# Large, positive, and persistent effects of ALMPs: Evidence from Slovak administrative data

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January 2026

**Abstract**

This paper contributes to the literature on the effectiveness of labour market policy programmes. The evaluation of three different Active Labour Market Policies (ALMPs) from Slovak administrative data over the period from the second half of 2021 to March 2024 is presented. Using a matched sample of participants and non-participants to ensure common support, we find in a differences-in-differences framework numerically large and statistically significant positive employment effects for all three examined interventions. A retraining scheme, *REPAS+*, in which participants had about 10 percentage points (pp) higher chances of being employed during the 24-months of post-intervention period compared to non-participants. An internship scheme, *Youth Internship*, has led to an approximately 11.6 pp higher chance of employment during the 12-month follow-up period compared to non-participants. A counselling programme, *Individual Counselling for Disadvantaged Job Seekers*, in which the participants experienced approximately 13 pp higher chances of being employed during the follow-up period compared to non-participants. The results show the importance of ALMP schemes in Slovak labour market context and the implied return on investment warrants further support of such measures.

**Keywords:** Active labour market policy; Retraining; Youth unemployment, Disadvantaged job seekers, Treatment effects, Programme evaluation

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# 1 Introduction

Active labour market policies (ALMPs) have become a central instrument of modern labour market governance, particularly in small open economies facing structural transformation, demographic pressures, and recurrent macroeconomic shocks. In the European context, and especially within countries characterized by persistent regional (as emphasised e.g. in van Ours, 2001) disparities and skill mismatches, ALMPs are expected not only to accelerate transitions from unemployment to employment but also to enhance human capital, reduce hysteresis effects, and promote more inclusive labour market outcomes. Against this background, rigorous evaluation of ALMP interventions is indispensable. Public expenditures on labour market programmes are substantial, and their opportunity costs are non-trivial. In the absence of credible evidence on their effectiveness, policymakers risk misallocating scarce fiscal resources or perpetuating ineffective schemes.

This paper examines three ALMP measures implemented in Slovakia that target distinct segments of job seekers. The first programme, REPAS+, supports individuals who choose to acquire additional qualifications or skills in order to improve their employability. The second measure, Youth Internship, is designed to ease the entry into the labour market for for recent graduates, who seek to gain work experience. The third intervention, Individual Counselling for Disadvantaged Job Seekers, was introduced in the aftermath of the COVID-19 pandemic and focuses on individuals who lost employment during the crisis and face heightened barriers to re-employment. By analysing these three measures jointly, we shed light on the effectiveness of human capital–oriented training, school-to-work transition support, and targeted counselling designed to combat an adverse macroeconomic episode.

The importance of evaluating ALMPs arises from several interrelated considerations. First, from a theoretical perspective, labour market frictions—such as imperfect information, search costs, skill mismatches, and credit constraints—may justify policy intervention. Training programmes can mitigate human capital deficiencies; internships may alleviate information asymmetries between firms and inexperienced workers; and counselling may reduce search frictions and improve job matching efficiency. However, standard models of job search and human capital accumulation also highlight potential unintended effects. Participation in programmes may generate lock-out effects by temporarily reducing job search intensity, and training content may not align with employer demand. Consequently, the net impact of ALMPs is an empirical question that depends on programme design, target population, and labour market conditions.

Second, ALMPs differ markedly in their cost structures and expected channels of impact. Training measures such as REPAS+ involve direct expenditure on course provision and potentially higher short-run non-employment, but they may yield longer-term productivity gains and wage growth if skills are well aligned with labour demand. Youth internship schemes aim to overcome the potentially significant scarring effects associated with early-career unemployment (e.g. De Fraja et al., 2021) by facilitating the accumulation of firm-specific and general work experience. Their success depends on whether internships translate into stable employment rather than revolving-door placements. Targeted counselling for disadvantaged job seekers, particularly in the wake of the COVID-19 shock, seeks to address compounded barriers—ranging from sectoral displacement to psychosocial challenges—through individualized support. The effectiveness of such counselling hinges on the capacity to tailor interventions and align them with local labour demand.

Third, the Slovak labour market presents features that make careful evaluation especially salient. The COVID-19 pandemic introduced abrupt sectoral disruptions, potentially altering the returns to training and work experience. Evaluating ALMPs in this context provides insight not only into programme-specific performance but also into the resilience of labour market institutions under stress.

Methodologically, credible causal inference is crucial for policy relevance. Simple comparisons of participants and non-participants are likely to be biased due to selection on observable and unobservable characteristics. Individuals opting into training or internships may differ systematically in motivation, prior experience, or employability (Gabrikova and Svabova, 2022). To address these concerns, we employ two complementary empirical strategies. First, we construct a comparison group of non-participants using matching techniques, enabling us to estimate the effect of programme participation relative to observationally similar job seekers. Second, we implement a double machine learning framework as a robustness check, leveraging flexible functional forms while preserving valid inference for treatment effects. This combination strengthens the credibility of our findings and aligns with recent advances in applied microeconometrics.

The paper proceeds as follows. We first review the relevant literature in relation to the evaluated ALMP measures in Slovakia and situate our analysis within the broader empirical evidence. We then describe the three programmes in detail and provide descriptive statistics based on administrative data. Next, we outline the construction of the analytical datasets and the empirical strategies used to estimate programme effectiveness. Finally, we present the results on employment and wage outcomes and discuss their implications for labour market policy design and resource allocation.

# 2 Slovak labour market in ALMP context

The long-term development of the Slovak labour market is rather positive in terms of labour force participation and unemployment rates compared to other eurozone countries. Despite this favourable trend, key risk areas such as unemployment among the low-skilled workers, regional differences, long-term unemployment, youth unemployment, and high unemployment rate of marginalized Roma communities persist (Štefánik et al., 2018; Polačková, 2020). One way to enable a fuller utilisation of labour potential is through the use of active labour market policy (ALMP) instruments. ALMPs, however, are costly both in terms of the direct expenditure involved and in terms of opportunity costs, should they be targeted inefficiently. In order to avoid the unnecessary costs, it remains vital to provide careful and rigorous analysis which measures work for whom (Bredgaard, 2015).

In Slovakia, expenditure on active labour market policies, which are designed to facilitate access to suitable employment for potential employees, has long been significantly below the average both for the eurozone countries and the other V4 countries (the Czech Republic, Poland, and Hungary). This spending gap plausibly indicates that there is a potential for increased use of such measures. Slovakia spends only between 0.02% to 0.05% of its GDP compared to more developed countries like Denmark, which spends between 0.3% and 0.4%.[1] Furthermore, the limited spending on ALMPs in Slovakia is combined by a relative dearth of evaluations of the measures employed. In comparison with other European economies, few papers have been published on Slovak experience with ALMPs (Card et al., 2018). More developed countries such as Germany, Denmark, Sweden, Norway or Latvia focus a lot more effort on evaluating these policies, so the policy makers can plan more effectively (Gabrikova and Svabova, 2022). The need for policy evaluation has been underscored recently with the COVID-19 pandemic, which arguably disrupted the functioning of pre-existing labour market structures and thus it is an open question to what extent can earlier studies be relied upon. Unforeseen developments such as the coronavirus pandemic and the invasion of Ukraine in 2022 have had a profound impact across Europe (Rotar, 2022; Honorati et al., 2024; Hora and Suchanec, 2024) and new studies focusing on the developments following these disturbances are needed. Finally, despite increasing integration between European markets, each country retains its domestic specifics (Martin, 2015) and hence differing results in ALMP success are to be expected, which prompts the country-specific research presented here.

## 2.1 ALMPs in Slovakia - literature overview

High youth unemployment has been seen in the literature as the driving factor in labour policy implementation (Lafférs and Štefánik, 2024). For this reason, a class of policies targeting young job seekers has been an important locus of scholarly attention among ALMP evaluations in Slovakia (including this one, see also Štefánik et al. (2018) for a more general overview). Štefánik et al. (2020) examine Slovakia's leading labour market programme for unemployed youth, highlighting long-term employment effects of state-supported trainee schemes. The results from three methods confirm that participation significantly boosts employment chances post-programme, even after 30 months, though income effects are negative. A newer analysis evaluating three programmes supporting young job seekers shows that these programmes have positive effects on the employment of specific subgroups but ambiguous overall effect (Štefánik and Lafférs, 2024). Similar findings were obtained by Petráš (2023), who evaluated a similar ALMP aimed at youths no older than 28, finding a

[1] See Public expenditure on labour market policies, by type of action, available at Eurostat under data code `lmp_expsumm`

12 percentage point (pp) increase in employment rates of participants compared with observationally similar non-participants. A somewhat more modest effect on younger job-seekers from an earlier version of the scheme aimed at providing youths no older than 26 of about 6pp increase in employment was shown in Petráš (2021).

Slovakia also takes advantage of the EU-wide Youth Guarantee initiative (Escudero and López Mourelo, 2017). One significant way to channel this increased support is through ALMPs (Eichhorst and Rinne, 2018; Tosun et al., 2019). However, there is still conflicting evidence on the effects of such programmes (Caliendo and Schmidl, 2016; Eichhorst and Rinne, 2018; Kluve et al., 2019) so further impact evaluation is required.

The topic of young job seekers was also examined by Svabova et al. (2022) when they performed a counterfactual analysis of the recent-graduates' allowance funded by the state budget and EU social funds. The findings indicate a short-to-medium-term improvement in both employability and wages. These results stand in some tension with those obtained by Štefánik et al. (2020), highlighting the sensitivity of the effects to the precise policy setup.

In terms of more broadly-targeted, human-capital-acquisition schemes, the most prominent example in Slovakia is the REPAS programme, the newest iteration of which (REPAS+) is one of the three ALMP measures discussed here. REPAS+ scheme allows jobseekers to self-select into a training course subject to approval from the local office of the Public Employment Service. The jobseekers are free to select the provider and the specific course in a manner similar to Germany's HARTZ I system. Analysis shows positive employment effects before and after REPAS (an earlier iteration of the scheme), with short-term impacts tied to particular training specializations. However, the reform's positive long-term effects were found not to be driven by rare specializations nor high-skilled participants (Štefánik, 2021).

Results on the effectiveness of REPAS by Karasova et al. (2018, 2019) invite a more nuanced view of the scheme. Their analysis shows that external factors, such as business cycles, job vacancies, discrimination, and regional development, influenced the ALMP performance. Participants' risk of repeated job loss was affected by age, education, and ALMP participation length. Males were less likely to re-register, while older and less-educated job seekers were more likely. Thus, the results point to the need to tailor ALMPs to individual jobseekers' specific needs. Finally, according to these findings, REPAS had higher success during economic growth (2014–2016), which is somewhat discouraging, because it is the time of economic stagnation when the need for ALMPs is at its most urgent.

More optimistic view emerges from a study by Petráš (2019), who identified a robust increase in the employment rate of ALMP participants compared to those job seekers who did not participate by 15pp across different sub-groups. More recently, similarly robust findings were obtained by Svabova and Gabrikova (2024), who studied Slovakia's Contribution for Self-employment, which offers financial aid to unemployed individuals to cover business start-up costs. Their results show the intervention improves employment and supports entrepreneurship in various sub-populations, making it an effective tool for reducing unemployment. ALMP for upskilling was evaluated with an effect of 4pp on the employment rate (Petráš, 2018) with broad similarity across sub-groups. In contrast, a scheme designed to provide low-skill jobs for long-term unemployed (community service funded by the state government), called "activation work", has been found ineffective (Petráš, 2020).

In this paper, we contribute to the literature surveyed above by zooming in on the most recent iterations of the three prominent strands of ALMP measures: re/up-skilling measure (REPAS+), youth-directed scheme, and a general response to an exogenous economic disturbance. We present these three scheemes in more detail in the following subsections.

## 2.2 REPAS+

'Support for the retraining of job seekers' (REPAS+) is a scheme aimed at preparing unemployed persons for the labour market by providing them with the opportunity to complete a retraining course in which they will acquire new professional knowledge and skills. A job seeker under this scheme has the opportunity to choose the course and the provider of the retraining course, while the Labour Office reimburses the course fee (up to a certain amount) plus travel and food costs associated with participation. Part of the requirement for participation is to state the job position to which the job seeker would like to apply upon completion of the course and a document showing that such a position is available (e.g. a job advertisement).

REPAS+ was implemented from July 2017 to December 2023 and during this period a total of 4,865 approved courses were attended by a total of 42,554 job seekers (in case one person participated in REPAS+ more than once, we consider their last participation). Of these, 55% were women and 45% were men with an average age of 37 years. In terms of the highest level of education achieved, the largest group among the supported job seekers were high school graduates, who accounted for more than 57%. The second largest group was university graduates - 14%, followed by 13% of primary school graduates. The rest of the participants either did not have the specified education or were without education. A total of 34,134,094 euro were spent on REPAS+.

## 2.3 Youth Internship

The Youth Internship Project supports job seekers from the NEET category - i.e. young people up to the age of 29 who are not employed and are not in the process of education or vocational training. Young job seekers are supported through the participation in an internship corresponding to their education, with funding provided for this internship for three to six months. This project was implemented from September 2022 and the window for applications was closed on 31 July 2023. Of the total number of 2,531 job seekers supported during this period, 68% were women and 32% were men. The average age of the supported applicant was 23 years. The largest group among those supported was high school graduates, who made up 75% of all participants. University graduates amounted to 20% of those treated and only approx. 4% of participants reported primary education as the highest level of education attained. In total, 2,668,010 euro were spent on this scheme, with the average length of the completed internship lasting 4.5 months.

## 2.4 Individual Counselling for Disadvantaged Job Seekers

The aim of this measure was to help disadvantaged job seekers in the labour market in the aftermath of the COVID-19 pandemic. Disadvantaged job seekers were supported primarily by developing so-called soft skills, which are relevant to finding a job and increasing their own competitiveness in the labour market. These include, for example, activities to encourage the evaluation of their own skills, competencies, or, conversely, obstacles to successful participation in the labour market. The project was implemented from December 2022 and was completed on 31 December 2023, with the total amount of funds disbursed being 420,057 euro.

A total of 13,543 disadvantaged job seekers were supported within the project, of which 64% were women and 36% were men, with the structure of the disadvantaged being as follows: 2,684 fresh graduates (20%), 11,406 job seekers who never held a regular job (84%), 12,156 long-term unemployed (90%), 4,226 job seekers over 50 (31%), 4,387 job seekers with low education (32%), 457 young persons with disabilities and 461 job seekers with other types of disadvantages. We note that a job seeker may have multiple disadvantages, therefore the percentages do not add up to 100%. In terms of highest education level, 59% of those supported were high school graduates, 10% were university graduates, 26% were primary school graduates, and 5% were job seekers with no completed education.

# 3 Data

The analysis is based on data from the Employment Services Information System, which contains a rich and detailed set of job seekers' individual characteristics and information on their unemployment spells. In addition to the basic characteristics of job seekers (e.g., age, gender, highest level of education attained, previous employer, etc.), this dataset contains information on active labour market policies in which the job seeker participated (e.g., date of participation in ALMP or amount of support received under given ALMP), and other information relevant to potential employment in the labour market (e.g., preference of the job seeker to work in a specific sector, type of driver's license, level of foreign language proficiency, whether a job seeker has a disability, etc.).

The samples were constructed for each of the ALMPs separately, that is, we identified a treated and control groups for *REPAS+*, *Youth Internship*, and *Individual Counselling for Disadvantaged Job Seekers.* In the first step, only data on job seekers who were registered on or after January 1, 2021, were retained. This date was chosen for the following reasons:

1. Although the COVID-19 pandemic was not yet over, the situation in the labour market stabilized during the first half of the year and the registered unemployment rate began

to decline gradually.

2. This is the year in which the measures we are evaluating began to be implemented by public employment services (in contrast, during the first wave of the pandemic in 2020, many measures were suspended).

This initial data set contains *702,883 observations* (unemployment spells) and a total of *537,304 unique unemployed persons* (some were registered more than once). These job seekers include participants in various different ALMPs (not only the three examined) but also those that did not participate in any ALMP.

In the second step, we construct an inflow sample covering unemployment spells that start no more than a month before the intervention period shown in Table 1. During the intervention period, we observe the unemployed person in the relevant ALMP or performing a job search, in case of jobseekers in the control group. During the follow up period, we monitor the effect of the intervention as measured by employment recorded by Slovak Social Security. This followup period lasts for 12 to 24 months to evaluate the effect of treatment and its persistence in time. When evaluating REPAS+ which is a measure that has lasted for several years, two intervention periods were chosen. A period from July 2021 to the end of 2021 and from July 2022 to the end of 2022. Two periods were chosen partly as a cross validation exercise and robustness check whether results hold in time. For other programmes, only one intervention period was chosen given their shorter duration and lower number of participants. In the case of the Youth Internship programme, the entire duration of the programme was included, starting in mid 2022 and lasting for approximately one year. Finally, when evaluating Individual Counselling for Disadvantaged Job Seekers, a start of the scheme in March 2022 is chosen but is limited to a little more than a year.

Table 1: Period overview of examined ALMPs

| *ALMP programme* | *Intervention Period* |
|---|---|
| REPAS+ | 01.07.2021–31.12.2021 |
| | 01.07.2022–31.12.2022 |
| Youth Internship | 01.07.2022–30.06.2023 |
| Individual Counselling | 01.07.2022–31.12.2022 |

In the third step, data on other ALMPs were also processed so that we could exclude jobseekers who participated in unexamined ALMPs so the resulting estimate of the effectiveness of the examined measures remained as clear and unambiguous as possible. More formally, the parameter of interest is the causal effect of participation in a specific ALMP on subsequent labour market outcomes. When individuals participate in multiple programmes, the observed outcome reflects the joint effect of a sequence or bundle of interventions. In the group of participants in multiple ALMPs, the treatment is no longer well-defined, the Stable Unit Treatment Value Assumption (SUTVA) is jeopardised because the "treatment" varies in intensity, timing, and composition, and the estimated coefficients conflate direct effects of the focal programme with dynamic complementarities or substitution effects from other programmes. Hence, without modelling the entire treatment path, the estimand becomes ill-defined. Restricting the sample to individuals with a single participation episode restores a clean binary treatment: participation in programme $p$ versus non-participation.

At this point, it may be objected that individuals who only need one intervention might be inherently more employable or of higher unobserved quality. If true, restricting the sample would upwardly bias estimated programme effects. In the present setting, however, several factors argue against concerns of this type. First, while there might be some selection for more employable jobseekers in the treated group by selecting only those who took part in a single ALMP, the same or even stronger selection applies to the control group, who have not participated in *any* ALMPs. To the extent the treated group is more employable than some hypothetical mean jobseeker in Slovakia, the control group should be even more employable. Thus, the direction of bias may well be downward on this logic. Secondly, our preferred empirical strategy conditions on individual jobseekers' characteristics by matching them on observables and by using individual-specific fixed effects, which should nullify the variation arising from persistent individual characteristics. Finally, even if single-programme participants constitute an imperfect representation of the full population of the jobseekers in Slovakia, the estimand remains well-defined as the treatment effect for individuals who

Table 2: Sample mean comparisons of key variables for REPAS+ 2021 cohort

| Variable | Full sample | | | Matched sample | | |
|---|---|---|---|---|---|---|
| | Control | Treated | P-val | Control | Treated | P-val |
| Male | 0.52 | 0.52 | 0.89 | 0.51 | 0.51 | 0.94 |
| Health disability | 0.02 | 0.04 | 0.01 | 0.04 | 0.04 | 0.53 |
| Driving licence | 0.5 | 0.65 | 0 | 0.65 | 0.65 | 0.83 |
| PC skills | 0.55 | 0.64 | 0 | 0.68 | 0.64 | 0.2 |
| Foreign language | 0.6 | 0.66 | 0.02 | 0.67 | 0.65 | 0.56 |
| Academic title | 0.19 | 0.16 | 0.17 | 0.17 | 0.16 | 0.64 |
| Self-employed | 0 | 0 | 0 | 0 | 0 | 0.32 |
| Voluntary unempl. | 0.58 | 0.56 | 0.36 | 0.49 | 0.56 | 0.05 |
| Intr. in part-time | 0.04 | 0.06 | 0.02 | 0.07 | 0.06 | 0.64 |
| Intr. in training | 0.03 | 0.02 | 0.22 | 0.02 | 0.02 | 0.97 |
| Numb. children | 0.29 | 0.31 | 0.54 | 0.29 | 0.31 | 0.63 |
| Age | 36.33 | 35.37 | 0.08 | 35.23 | 35.28 | 0.94 |
| Prob. of treatment | 0.39 | 0.57 | 0 | 0.56 | 0.57 | 0.28 |
| Last obs. wage | 1002 | 1282 | 0.03 | 1092 | 1177 | 0.57 |
| Observations | 107136 | 488 | | 454 | 462 | |

Table 3: Sample mean comparisons of key variables for REPAS+ 2022 cohort

| Variable | Full sample | | | Matched sample | | |
|---|---|---|---|---|---|---|
| | Control | Treated | P-val | Control | Treated | P-val |
| Male | 0.49 | 0.49 | 0.89 | 0.48 | 0.48 | 0.75 |
| Health disability | 0.02 | 0.03 | 0.02 | 0.03 | 0.03 | 0.46 |
| Driving licence | 0.49 | 0.68 | 0 | 0.65 | 0.68 | 0.1 |
| PC skills | 0.53 | 0.67 | 0 | 0.68 | 0.67 | 0.55 |
| Foreign language | 0.58 | 0.7 | 0 | 0.67 | 0.7 | 0.09 |
| Academic title | 0.17 | 0.17 | 0.48 | 0.18 | 0.18 | 0.83 |
| Self-employed | 0 | 0.01 | 0.02 | 0 | 0.01 | 0.14 |
| Voluntary unempl. | 0.6 | 0.54 | 0 | 0.55 | 0.54 | 0.69 |
| Intr. in part-time | 0.05 | 0.09 | 0 | 0.08 | 0.09 | 0.82 |
| Intr. in training | 0.04 | 0.02 | 0 | 0.04 | 0.02 | 0 |
| Numb. children | 0.36 | 0.37 | 0.45 | 0.44 | 0.38 | 0.04 |
| Age | 37.01 | 35.03 | 0 | 35.01 | 34.95 | 0.89 |
| Prob. of treatment | 0.39 | 0.58 | 0 | 0.56 | 0.57 | 0.04 |
| Last obs. wage | 1027.91 | 1279.43 | 0 | 1080.56 | 1109 | 0.77 |
| Observations | 154636 | 1552 | | 1477 | 1519 | |

participate in exactly one programme. As we argue below, our results tally well with earlier literature that did not exclude multiple-programme participants, which further argues against systematic differences between those jobseekers that participate in one or multiple ALMPs.

Finally, the number of treated job seekers was slightly reduced based on technical criteria, such as dropping cases when the ALMP request was denied or jobseekers terminated their participation early. These are rare cases and the procedural details of ALMP administration go beyond the scope of this study. In the final dataset, we therefore retained a) unemployed persons for the control group, i.e. those who were not identified as supported under any of the ALMPs but would be eligible for the ALMP under consideration, and b) unemployed persons for the treated groups, i.e. those who were identified as supported unemployed persons only under the ALMPs examined in this analysis. Tables 2 through 5 present the summary statistics for key variables in the final dataset and its subset of matched treated and control jobseekers.

Table 2 describes the earlier REPAS+ cohort. In the full sample, the treated individuals are more likely to have health disabilities, substantially more likely to hold a driving licence, have higher PC and foreign language skills, and have earned higher pre-treatment wages. On the other hand, they show similar age and gender composition compared to controls. This pattern differs markedly from counselling and internships. Here, selection appears positively associated with employability, namely, higher wages and stronger skill profiles among treated

Table 4: Sample mean comparisons of key variables for Individual Counselling

| Variable | Full sample | | | Matched sample | | |
|---|---|---|---|---|---|---|
| | Control | Treated | P-val | Control | Treated | P-val |
| Male | 0.49 | 0.41 | 0 | 0.4 | 0.4 | 0.85 |
| Health disability | 0.03 | 0.04 | 0.13 | 0.02 | 0.04 | 0.07 |
| Driving licence | 0.43 | 0.41 | 0.1 | 0.4 | 0.4 | 0.8 |
| PC skills | 0.47 | 0.52 | 0 | 0.5 | 0.51 | 0.55 |
| Foreign language | 0.53 | 0.56 | 0.11 | 0.55 | 0.55 | 0.93 |
| Academic title | 0.14 | 0.11 | 0 | 0.11 | 0.11 | 0.96 |
| Self-employed | 0 | 0 | 0.02 | 0 | 0 | 0.3 |
| Voluntary unempl. | 0.62 | 0.55 | 0 | 0.59 | 0.55 | 0.1 |
| Intr. in part-time | 0.05 | 0.05 | 0.51 | 0.05 | 0.05 | 0.89 |
| Intr. in training | 0.04 | 0.05 | 0.35 | 0.05 | 0.05 | 0.93 |
| Numb. children | 0.35 | 0.33 | 0.54 | 0.31 | 0.34 | 0.41 |
| Age | 37.79 | 34.5 | 0 | 34.77 | 34.3 | 0.5 |
| Prob. of treatment | 0.4 | 0.61 | 0 | 0.49 | 0.61 | 0 |
| Last obs. wage | 871.94 | 634.45 | 0 | 530.66 | 547.17 | 0.8 |
| Observations | 116745 | 903 | | 820 | 855 | |

Table 5: Sample mean comparisons of key variables for Youth Internship

| Variable | Full sample | | | Matched sample | | |
|---|---|---|---|---|---|---|
| | Control | Treated | P-val | Control | Treated | P-val |
| Male | 0.51 | 0.34 | 0 | 0.34 | 0.33 | 0.76 |
| Health disability | 0 | 0.01 | 0.4 | 0.01 | 0.01 | 0.66 |
| Driving licence | 0.49 | 0.47 | 0.19 | 0.46 | 0.47 | 0.73 |
| PC skills | 0.66 | 0.82 | 0 | 0.79 | 0.82 | 0.1 |
| Foreign language | 0.74 | 0.9 | 0 | 0.86 | 0.9 | 0.02 |
| Academic title | 0.21 | 0.13 | 0 | 0.13 | 0.12 | 0.89 |
| Self-employed | — | — | — | — | — | — |
| Voluntary unempl. | 0.5 | 0.29 | 0 | 0.35 | 0.28 | 0.01 |
| Intr. in part-time | 0.06 | 0.05 | 0.45 | 0.05 | 0.05 | 0.77 |
| Intr. in training | 0.04 | 0.05 | 0.21 | 0.03 | 0.04 | 0.33 |
| Numb. children | 0.23 | 0.08 | 0 | 0.08 | 0.08 | 0.96 |
| Age | 23.8 | 21.28 | 0 | 21.28 | 21.18 | 0.5 |
| Prob. of treatment | 0.3 | 0.68 | 0 | 0.67 | 0.69 | 0.02 |
| Last obs. wage | 385.07 | 166.68 | 0 | 160.69 | 159.12 | 0.93 |
| Observations | 84495 | 655 | | 585 | 630 | |

individuals suggest that the programme attracts workers closer to the labour market core. The exception to this trend is somewhat higher incidence of health disability, indicating that the programme was still offered to those jobseekers with some perceived disadvantage. After matching, almost all differences vanish, including wage and skill gaps. The 2022 cohort described in Table 3 largely mirrors the 2021 chohort but with some intensified patterns, particularly with slightly younger treated individuals, slightly higher pre-treatment wages, higher likelihood of driving licences, PC skills, and foreign language skills. Their disability rates slightly closer to the control group compared with the 2021 cohort. The strong skill gradient suggests that participation is concentrated among individuals with relatively high employability just as in the previous year.

Individual Counselling is described in Table 4. In the raw data, treated individuals differ systematically from the control group. Participants are more likely to be female, slightly younger (about 3 years on average), characterised by significantly lower last observed wages. In contrast, they were more likely to report PC skills and there is a marked divergence in the predicted probabilities of treatment. The age and wage gap suggests negative selection into counselling, namely, individuals entering the programme appear to have weaker labour market attachment and lower pre-treatment earnings capacity. This is consistent with counselling being targeted at jobseekers facing integration difficulties or unstable employment histories. After matching, practically all observable differences disappear with the notable exception of the overall predicted probability of treatment, which remains appreciably lower for the control group (controls are less likely to be selected into treatment by about 12pp on average). This illustrates the difficulty in finding comparable non-participants for a compensatory intervention for weaker labour market attachment.

The internship comparison in Table 5 exhibits the strongest selection patterns: treated individuals are much younger, have dramatically lower prior wages (less than half the control mean), are substantially less likely to have children. As in the case of counselling they display higher levels of PC and foreign language skills and are less likely to be male. This profile is very intuitive economically. Internships typically attract young labour market entrants with limited work history and low prior earnings (i.e. those who did not manage to secure internships and/or part-time work during their studies). We note that we do not observe cases of self-employment in this young group of jobseekers. The lower wages reflect short employment histories with typical low-qualification part-time jobs.

# 4 Methodology

We identify the effect of ALMP on employment by matching ALMP participants and similar job seekers and then estimating the differences in differences on the matched sample.[2]

We search for a set of comparable participants and non-participants using nearest-neighbour matching with Mahalanobis distance. As matching characteristics of job seekers, we used: registration date in the job seeker registry, age, gender, education, region of the labour office where the applicant registered + identifier for the regional capital, earnings from the last job + binary indicator of missing earnings, number of days in the job seeker registry before the start of the sample period and probability of successful completion of ALMP estimated by machine learning. In effect, we are employing propensity-score matching, which has been extended to include additional matching variables. The literature shows that classical propensity-score matching can create highly heterogeneous pairs (King and Nielsen, 2019), which we seek to prevent by explicitly taking into account additional matching characteristics as suggested by Guo et al. (2020).

The date of registration is important in terms of the timing of the intervention, as it is necessary to capture persons who were registered at the time when ALMP was running. For matching, we use date as a continuous variable, as we do not require that the participants and non-participants be registered on the same day. Age, gender, education, and geographic location are basic variables that characterize the individual and their local labour market. Finally, we consider historical variables that reflect previous interactions between the individual and the labour market. These variables have been shown in the literature to be crucial for correctly comparing ALMP participants and non-participants (Dehejia and Wahba, 1999).

[2]Double-robust estimation (Chernozhukov et al., 2018) on the full sample was conducted as a robustness check with similar results, cf. sec. 6.1.

The variable "probability of successful completion of ALMP" represents a summary of several characteristics of job seekers. Specifically, this probability was estimated using a LightGBM model (Ke et al., 2017), the input of which consisted of the variables listed in Table 6.

Table 6: Overview of Variables Used in the Analysis

| **Variable Type** | **Variables** |
|---|---|
| **Categorical** | District of registration; Employment status prior to registration; Marital status; Nationality; Highest education attained; Field of education; District of permanent residence; District of temporary residence (if any); Previous employment sector (NACE, if any); Previous employment position (ISCO, if any); Number of children (censored at 4); Indicated willingness to commute. |
| **Binary** | Gender; Disability; Driver's license; Ability to work with a PC; Knowledge of a foreign language; University degree; Self-employed person; Voluntarily unemployed; Promise of future employment; Interest in going abroad; Interest in working abroad; Interest in working as a self-employed person; Interest in short-term full-time; Interest in further education; Interest in internship; Interest in lifelong learning. |
| **Numeric** | Age. |

The model was trained by 5-fold cross-validation, showing superior out of sample performance to other methods considered (parametric estimation by logit, non-parametric estimation by neural networks and support vector machines). The output of the model is the estimated probability that a participant with the observed characteristics will successfully participate in a given ALMP. Since matching on a large number of variables is practically impossible, we use this summary variable to capture additional characteristics without increasing the number of matching variables.

After identifying matched pairs,[3] we compare the employment of participants and non-participants in the period $\tau$ months after the end of the ALMP.[4] For the comparison in month $\tau$, we use the model:

$$\mathbb{E}[\text{employed}_{it}] = \alpha_i + \alpha_m + \alpha_\tau + \beta_\tau \text{treated}_i \times \mathbb{I}[\tau = t \wedge \tau \geq -12] \tag{1}$$

where $\mathbb{E}$ is the expectation operator, $\text{employed}_{it}$ is a binary variable equal to one if person $i$ was registered as working by the Social Security (as an employee, contract worker or self-employed person) in the period $t$ and zero otherwise; $\text{treated}_i$ is a binary variable equal to one if person $i$ was a participant in the ALMP and zero otherwise; similarly $\mathbb{I}[\cdot]$ is an indicator function equal to one if its argument is true and zero otherwise; parameters $\alpha_i$, $\alpha_m$, and $\alpha_\tau$ are fixed effects for person, time period, and time relative to the end of the intervention respectively. Different specifications are tried with varying sets of fixed effects:

(a) included $\alpha_i + \alpha_m + \alpha_\tau$, where $\alpha_m$ is defined as fixed effects for person $i$'s unemployment duration at time $t$ in months;[5]

(b) included $\alpha_m + \alpha_\tau$ only, sans person fixed-effects, where $\alpha_m$ is defined as monthly fixed effects of unemployment duration;

[3] There are instances when a single non-participant was matched to multiple participants. This is because we aimed for relatively tight matches by imposing a caliper of unity for the Mahalanobis-weighted sum of standardised differences, which excludes a substantial portion of potential control job seekers.

[4] For non-participants, the date of the intervention is taken to be the date when their matched participants were treated.

[5] Note that conditional on person fixed effect, the unemployment duration is the same as calendar time since a person who became unemployed, say, in March will automatically have unemployment duration of two months in April. Thus, the specification with person fixed effects and calendar month fixed effects will yield numerically identical estimates to specification (a).

(c) included $\alpha_m + \alpha_\tau$ only, sans person fixed-effects, where $\alpha_m$ is defined as fixed effects for calendar months.

Comparing specification (a), which includes person fixed-effects, with specifications (b) and (c) which do not, provides a convenient check on the success of the matching that preceded the estimation of the model in (1). To the extent that the matching found comparable participants and non-participants, their time-invariant characteristics should be equal in expectation, rendering the use of individual fixed effects superfluous. Thus, on a successful match, results from all specifications should be similar.

To obtain return-on-investment (ROI) on the ALMPs, we estimate the time horizon $T$ at which:

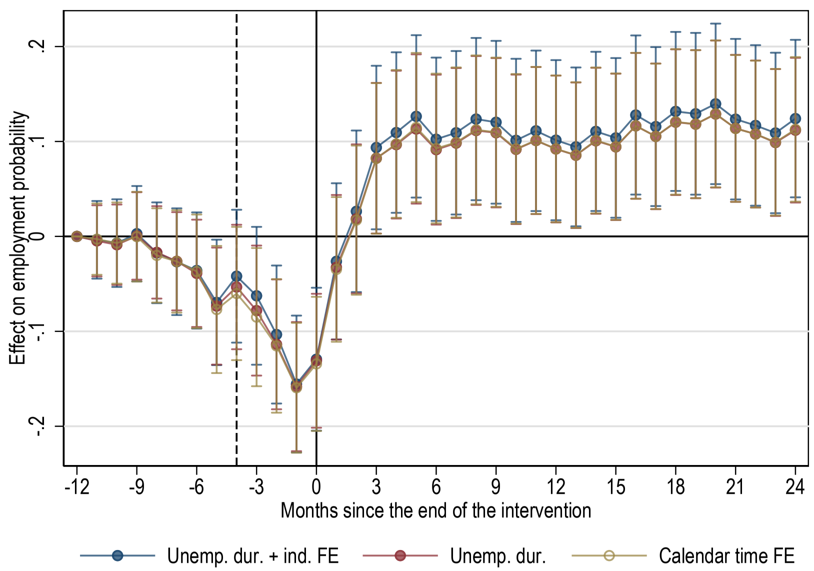
$$\text{costs of ALMP} - \underbrace{\sum_{\tau=t_0}^{T} \widehat{\beta}_\tau \times \text{costs of unemployment}}_{=\text{savings from lower unemployment}} = 0 \tag{2}$$

The results are shown in Table 7. The estimated coefficient $\widehat{\beta}_\tau$ from Equation (1) appears in Equation (2) with negative sign since it estimates the ALMP's effect on the probability of *employment*. The time period $t_0$ marks the start of the intervention (rather than its end) to account for the fact that participants have opportunity costs of attending ALMP rather than devoting the time spent on ALMP to job search.

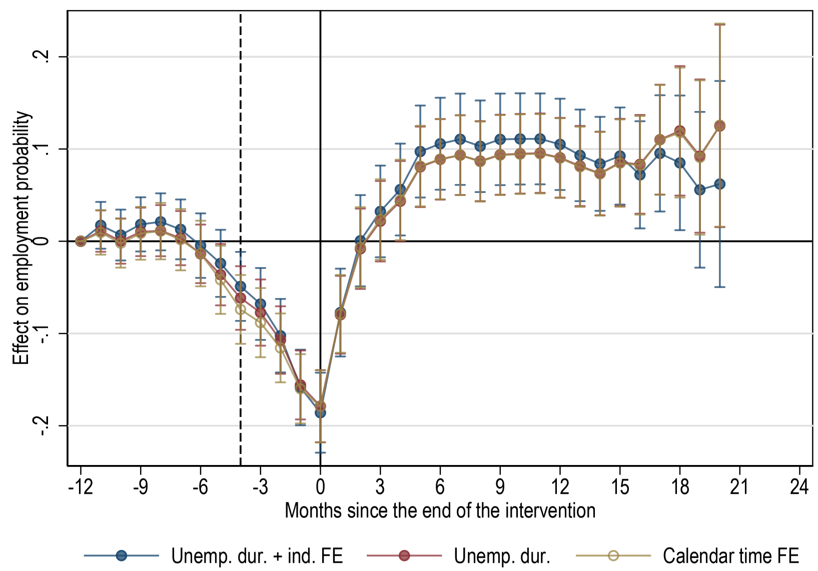
To be conservative, the costs of unemployment to the state were taken to be 600 euro per person per month, which is at the low end of the estimated costs of unemployment in Slovakia (Domonkos and König, 2015; Domonkos, 2022, after adjusting for inflation) and do not take into account any second-order costs such as unemployment scarring (e.g. Filomena, 2024). To the extent that the interventions have any positive effect at all, assuming lower costs of unemployment would lengthen the payback period $T$.

Figure 1: Estimated effects from Eq. (1) on matched sample (typical duration of the intervention denoted by the vertical dashed line)

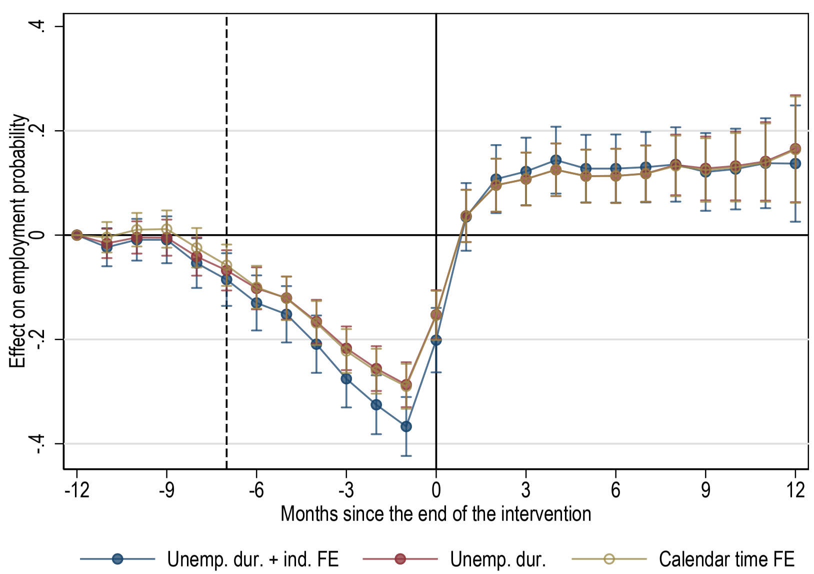
(a) REPAS+ 2021




(b) REPAS+ 2022




(c) Youth Internship




(d) Individual Counselling

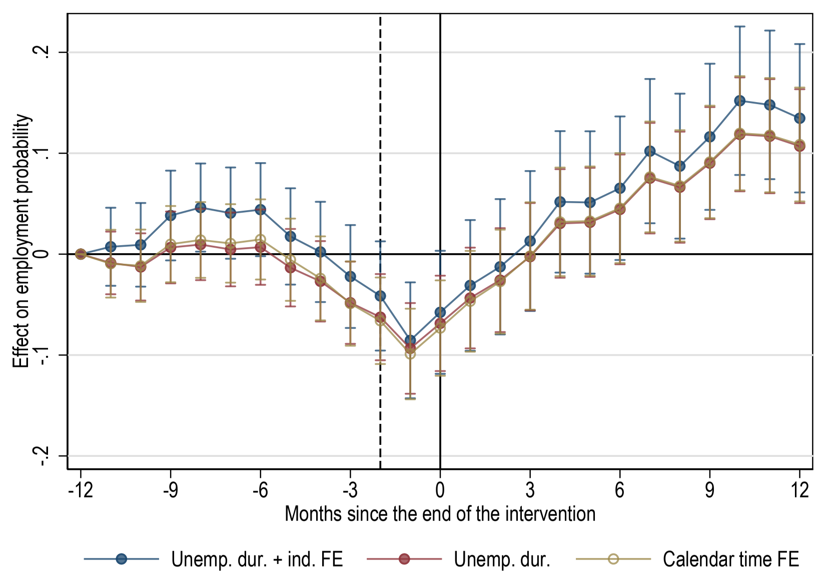


Table 7: Basic characteristics of the examined ALMPs and their estimated impacts

| ALMP | Number of job seekers treated | Money spent (eur) | Estimated effect on probability of employment | Estimated payback horizon |
|---|---|---|---|---|
| REPAS+ | 42 554 | 34 134 094 | 10 pp | 20 months |
| Youth Internship | 2 531 | 2 668 010 | 11.6 pp | 30 months |
| Ind. Counselling | 13 543 | 420 057 | 13 pp | 7 months |

# 5 Results

Table 7 summarises the results, showing employment effects at 12 months after the intervention end alongside estimated payback horizons implied by the ALMP costs. All three measures studied show sizeable employment effects but differing payback horizons. Individual counselling being the cheapest measure shows much more rapid payback than the Youth Internship scheme which was substantially more costly. The results are discussed more fully below.

## 5.1 REPAS+

Figure 1a graphically shows the estimated coefficients $\widehat{\beta}_\tau$ for REPAS+ participants who were treated during the second half of 2021. The coefficient for the twelfth month before the end of the intervention is normalized to zero and until the start of the ALMP we observe only small changes in employment from this baseline period, which would be consistent with the crucial 'parallel trends' assumption for difference-in-differences models.

As explained in the Methodology section, 3 sub-alternatives are presented: a variant with individual fixed effects + fixed effects (FE) for each month of the unemployment duration (blue line); a variant without individual FE but with monthly FE for each month of the unemployment duration (red line); and a variant without individual FE with constants for calendar months (yellow line).

A stable and practically zero difference compared to the baseline period has the interpretation that no differences in the trend of unemployment between ALMP participants and their matched non-participants are observed, which is an indication that the matching was successful. This is followed by the period of the ALMP itself, the typical length of which is delimited by vertical lines.[6] Here we observe reduced employment among participants compared to non-participants. This phenomenon can be interpreted as a head start of non-participants in finding a job while participants are engaged in the retraining programme. Finally, we observe the period after the end of the ALMP, which is marked by a stable difference of about 10 to 13 percentage points (pp) between participants and non-participants. This is the estimated employment advantage of participants gained from the REPAS+ programme.

It is important to note that the results do not change significantly depending on the inclusion of individual FEs in the model, suggesting that unobserved characteristics of individual job-seekers were adequately captured by matching.

As a robustness test, we estimated all models above on REPAS+ participants in the second half of 2022. The results are shown in Figure 1b and are substantively similar to those from the previous cohort (Figure 1a). Here, it is not possible to follow the full 24 months since the end of the ALMP, as employment data end in March 2024, but this second sample provides us with an independent view of the effect of this intervention.

The estimated effect obtained here is appreciably higher than the effect of the older REPAS programme analysed by Petráš (2018). Our results are closer to more recent estimates (Štefánik, 2021), which place the effects of the REPAS programme to be between 10 pp and 15 pp in the first year after the end of the intervention.

## 5.2 Youth Internship

The results are depicted in Figure 1c and are analogous to those from the REPAS+ measure, and therefore the interpretation above applies. The estimated effect of the Youth

[6] The length of ALMP can vary significantly, especially for individually targeted interventions. Further differences in the length of AOTP may arise for administrative or medical reasons. Therefore, the vertical lines in Figure 1 were drawn to encompass 90% of the observed treatment durations.

Internship after 6 months from its end was 11.6pp, meaning that participants had more than 11pp higher employment rate compared to non-participants six months after the end of the internship, other things being equal. This result is again significant at the 5% level and the corresponding confidence interval ranges from 3.9 to 19.2pp. The effect seems to persist a full year after the intervention albeit with slightly larger uncertainty. However, both in terms of magnitude and significance, our results accord well with those of a similar programme ("Praxou k zamestnaniu", roghly translated as "Internship-to-Employment"), which was analysed by Petráš (2023), who obtained practically the same effect. Similar results were found on older data by Štefánik et al. (2020).

### 5.3 Individual Counselling

The results for Individual Counselling are shown in Figure 1d and indicate slowly growing effects after the end of the intervention. Initially, the effects are insignificant, even after 6 months but after 12 months, the effect was estimated to be 13 pp with a 95% confidence interval ranging from 6 to 21pp. Thus, even the relatively modest intervention in terms of budget can have potentially large and positive impact but there is a considerable uncertainty attached to the results.

## 6 Ancillary models

### 6.1 Double-robust estimation

This section assesses the robustness of the baseline results by implementing an alternative identification strategy based on double-robust estimation. The primary specification relies on a matched differences-in-differences (DiD) framework comparing treated and untreated job-seekers. That approach constitutes our preferred design, as it combines the strengths of non-parametric matching with panel data methods, thereby addressing selection on observables and enforcing common support (Heckman et al., 1997) while controlling for time-invariant unobserved heterogeneity by introducing individual fixed effects.

The use of matching prior to DiD estimation plays a central role in the baseline analysis. By restricting comparisons to regions of overlapping covariate distributions, matching provides a flexible and intuitive way to ensure that treated and control job-seekers are comparable along observed dimensions. The subsequent DiD specification then wipes out any remaining unobserved heterogeneity that is constant over time, substantially weakening the identifying assumptions relative to similar estimators. Taken together, this design guards against bias arising from both observable and unobservable differences between treatment and control groups.

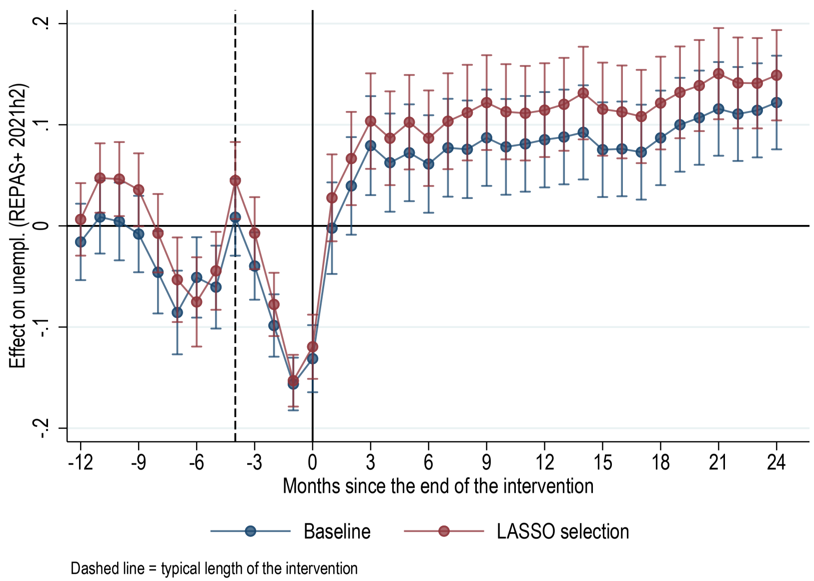
At the same time, this strategy is not without limitations. A reasonable concern with matching procedures is that they reduce the effective sample size by discarding observations for which an adequate match cannot be found. If excluded individuals differ systematically from those retained, external validity may be affected, and efficiency losses may arise. While comparing individuals who differ markedly on observed characteristics may not be advisable, this potential drawback motivates the use of an alternative estimator that exploits the full sample.

As a complementary approach, we therefore implement double-robust estimation. Unlike the matched DiD framework, this method does not require prior sample manipulation and instead relies on modelling both the treatment assignment process and the outcome equation (although common support of the propensity score is still required, of course). The estimator combines inverse-probability weighting with outcome regression, allowing all observations to contribute to identification under appropriate assumptions. This makes it a natural robustness check in settings where concerns about sample selection induced by matching may arise.

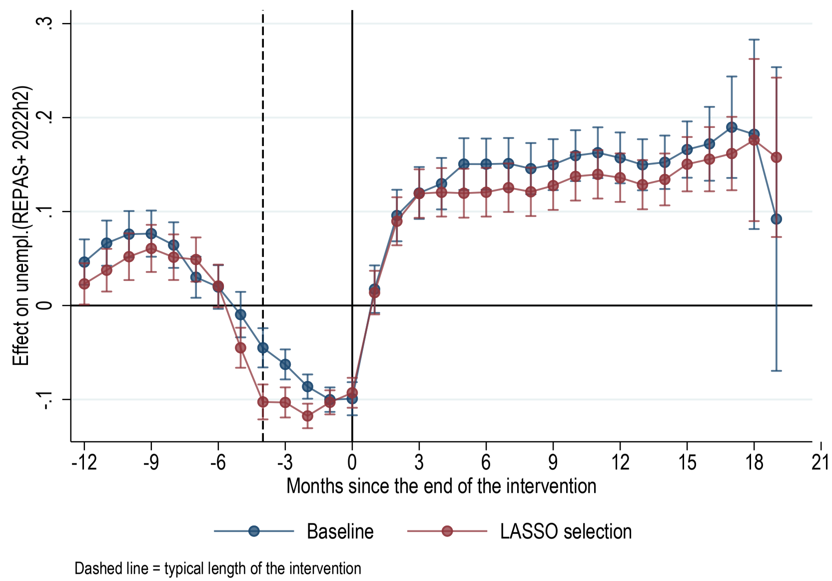
We consider two variants of the double-robust estimator. In the baseline implementation, both the treatment and outcome models are fully specified *ex ante* in a manner analogous to our baseline specification. In addition, we employ a regularised version that uses LASSO to select control variables in a data-driven manner. This approach is designed to reduce the risk of over-fitting and to accommodate potentially high-dimensional covariate spaces without imposing strong parametric restrictions.

Figure 2: Estimated effects using double robust estimation of full sample (typical duration of the intervention denoted by the vertical dashed line)

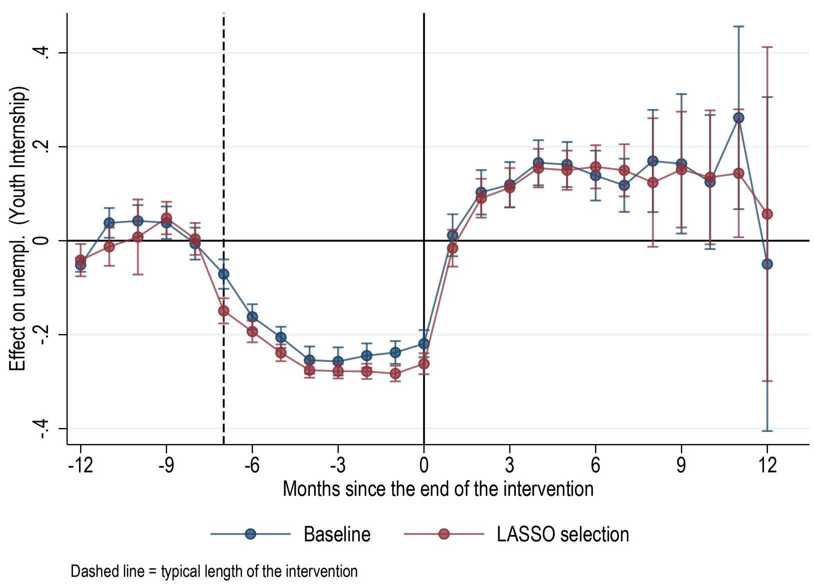
(a) REPAS+ 2021



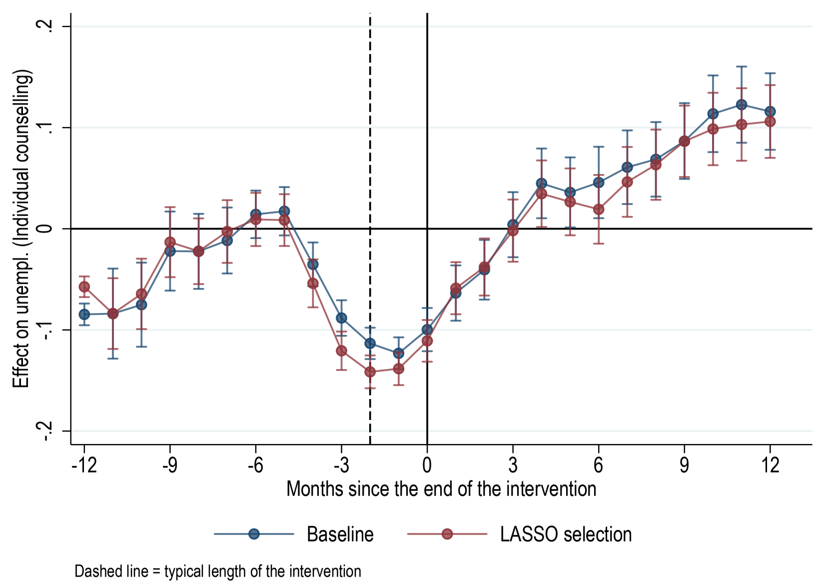

(b) REPAS+ 2022




(c) Youth Internship




(d) Individual Counselling



The theoretical appeal of double-robust estimation lies in its consistency properties. Specifically, the estimator remains consistent for the average treatment effect provided that either the treatment model or the outcome model is correctly specified, but not necessarily both. This feature has contributed to its widespread adoption in the applied microeconometric literature, particularly in contexts where model uncertainty is substantial and researchers seek protection against misspecification.

However, these advantages come at a cost. In contrast to the DiD framework, double-robust estimators do not readily incorporate individual fixed effects and therefore rely on the Conditional Independence Assumption. This assumption requires that, conditional on observed covariates, potential outcomes are independent of treatment assignment, which is more restrictive than the parallel trends assumption underlying DiD with fixed effects. As a result, the approach offers weaker protection against bias from time-invariant unobserved heterogeneity.

Despite these conceptual differences, the empirical results obtained from the double-robust specifications closely mirror those of the baseline matched DiD model. We continue to find positive and persistent effects of the active labour market programmes on job-seeker outcomes across specifications. While the pre-treatment coefficients are somewhat noisier than in the baseline analysis, they remain close to zero and are plausibly attributable to the weaker control for unobserved heterogeneity. Overall, the similarity of results across methods strengthens confidence in the main findings and suggests that they are not driven by a particular estimation strategy.

## 6.2 Wages

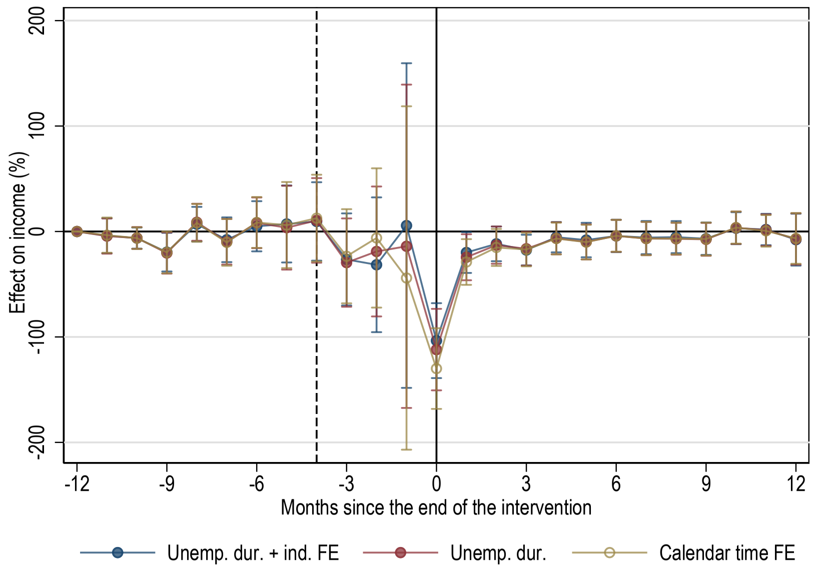
The principal findings of this study pertain to employment outcomes, reflecting the key concern for reduction of unemployment duration in the design and evaluation of active labour market policies. Employment constitutes a primary policy target because it captures the extensive margin of labour market integration and is observed for both programme participants and non-participants. However, employment alone does not fully characterise post-programme labour market performance. To provide a more comprehensive assessment of programme effectiveness, we therefore complement the analysis by estimating the impact of participation in the ALMP on post-treatment income, using identification strategy on the matched sample. This extension enables us to examine not only whether participants find employment, but also whether they access positions of comparable economic quality.

Estimating the causal effect on income is, however, substantially more demanding than estimating effects on employment. Whereas employment status is defined for the entire sample, income is observed only for individuals who are employed. Consequently, the income equation is estimated on a selected subsample, introducing a classic sample selection problem in the spirit of Ham and Lalonde (1996). If the unobserved determinants of employment are correlated with the unobserved determinants of earnings, conventional estimators may yield biased and inconsistent estimates of programme impacts. In the present setting, the difficulty is compounded by the absence of detailed information on individual job search preferences, reservation wages, or firm-level hiring criteria. Without such data, it is not possible to model explicitly the joint determination of employment and wages or to implement a structural correction for selection based on behavioural primitives.

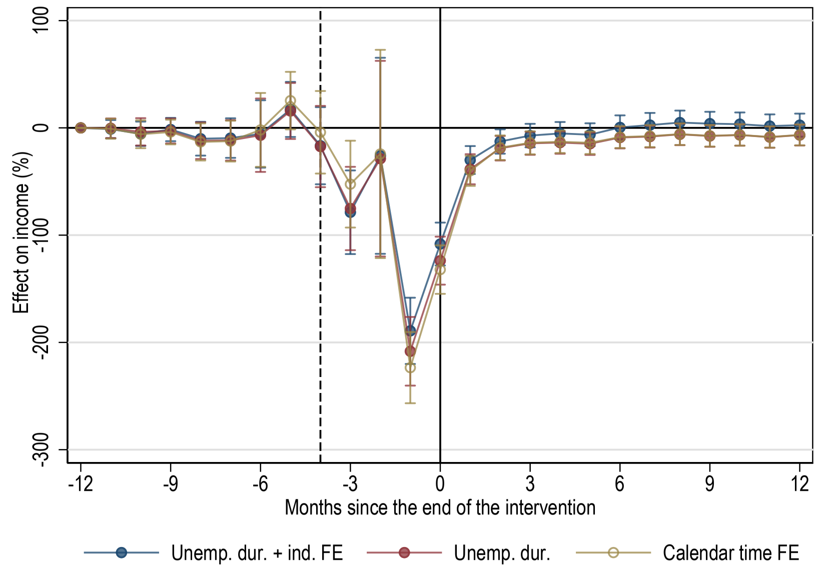
With these empirical constraints in mind, the estimated income effects presented in Figure 3 provide suggestive evidence. The results indicate that ALMP participants earn, on average, approximately the same wages as observationally comparable non-participants. This finding suggests that programme participants who secure employment are not channelled into systematically lower-quality jobs in terms of remuneration. In other words, the programme appears to facilitate labour market entry without generating wage penalties relative to similar individuals who did not receive support. From a policy perspective, this is an important complement to the positive employment effects, as it alleviates concerns that employment gains may be achieved at the expense of job quality.

Figure 3: Estimated effects on wages (typical duration of the intervention denoted by the vertical dashed line)

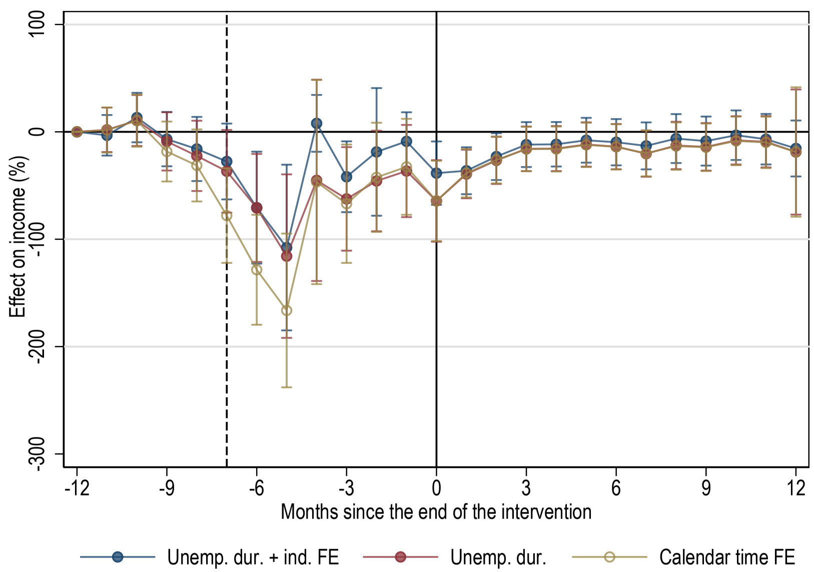
(a) REPAS+ 2021



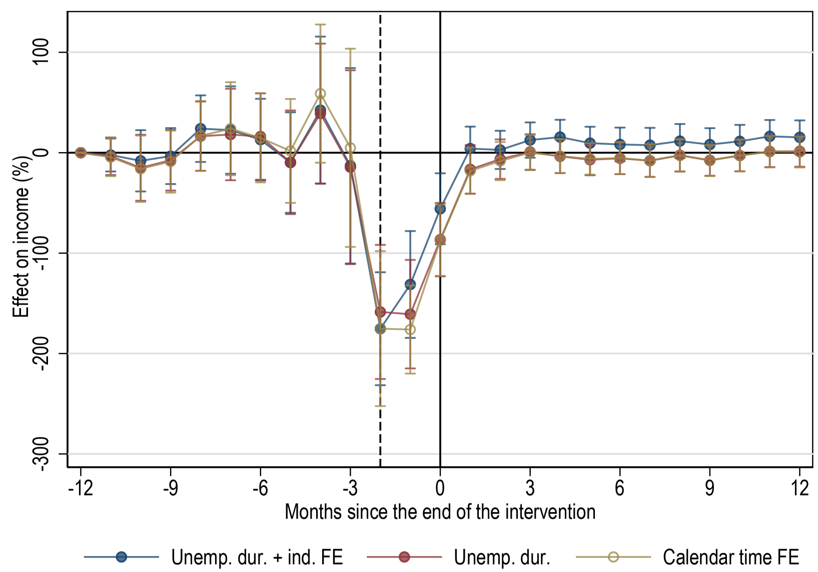

(b) REPAS+ 2022




(c) Youth Internship




(d) Individual Counselling



For the Youth Internship measure, the point estimates of the income effect are slightly negative, though statistically indistinguishable from zero at conventional confidence levels. A similar pattern has been documented by Štefánik et al. (2020), who interpret such findings as potentially reflecting a greater willingness among supported jobseekers to accept lower-paid positions in exchange for improved employment prospects. In our case, however, the lack of statistical significance warrants caution in advancing strong behavioural interpretations. The evidence does not support the conclusion that internship graduates are systematically disadvantaged in terms of wages; rather, it indicates that their remuneration is broadly comparable to that of non-participating peers.

Taken together, the income analysis reinforces the central conclusion of the study. While methodological limitations related to sample selection limit causal interpretation, the available evidence does not suggest adverse wage effects associated with programme participation. The ALMPs studied appear to enhance employment outcomes without materially altering earnings among those who become employed. For policymakers, this combination (improved employment probabilities alongside neutral wage effects) implies that the programme supports labour market integration without compromising short-run earnings quality, even when accounting for the inherent challenges of estimating income impacts in the presence of endogenous employment selection.

## 6.3 Effect heterogeneity

The REPAS+ programme is distinct among the three considered measures in that it allows jobseekers to self-select into a (re-)training scheme that they find useful for their prospective employment (subject to approval from the Labour Office).

Earlier analyses of the REPAS measure (Petráš, 2018; Štefánik, 2021) emphasised differences in employability between the individual types of courses that were provided within the framework of the earlier setup of this ALMP. In the REPAS measure, somewhat higher effects were found for jobseekers who participated in courses intended for employment in private security services compared to other participants in the REPAS measure. Similar to Petráš (2018), we estimate a modified version of the model from strategy on matched sample to decompose the total effect of the REPAS+ measure into separate effects according to the type of course completed:

$$\mathbb{E}[\text{employed}_{it}] = \alpha_i + \alpha_m + \alpha_{\tau,c} + \beta_{\tau,c}\text{treated}_i \times \mathbb{I}[\tau = t \wedge \tau \geq -12 \wedge \text{course } = c] \tag{3}$$

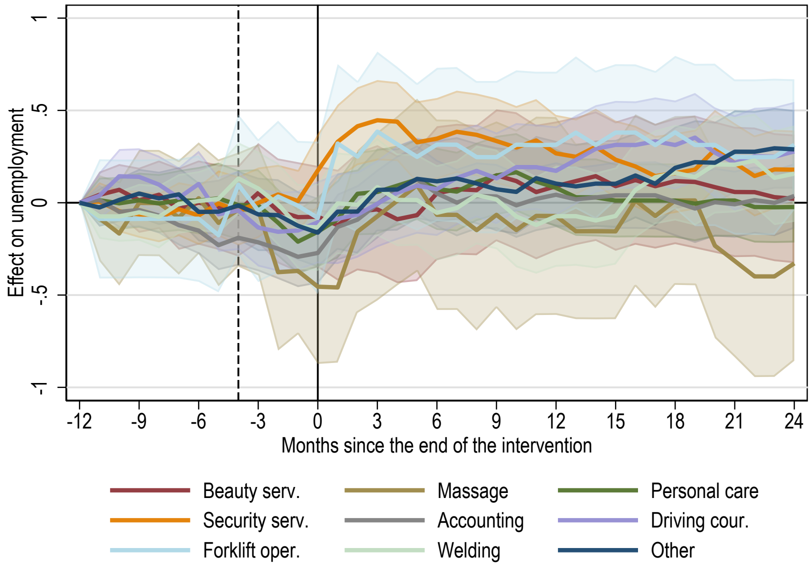
where the parameters $\beta_{\tau,c}$ indicate the average difference between participants in course $c$ and the control group $\tau$ months after the end of the ALMP. The constants $\alpha_{\tau,c}$ absorb the average employment for the given course type $\tau$ months after the end of the ALMP. In order to be able to identify $\alpha_{\tau,c}$ and $\beta_{\tau,c}$ separately, it was necessary to artificially assign individuals in the control group (who did not participate in any courses within the REPAS+ programme) to the course they would have likely participated in. Within each matched participant-non-participant pair, the participant's course was therefore also assigned to the non-participant. Since the number of courses themselves is too large to use in a statistical model, we use nine broader course groups (beauty services, massage services, personal care, security services, accounting, driving courses, forklift operation and related courses, welding, and 'other' as a catch-all category for miscellaneous course types).

In the empirical specification, nine distinct sets of coefficients $\beta_{\tau,c}$ are estimated to capture monthly differences across groups of courses. These coefficients are intended to measure heterogeneous programme effects by field of training and time since completion. However, attributing a strict causal interpretation to these differences is problematic. Participants self-select into specific types of courses, and this allocation process is unlikely to be random. Individuals may sort into programmes on the basis of unobserved characteristics (such as motivation, prior experience, or expectations about sectoral demand) that are themselves correlated with subsequent employment outcomes. As a result, cross-course comparisons of estimated effects may partly reflect selection rather than genuine differences in programme effectiveness.

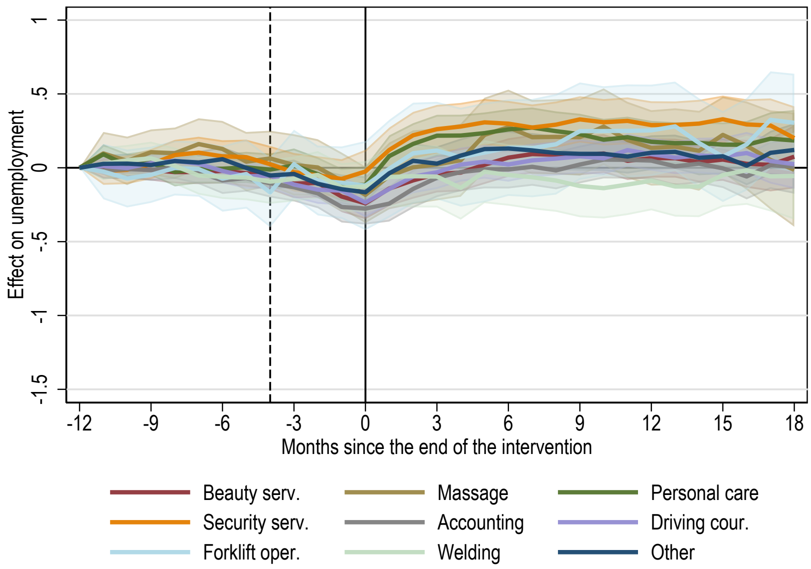
To mitigate this concern, the analysis employs course-specific employment trends, denoted $\alpha_{\tau,c}$. These terms are designed to absorb time-varying demand shocks for particular qualifications as well as systematic differences between groups of jobseekers enrolling in different types of training. By allowing for differential pre- and post-treatment baseline dynamics across course categories, the specification accommodates potentially differing em-

Figure 4: Estimated effects by course selected during REPAS+

(a) REPAS+ 2021




(b) REPAS+ 2022



ployment dynamics across the various groups of jobseekers and thereby strengthens identification. Nonetheless, the credibility of this approach depends critically on the quality of the matching procedure used to construct the comparison group. In the present case, matching was implemented at the level of the full sample rather than separately within each course category. Achieving covariate balance within individual subgroups would require course-specific matching, which, given the limited size of some categories, would raise additional concerns regarding finite-sample bias and the reliability of propensity score methods in small samples.

Within the cohort of jobseekers who completed REPAS+ in the second half of 2021, some heterogeneity in estimated employment effects emerges as shown in Figure 4a. The most favourable outcomes are observed among graduates of forklift operator courses, followed by graduates of security services training. By contrast, massage therapy, accounting, and welding courses exhibit the weakest performance, with point estimates occasionally suggesting negative employment effects. However, for massage courses in particular, the confidence intervals are wide and include zero, precluding firm conclusions about adverse impacts. Private security courses occupy an intermediate position in the distribution of estimated effects for this cohort, though still performing relatively well compared to several other training categories.

For the cohort completing REPAS+ in the second half of 2022 in Figure 4b, the ranking shifts somewhat. Graduates of security courses display the strongest employment gains relative to matched non-participants, followed by those completing caregiving courses and forklift operator training. Welding and accounting courses again appear among the least successful categories. The persistence of relatively weak outcomes in these latter fields across cohorts may reflect structural conditions in the relevant labour market segments, including sector-specific demand fluctuations or skill mismatches, rather than deficiencies in training quality per se.

Overall, the wide confidence intervals and broadly comparable point estimates point to a rather modest role of effect heterogeneity. Taken at face value, the evidence suggests that during the observed period, the largest relative employment advantages accrued to participants in security, caregiving, and forklift operator courses when compared to non-participants in active labour market programmes. Welding, cosmetology, and accounting courses appear less successful in terms of measured domestic employment outcomes. However, the administrative data used in this analysis capture only employment registered within the Slovak social insurance system. It is therefore not possible to exclude the possibility that graduates of certain courses—particularly those associated with internationally transferable skills—found employment abroad and thus remain unobserved in domestic records. A rigorous assessment of this hypothesis would require linked migration or cross-border employment data and an extension of the econometric framework to model endogenous migration decisions, which lies beyond the scope of the present study.

# 7 Conclusions

This analysis evaluated the net effectiveness of three different active labour market measures: a re-training programme REPAS+, the Youth Internship Project for young job seekers, and Individual Counselling for Disadvantaged Job Seekers in the period from the second half of 2021 to March 2024. We identified numerically large and statistically significant positive effects of all three interventions on employment.

*REPAS+* led to a 10 to 13 percentage point advantage in employment rates for participants compared to comparable non-participants. This effect is statistically significant and stable over two years after the end of the intervention.

The high efficiency and relatively quick ROI of the REPAS+ programme demonstrates the importance of developing new skills and upgrading qualifications, which is in line with the EU consensus on the need to build new skills to strengthen sustainable competitiveness, bolster social justice and build resilience in response to crises.

The effect of the *Youth Internship* measure was around 12 percentage points, which corresponds to results from earlier studies. The results, therefore, show that among younger job seekers it is important to gain work experience that helps them find employment. Based on these findings, it would be possible to recommend expanding cooperation between schools and employers so that students can gain work experience during their studies through internships or temporary work, which will make them more attractive to employers after graduation.

The internship ALMP was the measure with the longest payback period among the studied interventions but this fact ought to be viewed in context of the ALMP's implementation. Youth Internship was evaluated in the period of the second half of 2023 and the first half of 2024, which was characterised by high employment and relatively rapid entry of graduates into the labour market. This situation meant that the counterfactual outcomes for participants were very good, "setting the bar" rather high for the ALMP. Nevertheless, positive and statistically significant effects of the internship programme were found, which supports the usefulness of this measure. A plausible conjecture in light of these results would be that an effect of an analogous measure in periods of economic slowdown would be even more pronounced. Thus, our results advocate for cooperation between the education system and the employers, whether through internships, dual education and other channels through which students and graduates gain work experience.

The effect of *Individual Counselling* for disadvantaged job seekers was estimated with high uncertainty. After half a year from the end of the counselling, no statistically significant effect was observed, but over time the effect grew to approximately 15 pp but with an uncertainty of ± almost 7 pp (at the 5% significance level). However, it should be noted that individual counselling is a relatively inexpensive measure, which compensates for the higher level of uncertainty in the measured effects. The costs of individual counselling are much lower than for other ALMPs in this study, and the shorter duration of counselling creates fewer negative effects on employment during the duration of counselling.

The results of Individual Counselling indicate that in the case of disadvantaged job seekers, even a relatively low-cost investment has a significant and positive impact. The implied policy recommendation would be to focus on training Labour Office staff so that they can be in a position to provide better quality counselling services.

From the policy makers' perspective, the relatively fast returns on investment are salient. All three measures have estimated positive ROI within a three-year horizon, which would generally be seen as attractive payback period for investment decisions (e.g. Yard, 2000). The longest positive ROI was for Youth Internship (about 2.5 years), while the positive ROI for REPAS+ was in the range of 1.5 years for the 2021 cohort and 1.7 years for the 2022 cohort. Youth Internship was the most expensive measure among the AOTPs studied, so its costs were recovered more slowly, although its effect was similar to REPAS+. Individual counselling had an estimated positive ROI at about half a year due to its low cost and positive employment effects. The length of of the payback period is mainly driven by the costs of unemployment and therefore even the more modestly-priced interventions take time to recover their costs.

# References

T. Bredgaard. Evaluating what works for whom in active labour market policies. *European Journal of Social Security*, 17(4):436–452, 2015.

M. Caliendo and R. Schmidl. Youth unemployment and active labor market policies in Europe. *IZA Journal of Labor Policy*, 5:1–30, 2016.

D. Card, J. Kluve, and A. Weber. What works? a meta analysis of recent active labor market program evaluations. *Journal of the European Economic Association*, 16(3):894–931, 2018.

V. Chernozhukov, D. Chetverikov, M. Demirer, E. Duflo, C. Hansen, W. Newey, and J. Robins. Double/debiased machine learning for treatment and structural parameters. *The Econometrics Journal*, 21(1):C1–C68, 2018. ISSN 1368-4221. doi: 10.1111/ectj.12097. URL `https://doi.org/10.1111/ectj.12097`.

G. De Fraja, S. Lemos, and J. Rockey. The wounds that do not heal: The lifetime scar of youth unemployment. *Economica*, 88(352):896–941, 2021. doi: https://doi.org/10.1111/ecca.12384. URL `https://onlinelibrary.wiley.com/doi/abs/10.1111/ecca.12384`.

R. H. Dehejia and S. Wahba. Causal effects in nonexperimental studies: Reevaluating the evaluation of training programs. *Journal of the American Statistical Association*, 94(448):1053–1062, 1999. ISSN 01621459. doi: 10.2307/2669919. URL `http://www.jstor.org/stable/2669919`.

T. Domonkos. Odhad nákladov nezamestnanosti v SR pre rok 2020 = Costs of unemployment in Slovakia in 2020. In I. Lichner, editor, *Zborník abstraktov z vedeckej konferencie EKOMSTAT 2022*, pages 4–5. Slovenská štatistická a demografická spoločnosť, Bratislava, 2022. ISBN 978-80-88946-92-2.

T. Domonkos and B. König. Estimation of the cost of unemployment in Slovak Republic. *Politická ekonomie*, 63(4):498–516, 2015. ISSN 00323233. URL `http://dx.doi.org/10.18267/j.polek.1032`.

W. Eichhorst and U. Rinne. Promoting youth employment in Europe: Evidence-based policy lessons. *European youth labour markets: Problems and policies*, pages 189–204, 2018.

V. Escudero and E. López Mourelo. The European Youth Guarantee: A systematic review of its implementation across countries. *ILO Working Papers*, 21:189–204, 2017.

M. Filomena. Unemployment scarring effects: An overview and meta-analysis of empirical studies. *Italian Economic Journal*, 10(2):459–518, 2024. ISSN 2199-3238. doi: 10.1007/s40797-023-00228-4. URL `https://doi.org/10.1007/s40797-023-00228-4`.

B. Gabrikova and L. Svabova. Allowance for self-employed gainful activity in Slovakia: A closer look into the factors involved. *Folia Oeconomica Stetinensia*, 22(2):55–77, 2022.

S. Guo, M. Fraser, and Q. Chen. Propensity score analysis: Recent debate and discussion. *Journal of the Society for Social Work and Research*, 11(3):463–482, 2020. doi: 10.1086/711393. URL `https://doi.org/10.1086/711393`.

J. C. Ham and R. J. Lalonde. The effect of sample selection and initial conditions in duration models: Evidence from experimental data on training. *Econometrica*, 64(1):175–205, 1996. ISSN 00129682, 14680262. doi: 10.2307/2171928. URL `http://www.jstor.org/stable/2171928`.

J. J. Heckman, H. Ichimura, and P. E. Todd. Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The Review of Economic Studies*, 64(4):605–654, 1997. ISSN 00346527, 1467937X. doi: 10.2307/2971733. URL `http://www.jstor.org/stable/2971733`.

M. Honorati, M. Testaverde, and E. Totino. Labor market integration of refugees in Germany: new lessons after the Ukrainian crisis. Technical report, The World Bank, 2024.

O. Hora and M. Suchanec. Comparing the impacts of Czech ALMP training programmes implemented during the 2020 COVID-19 pandemic to programmes in 2016 and 2019. *Social Policy & Administration*, 2024.

K. Karasova, V. Baláž, and M. Chrancokova. Active labour market policies in Slovakia in 2007-2017. *Economic and Social Development: Book of Proceedings*, pages 369–379, 2018.

K. Karasova, V. Baláž, and Z. Poláčková. Efficiency of the active labour market policies: Evidence from the Slovak Republic. *Ekonomickỳ časopis*, 67(1):11–32, 2019.

G. Ke, Q. Meng, T. Finley, T. Wang, W. Chen, W. Ma, Q. Ye, and T.-Y. Liu. Lightgbm: A highly efficient gradient boosting decision tree. *Advances in neural information processing systems*, 30, 2017.

G. King and R. Nielsen. Why propensity scores should not be used for matching. *Political Analysis*, 27(4):435–454, 2019. ISSN 1047-1987. doi: 10.1017/pan.2019.11. URL `https://www.cambridge.org/core/product/94DDE7ED8E2A796B693096EB714BE68B`.

J. Kluve, S. Puerto, D. Robalino, J. M. Romero, F. Rother, J. Stöterau, F. Weidenkaff, and M. Witte. Do youth employment programs improve labor market outcomes? A quantitative review. *World Development*, 114:237–253, 2019.

L. Lafférs and M. Štefánik. *Locking in Or Pushing Out: the Caseworker Dilemma*. Institute of Economic Research SAS, 2024.

J. P. Martin. Activation and active labour market policies in OECD countries: stylised facts and evidence on their effectiveness. *IZA Journal of labor policy*, 4:1–29, 2015.

J. C. van Ours. Do active labor market policies help unemployed workers to find and keep regular jobs? In M. Lechner and F. Pfeiffer, editors, *Econometric Evaluation of Labour Market Policies*, pages 125–152, Heidelberg, 2001. Physica-Verlag HD. ISBN 978-3-642-57615-7.

J. Petráš. Kto chce zat, musi siat: Analyza cistých efektov opatrenia REPAS, 2018. URL `https://www.mpsvr.sk/files/slovensky/ministerstvo/analyticke-centrum/analyticke-komentare/kto_chce_zat_musi_siat.pdf`.

J. Petráš. Dočasná práca ako šanca pre znevýhodnených. *Inštitút sociálnej politiky*, 2019. URL `https://institutsocialnejpolitiky.sk/wp-content/uploads/2020/08/analyza-50j-docasna-praca-ako-sanca-znevyhodnenych.pdf`.

J. Petráš. Aktivačné práce neaktívnych neaktivujú. *Inštitút sociálnej politiky*, 2020. URL `https://www.employment.gov.sk/files/slovensky/ministerstvo/analyticke-centrum/analyticke-komentare/komentare_2022/aktivacne-prace.pdf`.

J. Petráš. Čo sa počas praxe naučíš, počas práce zúročís. *Inštitút sociálnej politiky*, 2021. URL `https://analyzy.gov.sk/files/archiv/86/Analyza_absolventskej_praxe_FINAL.pdf`.

J. Petráš. Mentoring pomaha mladym zamestnať sa: Analyza cistej ucinnosti narodneho projektu "praxou k zamestnaniu", 2023. URL `https://www.institutsocialnejpolitiky.sk/wp-content/uploads/2023/10/Petras_2023_Mentoring.pdf`.

Z. Polačková. The role of organizations of the non-profit sector in the employment of people disadvantaged in the labour market in Slovakia. *Problemy Polityki Społecznej. Social Policy Issues*, 50(3):27–41, 2020.

L. J. Rotar. Effectiveness of active labour market policies in the EU countries for the young unemployed people and implications for the post-pandemic period. *Engineering Economics*, 33(3):326–337, 2022.

M. Štefánik and L. Lafférs. Supporting the right workplace experience: a dynamic evaluation of three activation programmes for young job seekers in Slovakia. *Journal for Labour Market Research*, 58(1):16, 2024.

M. Štefánik, R. Džambazovic, D. Gerbery, K. Karasová, I. Lichner, T. Miklošovic, Z. Polacková, M. Radvanský, E. Rublíková, and I. Studená. *Labour Market in Slovakia 2019.* Ekonomickỳ Ústav SAV, 2018.

M. Štefánik. Shifting the training choice decision to the jobseeker—the Slovak experience. *LABOUR*, 35(2):192–213, 2021. ISSN 1121-7081. doi: https://doi.org/10.1111/labr.12189. URL `https://onlinelibrary.wiley.com/doi/abs/10.1111/labr.12189`.

M. Štefánik, K. Karasová, and I. Studená. Can supporting workplace insertions of unemployed recent graduates improve their long-term employability? *Empirica*, 47(2):245–265, 2020. ISSN 1573-6911. doi: 10.1007/s10663-018-9413-y. URL `https://doi.org/10.1007/s10663-018-9413-y`.

L. Svabova and B. Gabrikova. A measure that really works? Impact evaluation of the contribution for self-employment as a tool of active labour market policy in Slovakia. *Economies*, 12(5):116, 2024.

L. Svabova, K. Kramarova, and B. Gabrikova. Counterfactual assessment of the allowance for school-leaver practice performance as a measure of active labour market policy in Slovakia. *Ekonomicky Casopis*, 70(2):99–123, 2022.

J. Tosun, O. Treib, and F. De Francesco. The impact of the European Youth Guarantee on active labour market policies: A convergence analysis. *International Journal of Social Welfare*, 28(4):358–368, 2019.

S. Yard. Developments of the payback method. *International Journal of Production Economics*, 67(2):155–167, 2000. ISSN 0925-5273. doi: https://doi.org/10.1016/S0925-5273(00)00003-7. URL `https://www.sciencedirect.com/science/article/pii/S0925527300000037`.