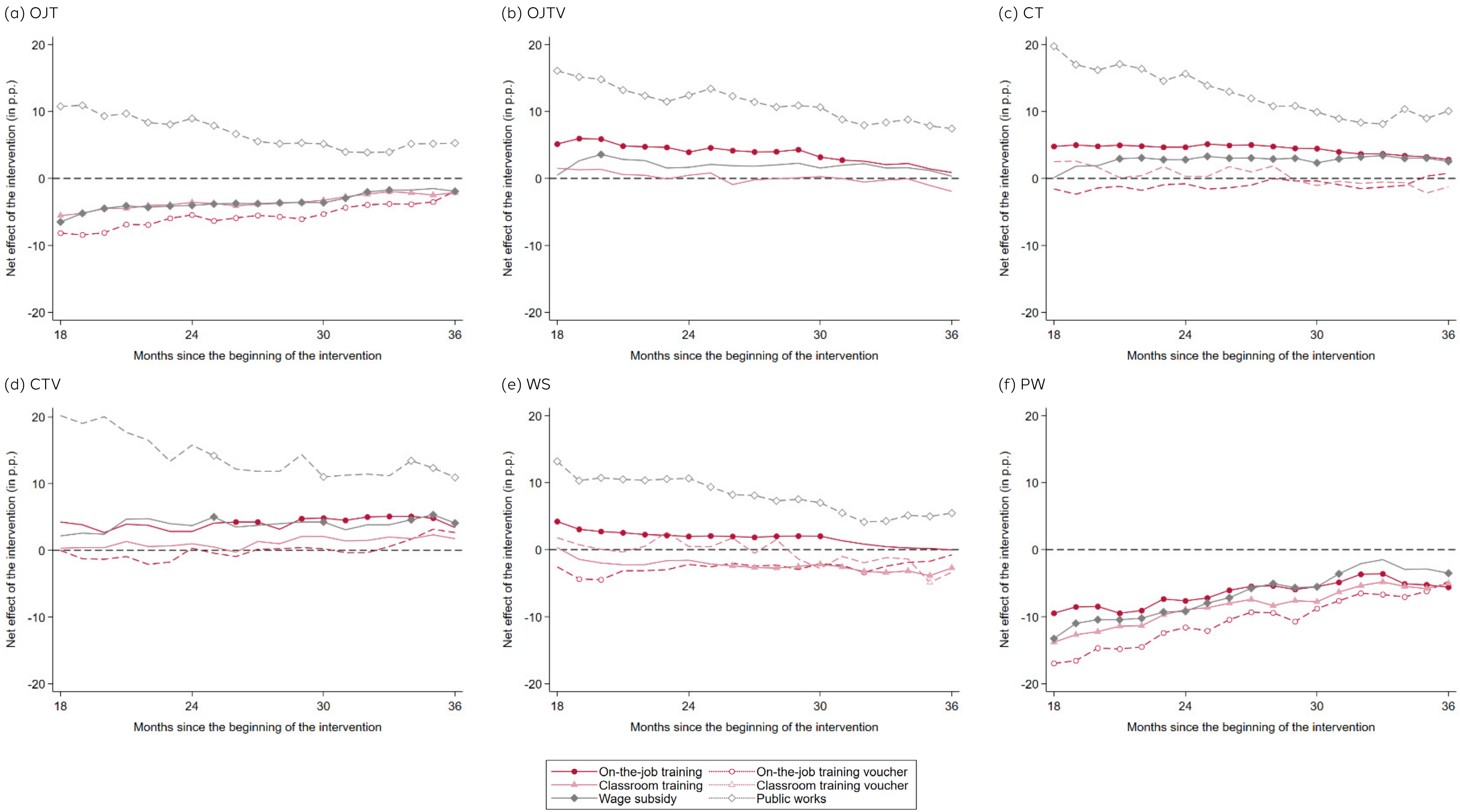
Figure C2. Dynamics of ALMP effects – women



Notes: Figure shows the average treatment effect on the treated of participating in programme m instead of programme n. Subfigures titles indicate m programme, while the lines on the figures indicate the programme n to which m is compared. The marker on the line at a particular point in time indicates whether the difference in effectiveness is statistically significant at the 5% significance level. Subfigure (a) reads as follows: 18 months after the beginning of the ALMP, the participants in OJT were more likely to be out of unemployment (by about 8 p.p.) than they would have been if they had participated in the PW (the counterfactual), and the effect is statistically significant. Estimated with PSM, the balancing scores can be found in Appendix B, and the variables used in the matching procedure are summarised in Table 1. Additionally, the year and quarter of the beginning of the ALMP are controlled for.

Source: Authors' calculations based on PES data.

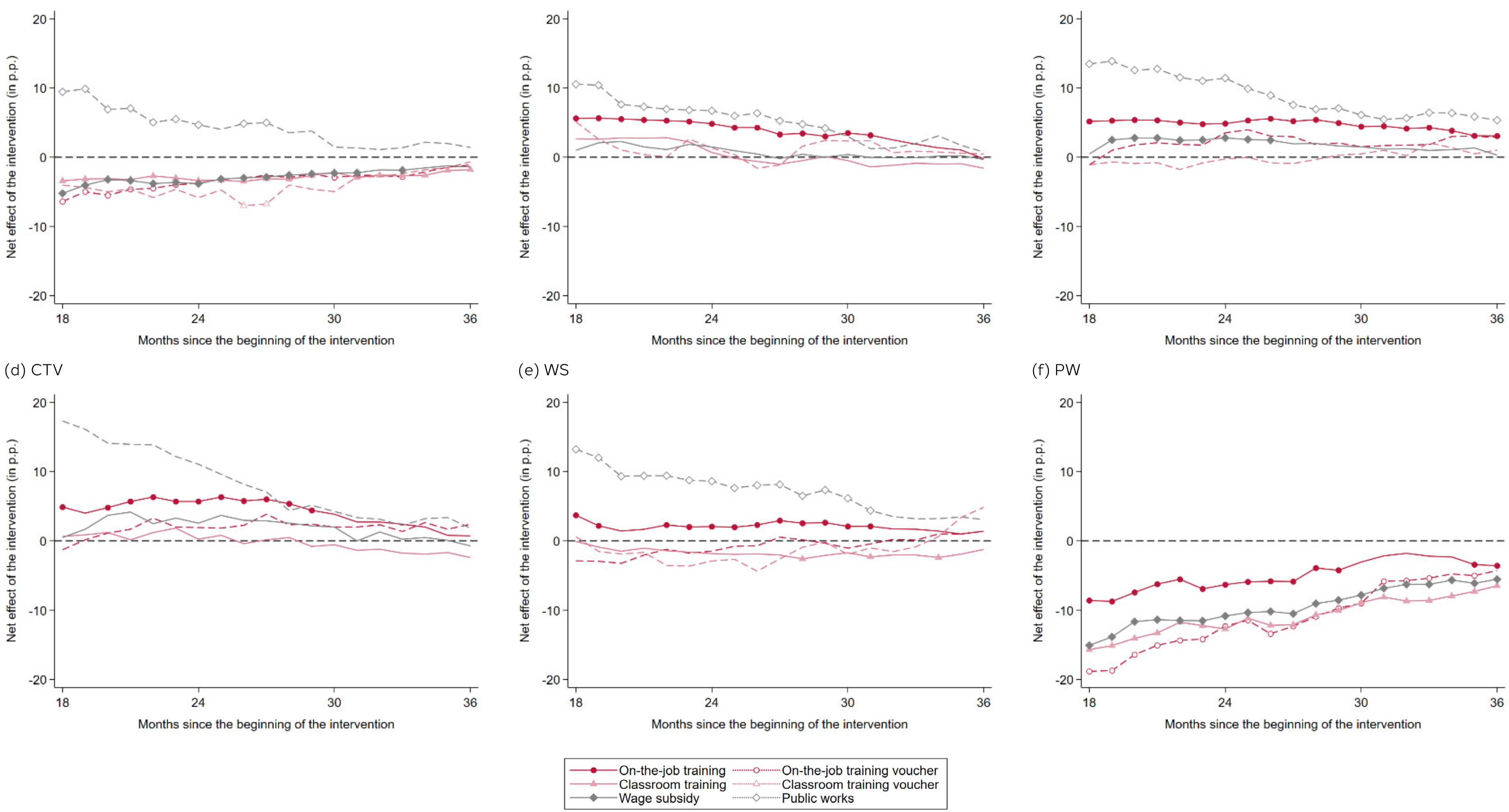
Figure C3. Dynamics of ALMP effects – rural area



Notes: Figure shows the average treatment effect on the treated of participating in programme m instead of programme n. Subfigures titles indicate m programme, while the lines on the figures indicate the programme n to which m is compared. The marker on the line at a particular point in time indicates whether the difference in effectiveness is statistically significant at the 5% significance level. Subfigure (a) reads as follows: 18 months after the beginning of the ALMP, the participants in OJT were more likely to be out of unemployment (by 10 p.p.) than they would have been if they had participated in the PW (the counterfactual), and the effect is statistically significant. Estimated with PSM, the balancing scores can be found in Appendix B, and the variables used in the matching procedure are summarised in Table 1. Additionally, the year and quarter of the beginning of the ALMP are controlled for.

Source: Authors' calculations based on PES data.

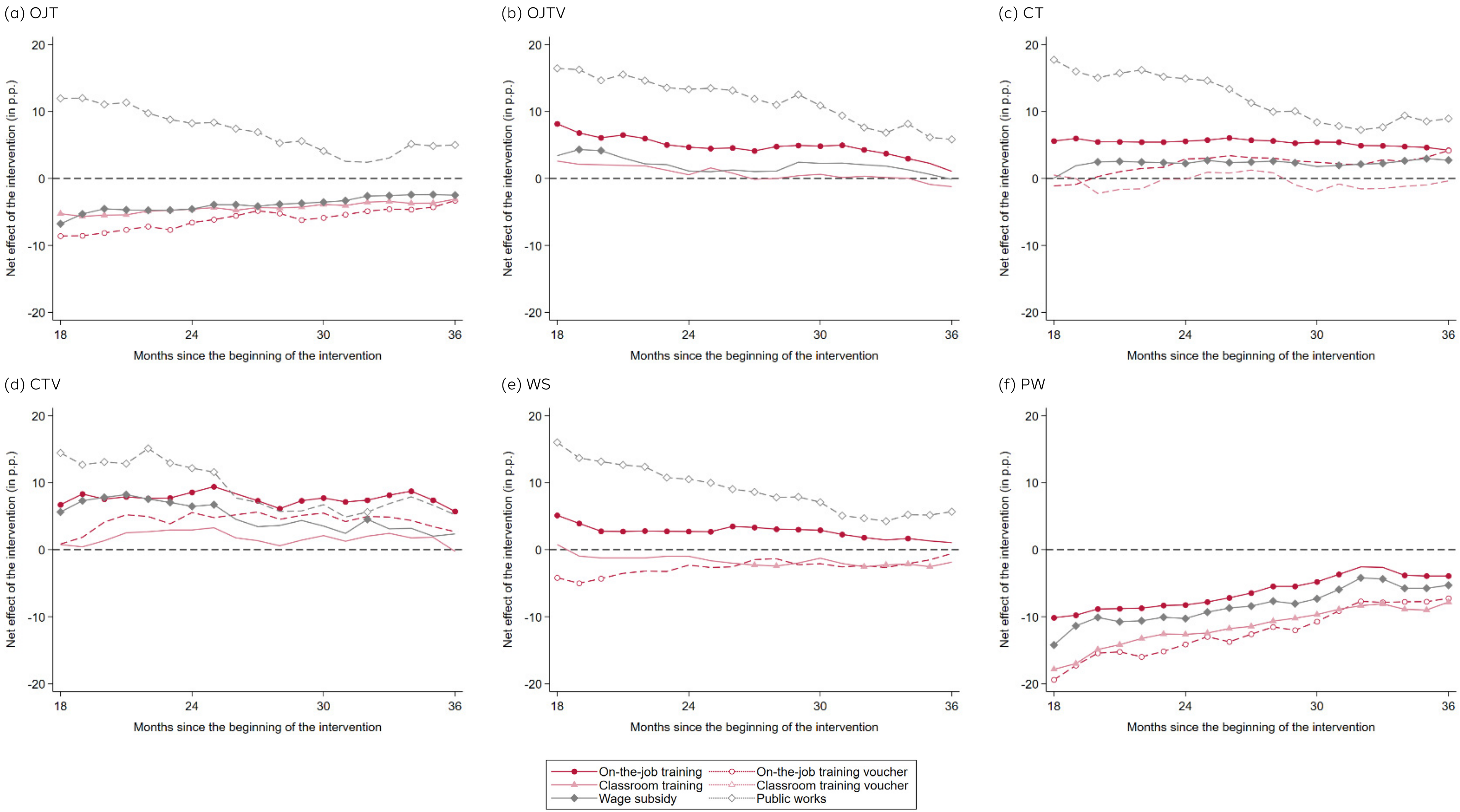
Figure C4. Dynamics of ALMP effects – urban area



Notes: Figure shows the average treatment effect on the treated of participating in programme m instead of programme n. Subfigures titles indicate m programme, while the lines on the figures indicate the programme n to which m is compared. The marker on the line at a particular point in time indicates whether the difference in effectiveness is statistically significant at the 5% significance level. Subfigure (a) reads as follows: 18 months after the beginning of the ALMP, the participants in OJT were more likely to be out of unemployment (by 10 p.p.) than they would have been if they had participated in the PW (the counterfactual), and the effect is statistically significant. Estimated with PSM, the balancing scores can be found in Appendix B, and the variables used in the matching procedure are summarised in Table 1. Additionally, the year and quarter of the beginning of the ALMP are controlled for.

Source: Authors' calculations based on PES data.

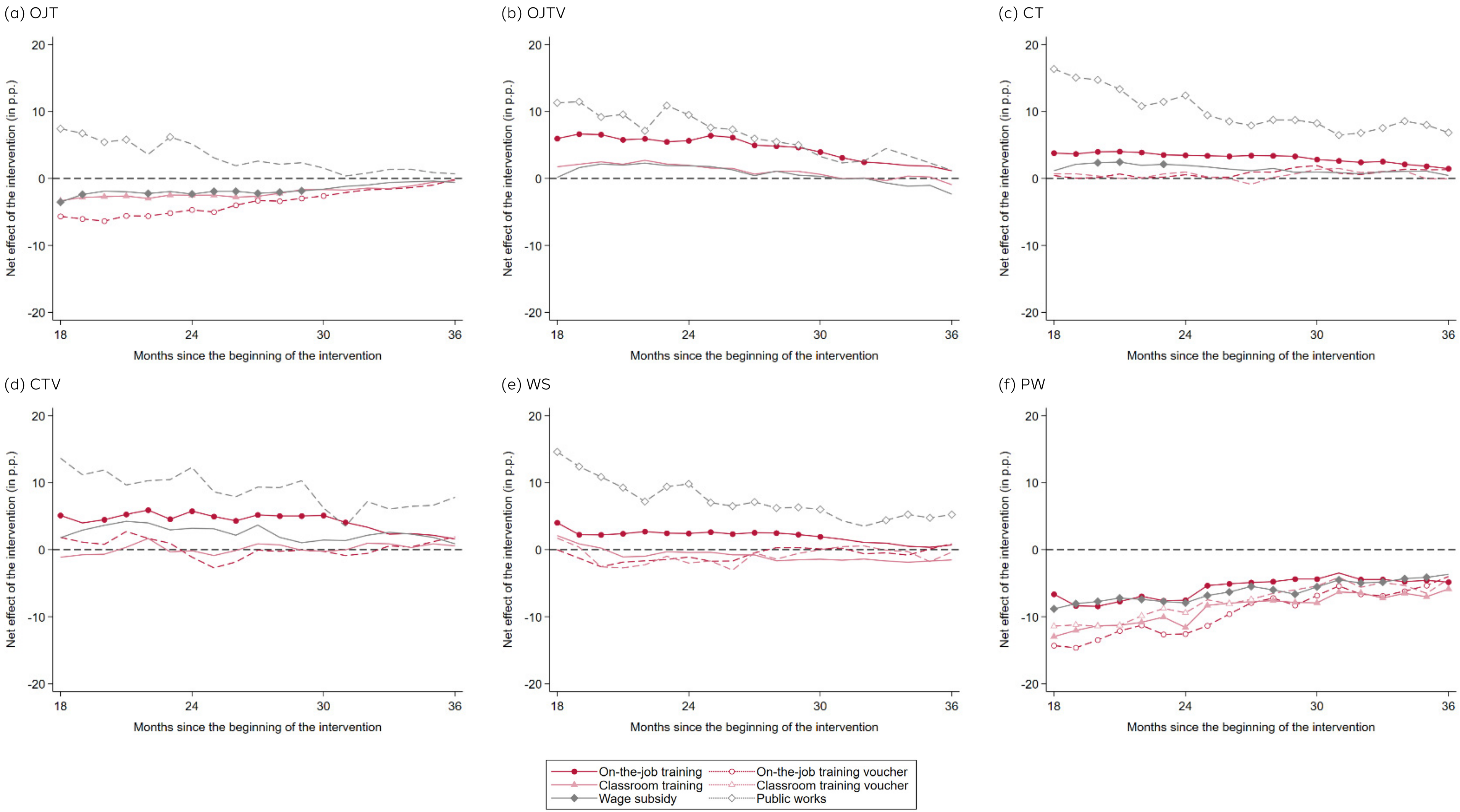
Figure C5. Dynamics of ALMP effects – unemployment in poviat above median



Notes: Figure shows the average treatment effect on the treated of participating in programme m instead of programme n. Subfigures titles indicate m programme, while the lines on the figures indicate the programme n to which m is compared. The marker on the line at a particular point in time indicates whether the difference in effectiveness is statistically significant at the 5% significance level. Subfigure (a) reads as follows: 18 months after the beginning of the ALMP, the participants in OJT were more likely to be out of unemployment (by about 12 p.p.) than they would have been if they had participated in the PW (the counterfactual), and the effect is statistically significant. Estimated with PSM, the balancing scores can be found in Appendix B, and the variables used in the matching procedure are summarised in Table 1. Additionally, the year and quarter of the beginning of the ALMP are controlled for.

Source: Authors' calculations based on PES data.

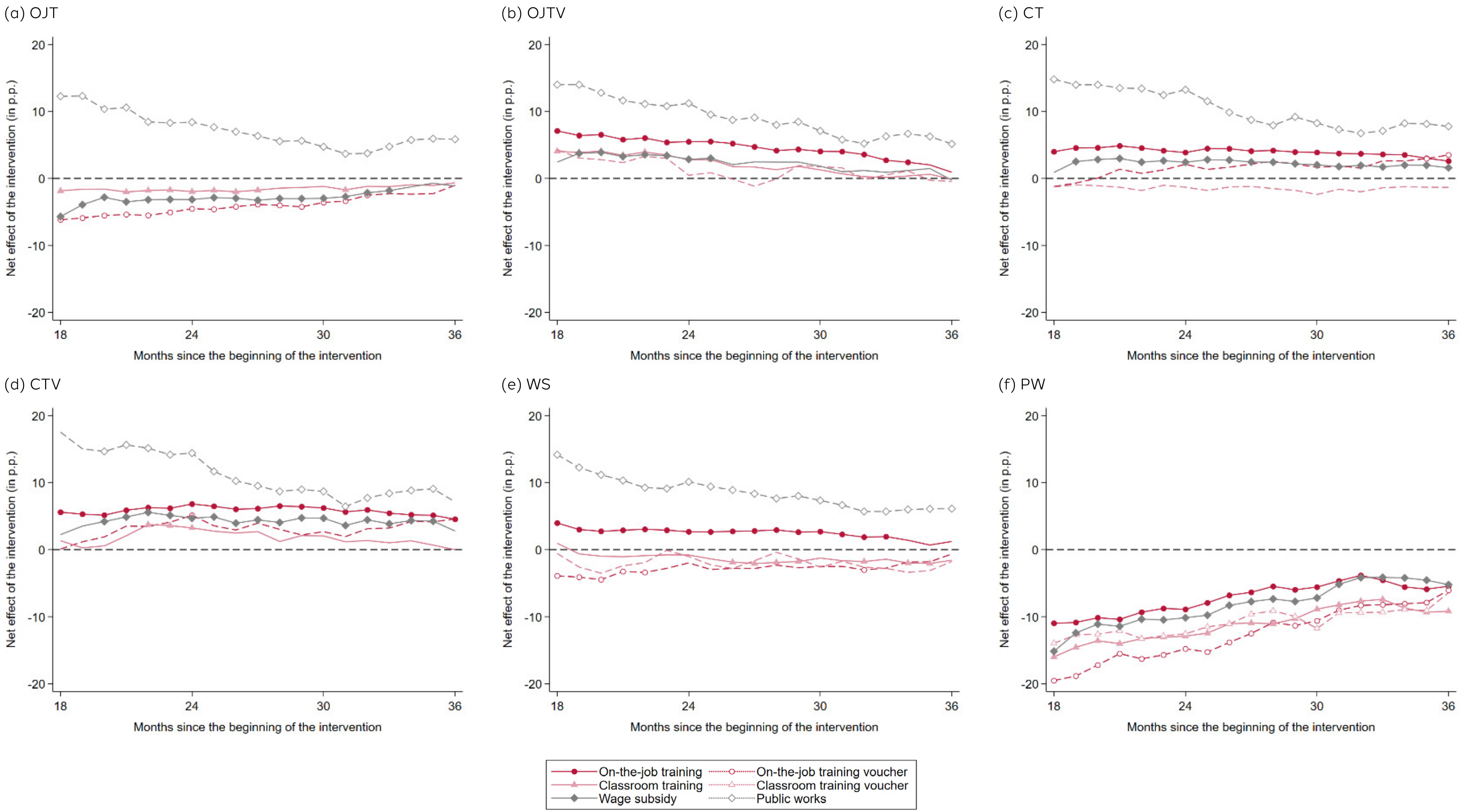
Figure C6. Dynamics of ALMP effects – unemployment in poviat below median



Notes: Figure shows the average treatment effect on the treated of participating in programme m instead of programme n. Subfigures titles indicate m programme, while the lines on the figures indicate the programme n to which m is compared. The marker on the line at a particular point in time indicates whether the difference in effectiveness is statistically significant at the 5% significance level. Subfigure (a) reads as follows: 18 months after the beginning of the ALMP, the participants in OJT were more likely to be out of unemployment (by about 8 p.p.) than they would have been if they had participated in the PW (the counterfactual), and the effect is statistically significant. Estimated with PSM, the balancing scores can be found in Appendix B, and the variables used in the matching procedure are summarised in Table 1. Additionally, the year and quarter of the beginning of the ALMP are controlled for.

Source: Authors' calculations based on PES data.

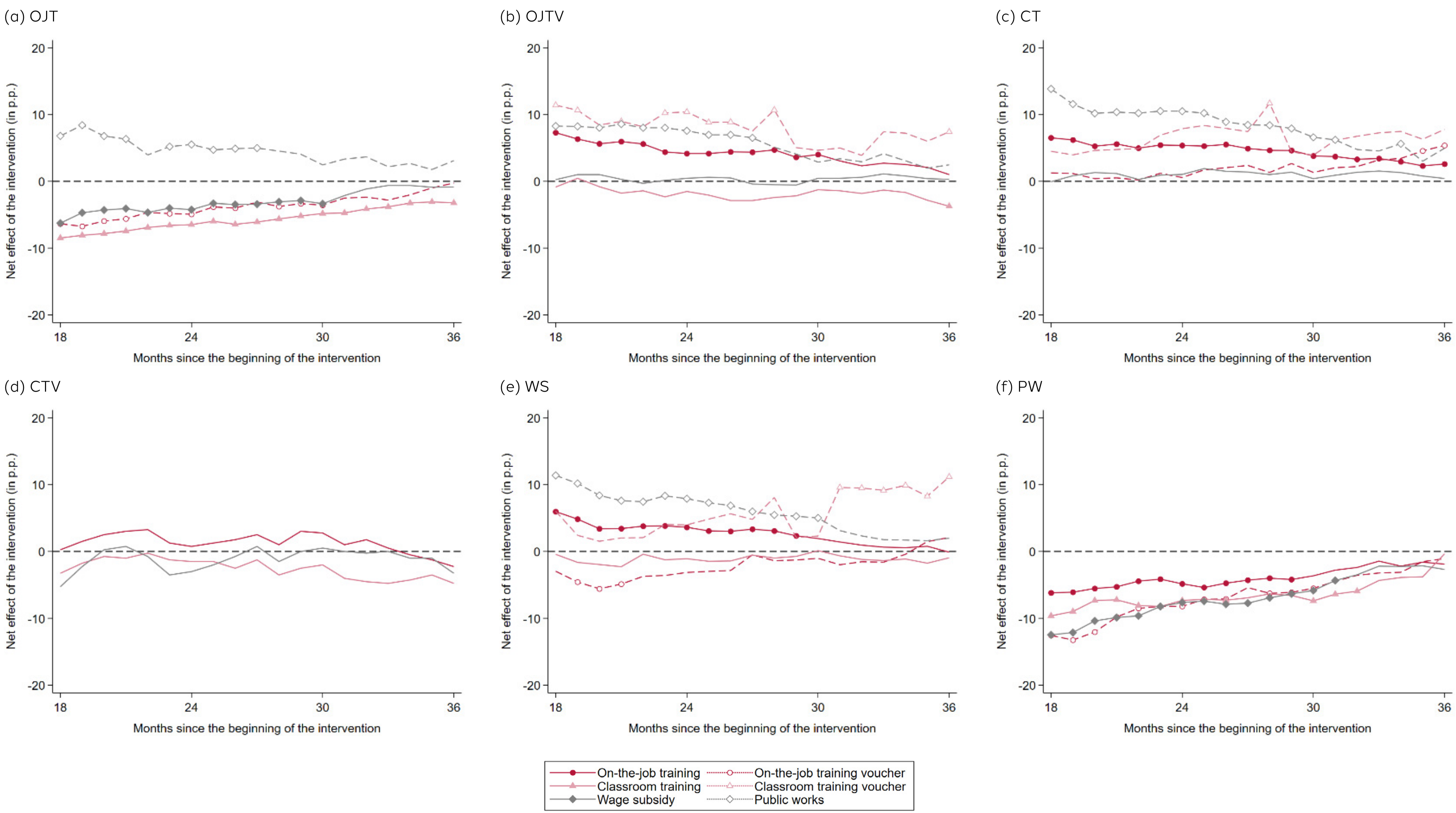
Figure C7. Dynamics of ALMP effects – primary and secondary education



Notes: Figure shows the average treatment effect on the treated of participating in programme m instead of programme n. Subfigures titles indicate m programme, while the lines on the figures indicate the programme n to which m is compared. The marker on the line at a particular point in time indicates whether the difference in effectiveness is statistically significant at the 5% significance level. Subfigure (a) reads as follows: 18 months after the beginning of the ALMP, the participants in OJT were more likely to be out of unemployment (by about 12 p.p.) than they would have been if they had participated in the PW (the counterfactual), and the effect is statistically significant. Estimated with PSM, the balancing scores can be found in Appendix B, and the variables used in the matching procedure are summarised in Table 1. Additionally, the year and quarter of the beginning of the ALMP are controlled for.

Source: Authors' calculations based on PES data.

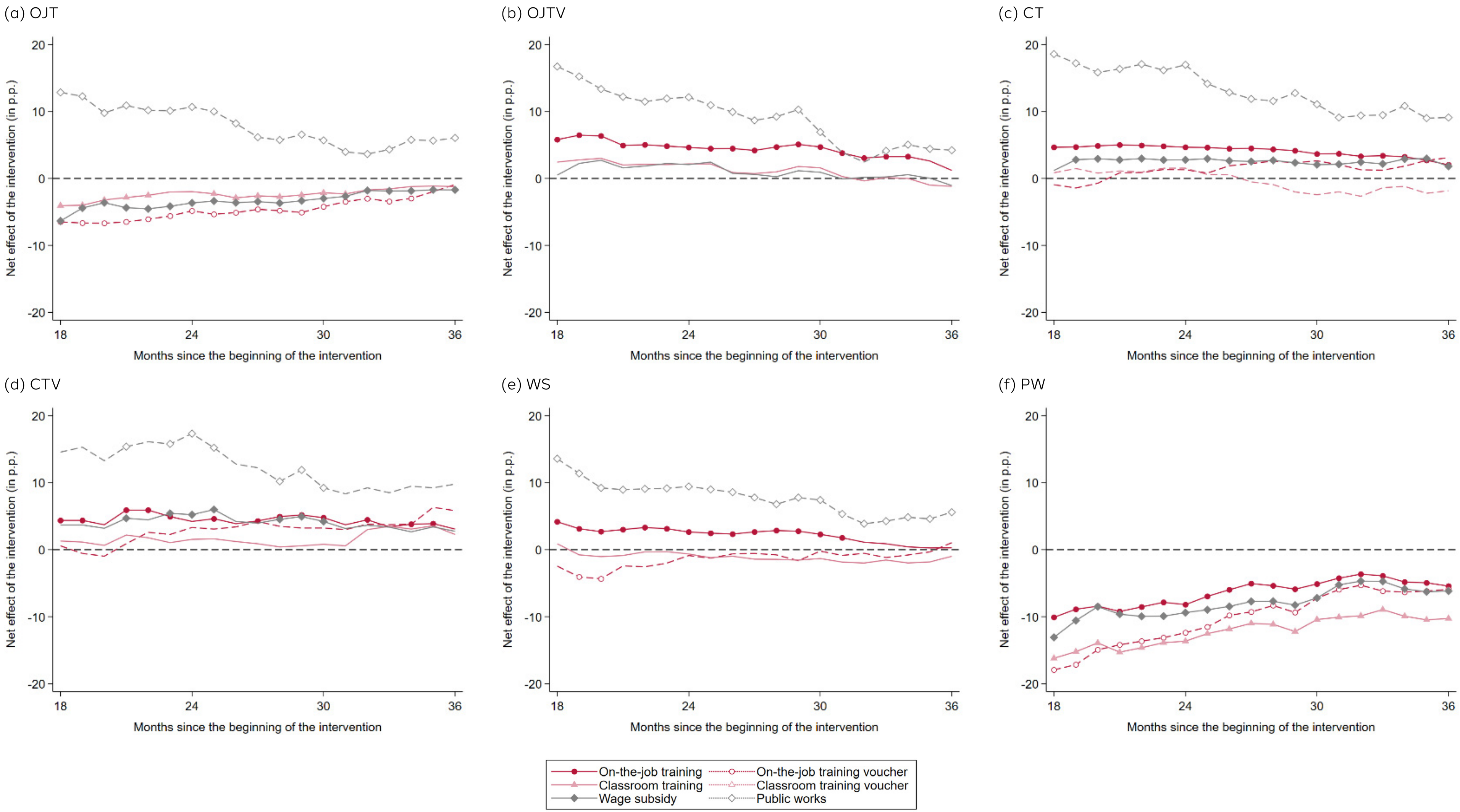
Figure C8. Dynamics of ALMP effects – tertiary education



Notes: Figure shows the average treatment effect on the treated of participating in programme m instead of programme n. Subfigures titles indicate m programme, while the lines on the figures indicate the programme n to which m is compared. The marker on the line at a particular point in time indicates whether the difference in effectiveness is statistically significant at the 5% significance level. Subfigure (a) reads as follows: 18 months after the beginning of the ALMP, the participants in OJT were more likely to be out of unemployment (by about 7 p.p.) than they would have been if they had participated in the PW (the counterfactual), and the effect is statistically significant. Estimated with PSM, the balancing scores can be found in Appendix B, and the variables used in the matching procedure are summarised in Table 1. Additionally, the year and quarter of the beginning of the ALMP are controlled for.

Source: Authors' calculations based on PES data.

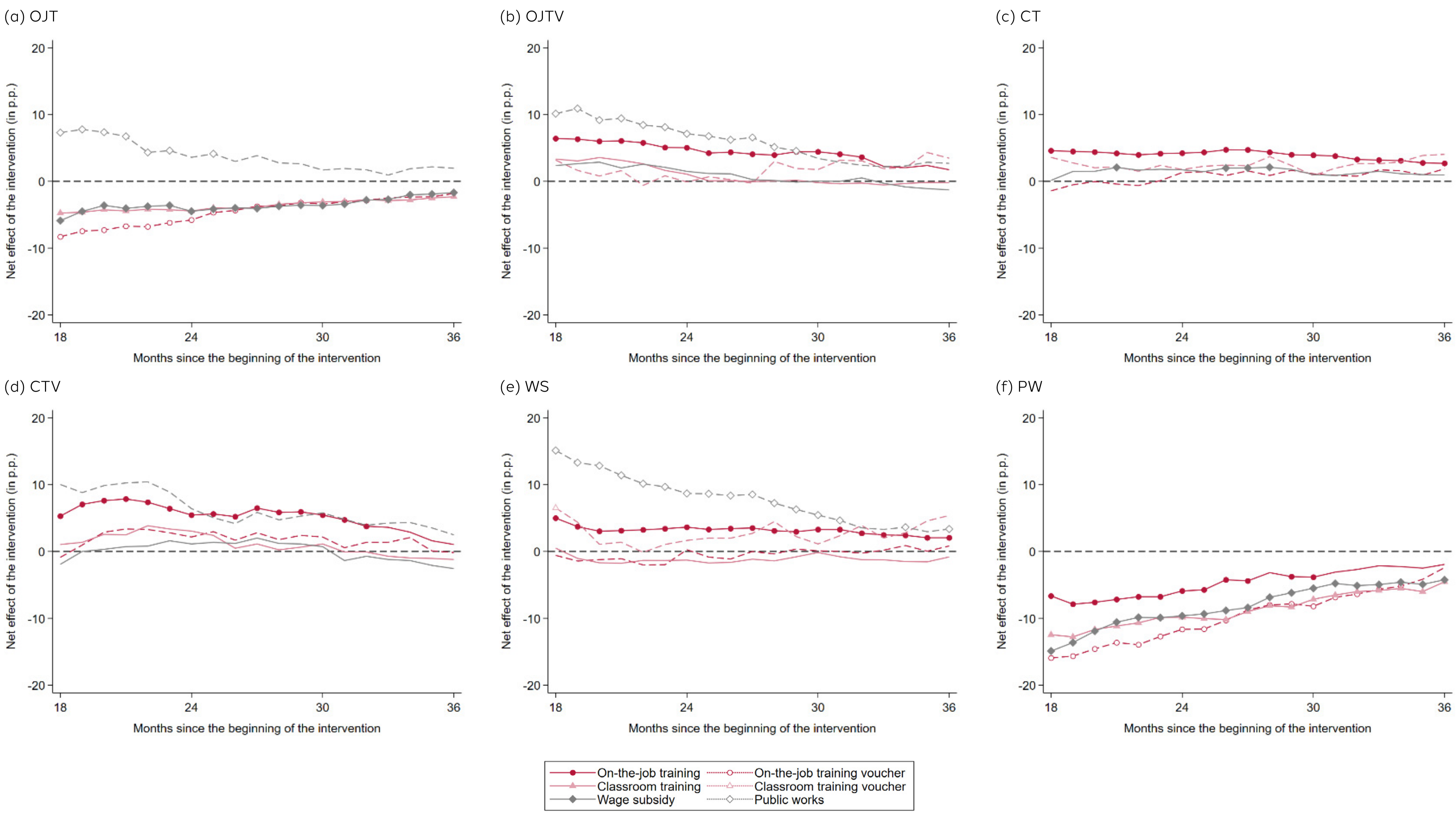
Figure C9. Dynamics of ALMP effects – long distance to county town



Notes: Figure shows the average treatment effect on the treated of participating in programme m instead of programme n. Subfigures titles indicate m programme, while the lines on the figures indicate the programme n to which m is compared. The marker on the line at a particular point in time indicates whether the difference in effectiveness is statistically significant at the 5% significance level. Subfigure (a) reads as follows: 18 months after the beginning of the ALMP, the participants in OJT were more likely to be out of unemployment (by about 13 p.p.) than they would have been if they had participated in the PW (the counterfactual), and the effect is statistically significant. Estimated with PSM, the balancing scores can be found in Appendix B, and the variables used in the matching procedure are summarised in Table 1. Additionally, the year and quarter of the beginning of the ALMP are controlled for.

Source: Authors' calculations based on PES data.

Figure C10. Dynamics of ALMP effects – short distance to county town



Notes: Figure shows the average treatment effect on the treated of participating in programme m instead of programme n. Subfigures titles indicate m programme, while the lines on the figures indicate the programme n to which m is compared. The marker on the line at a particular point in time indicates whether the difference in effectiveness is statistically significant at the 5% significance level. Subfigure (a) reads as follows: 18 months after the beginning of the ALMP, the participants in OJT were more likely to be out of unemployment (by about 8 p.p.) than they would have been if they had participated in the PW (the counterfactual), and the effect is statistically significant. Estimated with PSM, the balancing scores can be found in Appendix B, and the variables used in the matching procedure are summarised in Table 1. Additionally, the year and quarter of the beginning of the ALMP are controlled for.

Source: Authors' calculations based on PES data.