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Locking in or Pushing out: The Caseworker Dilemma

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ABSTRACT

Using rich administrative data on job seekers (JSs) registered by the public employment service (PES), we describe the implementation of the Youth Guarantee (YG) initiative through the Slovak Active Labour Market Policy (ALMP). By adopting a dynamic estimation technique based on double machine learning (DML), we generate evidence on the impact of various types of ALMP programs provided in different periods of unemployment. The spectrum of ALMP programs ranges from classroom training through hiring incentives and subsidized employment in the private sector to public works organized at the municipality level. We identify the impact of participation in a particular ALMP program or sequences of ALMP programs on the absence of individuals from registered unemployment after three years. We demonstrate that due to the functionality of the dynamic DML estimator, one case study can generate comparative evidence affirming the conclusions of ALMP impact evaluation meta-analyses. Additionally, aiming to address the operational-level PES case-worker dilemma, we quantify the impact of the evaluated ALMP programs compared with those of two alternative counterfactual situations, assuming a more and less employable client.

KEYWORDS: active labor market policy; program evaluation; causal inference; machine learning; youth unemployment

JEL CLASSIFICATION: J08, D04, C21

Viac školenia alebo skorší návrat na trh práce: dilema sociálneho pracovníka úradu práce

ABSTRAKT

Na základe bohatých administratívnych údajov o uchádzačoch o zamestnanie (UoZ) registrovaných verejnými službami zamestnanosti opisujeme implementáciu iniciatívy Záruky pre mladých ľudí prostredníctvom slovenskej aktívnej politiky trhu práce (APTP). Použitím techniky dynamického odhadu založenej na dvojitom strojovom učení (DML) vytvárame dôkazy o vplyve rôznych typov programov APTP poskytovaných v rôznych obdobiach nezamestnanosti. Spektrum programov APTP siaha od školení v triedach cez náborové stimuly a dotované zamestnávanie v súkromnom sektore až po verejné práce organizované na úrovni obcí. Zisťujeme vplyv účasti na konkrétnom programe APTP alebo sekvenciách programov APTP na absenciu jednotlivcov v evidovanej nezamestnanosti po troch rokoch. Ukazujeme, že vďaka funkčnosti dynamického odhadu DML môže jedna prípadová štúdia preniesť komparatívne dôkazy potvrdzujúce závery metaanalýz hodnotenia vplyvu APTP. Okrem toho, s cieľom riešiť dilemu na operatívnej úrovni sociálnych pracovníkov úradu práce, kvantifikujeme vplyv hodnotených programov APTP v porovnaní s vplyvom dvoch alternatívnych kontrafaktuálnych situácií, pričom predpokladáme viac a menej zamestnateľného klienta.

KĽÚČOVÉ SLOVÁ: aktívna politika trhu práce; hodnotenie opatrení; strojové učenie; príčinná inferencia; zamestnanosť mladých

JEL KLASIFIKÁCIA: J08, D04, C21

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Introduction

Despite the indisputable, long-term focus of public employment policies, youth unemployment remains a pressing issue. Especially in times of economic downturns, such as during the coronavirus disease 2019 (COVID-19) pandemic, youth cohorts entering the labor market face a higher risk of unemployment. Early career unemployment appears to have a scarring effect on an individual's subsequent career path in terms of income (De Fraja et al., 2021) or prime-age unemployment (Schmillen and Umkehrer, 2017)[2]. The negative effects of youth unemployment have motivated an enormous degree of policy response since 2014, concentrated under the European Union (EU)-wide Youth Guarantee (YG) initiative (Escudero and López, 2017). Active labor market policies (ALMPs) present an important mode through which this intensified support is channeled (Eichhorst and Rinne (2018); Tosun et al. (2019)). Nevertheless, the evidence on the impact of such policies remains ambiguous (Caliendo and Schmidl (2016); Eichhorst and Rinne (2018); Kluve et al. (2019)).

Here, we describe one particular country-level implementation of the YG initiative through a portfolio of ALMP programs. By adopting a novel double-machine-learning (DML)-based, dynamic estimation technique (Bodory et al., 2022), we generate evidence on the impact of various types of ALMP programs provided in two different periods of unemployment. The spectrum of ALMP programs ranges from classroom training through hiring incentives and subsidized employment in the private sector to public works organized at the municipality level. We document that the functionality of the dynamic DML estimator particularly suits the context of ALMP implemented under the YG, with a high level of access to programs and frequent combinations (sequences) of program participation. In this context, we aim to generate evidence tailored to support caseworkers' decisions supporting individual job search decisions.

A caseworker at the public employment service (PES) office first assesses the client's employability to propose a suitable activation strategy. While doing so, (s)he has to weigh the risk of locking a readily employable client into a too-intensive or lengthy ALMP program against the potential benefit gained through such participation. Under the unconfoundedness assumption, we quantify the potential gain of participation in various types of ALMP programs compared to two alternative counterfactual situations, assuming the following:

- a less employable client remaining unemployed for more than 6 months and
- a more employable client remaining unemployed for up to six months.

Our empirical approach allows for the painting of a complex picture of the impact of the support provided under the Slovak YG initiative. A picture in line with the findings of earlier meta-analyses (e.g., Caliendo and Schmidl (2016); Card et al. (2018); Kluve et al. (2019)) or knowledge-synthesizing studies (e.g., Martin and Grubb (2005); Brown (2015)). For example, we document that those ALMP interventions applied earlier yield a greater impact than do those applied later (Martin and Grubb, 2005); that workplace experience collected in the private sector improves the employment chances of unemployed youth, which is in contrast with public works-type programs (Caliendo and Schmidl, 2016); and that training improves long-term employment chances (Card et al., 2018), even more so if combined with other ALMPs (Kluve et al., 2019). Additionally, we document that the shortening of the unemployment period by itself, without ALMP participation, has a long-term impact on the absence of individuals from the unemployment register(Schmillen and Umkehrer, 2017).

[2]In addition to the impact on present and future labor market outcomes, youth unemployment also has immediate negative implications at the social and individual levels such as, among other outcomes, increased crime rates, the obsolescence of recently acquired education, and greater pressure in terms of social policy budgets. For an overview, see Bell and Blanchflower (2010).

Despite the temptation to produce program-design relevant information addressing the "What works" question, studies applying one homogeneous empirical strategy to identify the impact of various ALMP programs remain scarce (e.g., Caliendo and Schmidl (2011); Madoń et al. (2021)). New alleys are being opened by employing machine learning (ML) in policy impact evaluation (Athey and Imbens (2017)). This study explores one such alley, joining a recent stream of studies, by documenting the advantages of ML in the impact evaluation of ALMP programs (e.g., Cockx et al. (2019); Goller et al. (2021); Knaus et al. (2022)).

The remainder of this paper is structured as follows. In the next section, describes the policy context of ALMPs available to unemployed youth in Slovakia. The third section reviews the relevant literature on what works in activating unemployed youth and explains the caseworker dilemma. The fourth section describes our identification strategy and estimation technique. The description of the data and the definition of the sample can be found in the fifth section. The results are presented in the sixth section, followed by a brief discussion in the seventh section. Additional supporting evidence can be found in the Appendix as well as in the Online Annex[3].

1 Public employment services in Slovakia

Slovakia ranks among those countries with the most turbulent unemployment development in Europe. Its unemployment rate rose from zero at the end of the socialist period in 1990 to the highest level in the EU in one decade, culminating shortly after 2000. Moreover, population ageing with a sharp decline in the labour force has been pressing the unemployment rate down sharply since 2013. This turbulent period challenged the management of Slovak PES; at the operational level struggling with enormous regional differences in both the local labour market performance and the composition of unemployed individuals Duell and Kureková (2013). The situation has become even more complicated due to the spatially unevenly distributed population of marginalized Roma communities. Although these multidimensionally disadvantaged PES clients need special attention, they often face discrimination at local labour offices Mikula and Montag (2022). Despite the post-2013 decline in unemployment (driven mainly by the decline in the labour force), Slovak PESs remain in a complex position. Although youth unemployment is among the top priorities in the country, it definitely is not its most urgent problem.

The YG has been added to the resources already flowing into ALMPs across the EU. In line with the main idea of this guarantee, activation became more accessible to youth during the early stages of their unemployment. This shift has been even more pronounced in the case of the Central and Eastern European (CEE) countries, where EU funding comprises a more substantial share of the ALMP budget and the pre-YG accessibility of ALMP is lower[4] The above mentioned increase in accessibility was only marginally driven by an absolute increase in the amount of funding flowing to ALMPs; a rapid decline in the total number of registered JSs contributed more substantially. Moreover, steady economic growth combined with the impact of population ageing decreased the total number of unemployed individuals registered in Slovakia during the period from 2014 to 2019 (Morvay et al., 2021). Additionally, in reaction to this situation, the provision of youth-oriented ALMP programs was extended to JSs up to 29 years of age.

[3] http://www.lmevidence.sav.sk/data_uploads/DML_Online_Annexe.html

[4] While in Germany, over 98 percent of registered JSs under 25 years old were activated within the first 12 months since the start of their unemployment in 2013, this value was only 69 percent in Slovakia. During the YG implementation phase after 2014, this share stayed above 98 percent in Germany and increased to 90 percent in Slovakia in 2019 (Labor Market Policy Database: Timely Activation, European Commission - Directorate-General for Employment, Social Affairs and Inclusion, accessed 29.03.2022).

1.1 The portfolio of ALMP programmes

The ALMP programs provided to young JSs in Slovakia in 2016 can be clustered into the following categories:

- Employment incentives (EI)
- Graduate practice (GP)
- Training (TR)
- Public works (PW)

The category EI shelters relatively expensive programs on the border of hiring incentives and subsidized employment. Under these programs, mostly private-sector employers apply for a contribution of up to 75 percent of labour costs associated with employing youth from the register of unemployed JSs. This contribution is usually provided for 12 months and followed by a 6-month-long period of mandatory employment. Available impact evaluation studies estimate positive employment effects for some of the programs in this category (Institute of Fiscal Policy, 2016; Institute of Social Policy, 2019). However, although these observed effects are high in the short term, they are not persistent in the long run.

GP was the only youth-oriented ALMP program available to registered unemployed individuals in Slovakia before the YG initiative since 2004, presenting a less expensive alternative to the EI programs introduced after 2014. Both types of programs facilitate the collection of early-career workplace experience, but the GP is associated only with a less generous contribution paid directly to participants. Earlier impact evaluations point at its moderately but significantly positive employment effect (Svabova and Kramarova, 2021), associated with a negative impact on earnings (Štefánik et al., 2020). A report of the Institute of Fiscal Policy (2016) underlines the favourable cost-benefit assessment of GP in comparison to its alternatives.

TR programs have been provided dominantly under the model allowing JSs to choose the training provider and topic covered. This category shelters two ALMP programs: one delivers vocational training, and the other delivers soft-skills training. Earlier studies estimate positive employment and income effects of the vocationally oriented program (REPAS) (Institute of Social Policy, 2018; Stefanik, 2021).

PW comprise the community service type of jobs organized by municipalities. Support is paid either as a contribution directly to the participant or as a financial transfer to the municipality associated with creating a new job either under the municipality or another public organization. Previous evaluations point to a negative or nonexistent employment effect on post-participation employment (Institute of Fiscal Policy, 2016), which is also in line with international experience (e.g., Card et al. (2018); Caliendo and Schmidl (2016)).

1.2 Selection of program participants

Although the PESs in Slovakia are designed and managed centrally, they are delivered through 46 regional PES offices. The service model of regional PES offices differs in terms of the ALMP portfolio, client outreach, employment counselling, or job search effort monitoring. Moreover, regional PES offices distribute the minimum subsistence payments. The unemployment benefit is conditional on an individual being employed for at least 24 of the last 48 months and amounts to 50 percent of his/her preceding gross salary. This benefit is paid as a flat monthly payment for six months after the start of registered unemployment.

Caseworkers apply job search monitoring and penalizing measures at their discretion. Commonly used methods are random calls for a visit to the regional office or requests for print or email documentation of job search efforts. Repeatedly declining a job offer or participation in an ALMP program is a reason for individuals to be deregistered from unemployment benefits. Jobseekers need to apply for ALMP participation; particular programs take the form of financial contributions paid to the JS, employer or TR provider. Although the application needs to be submitted by the JS himself/herself, the caseworker plays a crucial role in helping the individual select which program to join by conveying information about program availability (the absence of funding is universally assumed). Moreover, caseworkers can, on several occasions, veto such applications. Firstly, by not conveying the information about the ALMP programme being available. Secondly, by not instructing clients about their obligation to submit an application. Finally, application acceptance is decided by the management of the regional PES office. The management decides under budgetary constraints based on the recommendation of the caseworkers.

A significant fraction of the variability in the selection into the programme is, therefore, explained by regional-level characteristics, such as the local unemployment rate, the distance from the municipality of permanent residence to the nearest local PES office, or the share of Roma in the population of the municipality of permanent residence. For this reason, we pay particular attention to capturing these regional differences through an exhaustive list of regional-level control variables.

Out of the programs evaluated here, GP enables workplace insertions with no eligibility restriction in terms of the duration of the preceding unemployment period. As a result, GP participation takes place dominantly in the first six months of the unemployment period. Such programs identify those more employable youth JSs (i.e., "skim the cream"). EI programs present a more expensive but also more intensive (full-time employment contract) mode and longer workplace insertion than do GP programs. Moreover, participation in EI programs is conditioned on being in registered unemployment for at least 3 months. "Cream skimming" is less pronounced but still present in the case of EI programs. PW shelter workplace insertions, in terms of duration and financial support, are comparable to those of GP but in a completely different workplace setting. PW programs are last-resort programs, picking up the least educated and least employable clients; such programs are widely used by clients from segregated Roma communities and commonly perceived as those programs engaging Roma in communal services for municipalities. Additionally, TR is underrepresented in the portfolio of Slovak ALMPs in the long run. Although TR availability is increasing, it remains lower compared to that in other EU countries. Only short-term TR is financed by the Slovak PES. TR courses are picked from the supply of accredited TR providers, and PES clients are free to pick the TR topic and provider when applying for reimbursement for TR costs, but only selected applications are supported due to a lack of resources. Training on vocational skills and soft skills is supported. Moreover, the strategies used to select TR participants differ between regional PES offices. Although there is no eligibility restriction on the length of previous unemployment, perhaps because of the scarcity of TR, some regional PES offices systematically pick TR participants out of long-term unemployed individuals, while others allow for participation shortly after registration.

2 International experiences with youth activation

Our analysis joins the stream of literature studying the impact of ALMP programs to generate information relevant to policy-making, asking the question "What works?" in youth activation—a question frequently addressed in the literature by meta-analyses (e.g., Caliendo and Schmidl (2016); Card et al. (2018); Kluve et al. (2019)), qualitative assessments of the available empirical studies (e.g., Martin and Grubb (2005); Brown (2015)), or by cross-program-comparison impact evaluation studies (e.g., Caliendo et al. (2013); Madoń et al. (2021)). We contribute to the third stream of the literature by applying a unified empirical strategy to estimate the impact of participation in multiple ALMP programs.

While experiencing early-career unemployment appears to have a lasting scarring effect on mid-career unemployment (Schmillen and Umkehrer, 2017) or income (De Fraja et al., 2021), the impact of ALMP programs on the labour market outcomes of unemployed youth tends to be lower in comparison to that on the outcomes of unemployed individuals of prime age(Card et al., 2018).

Studying the differences in the impact of different types of ALMP programs on future unemployment chances might contribute to our understanding of the relative importance of early-career labour market entry.

Compared to other youth-oriented ALMPs, those facilitating workplace experience appear to perform relatively better (Caliendo and Schmidl (2011); Auray and Lepage-Saucier (2021)). This finding is in line with the explanation provided by Papageorgiou (2014) that it is not only a simple easing of the transition from school to work but also an enabling of the collection of multiple different types of workplace experience that might affect youths´ employment chances in the long run. In our example, this type of ALMP program is represented by a less costly option—graduate practice (GP)—and a more expensive employment incentives (EI).

In contrast, workplace experience acquired in the public sector and particularly in communal services tends to have no or even a negative impact on postparticipation employment (Caliendo and Schmidl (2016) for youth-oriented programs and Martin and Grubb (2005) and Card et al. (2018) and Vooren et al. (2019) for ALMP programs in general). Conversely, such experience often serves as a last-resort ALMP sheltering the least employable PES clients in need of multidimensional activation, such as in the case of Slovak PW. Participation in this type of ALMP program is more often associated with a stigmatizing effect (Biewen and Steffes, 2010; Duell and Kureková, 2013), thus potentially negatively affecting the mid-career employment chances of participants.

Finally, through the well-described human capital or, more specifically, skill-upgrading effect, the impact of training participation on employment and income, in the long run, should be observable (Card et al., 2018; Kluve et al., 2019; Vooren et al., 2019). The short-term training offered to registered job seekers (JSs) in Slovakia supports occupational mobility and compensates for skill deterioration during longer periods of unemployment.

Additionally, in the case of youth-oriented ALMP programs, the combination of multiple services (types of ALMP programs) appears to yield a more favourable impact (Kluve et al., 2019; Vooren et al., 2019). Moreover, client profiling at registration and better targeting of clients is generally linked with an increased impact of such programs (Brown (2015); Kluve et al. (2019); Desiere et al. (2019)). Based on a review of North American evaluations, Martin and Grubb (2005) conclude that in the case of youth-oriented programs, early and sustained interventions are likely to be the most effective. Furthermore, earlier interventions appear to also work relatively better in the case of youth (Carling and Larsson, 2005) and asylum seekers (Dahlberg et al. (2022); Arendt (2022)).

Complementary to ALMP participation are measures aimed at shortening the unemployment period and thus preventing the negative consequences of long-term unemployment for future career prospects (Schmillen and Umkehrer, 2017). A policy measure or intervention might not always come as participation in an ALMP program. At the operational-level, PES often employs job search monitoring and sanctioning measures caseworkers impose on their clients. Empirical studies refer to this set of measures as "stick" measures and point to not only their positive impact on re-employment probability (Crépon and van den Berg, 2016) but also the potential risks regarding pushing clients out of the labour force (van den Berg et al., 2020) or negative impact on their re-employment wage (Van der Klaauw and Van Ours, 2013). Imposing the stick type of measures is, in our analysis, represented by the length of unemployment duration. The situation of a less employable client leaving the PES register earlier is assumed to be a result of the "stick" type of measures, the application of which in the Slovak context (as in other countries (Arni et al., 2022)) is extensively subject to the strictness of a particular PES caseworker.

2.1 The caseworker´s dilemma: alternative counterfactual situations to consider

PES caseworkers act as the field officers of PES implementation; they possess the most complex information about the employability of their particular clients, whom they are able to confront with their field-specific experience (e.g., Desiere et al. (2019); McDonald et al. (2019)). Their decisions significantly impact the labour market performance of their clients (Rosholm, 2014; Schiprowski, 2020). Arni et al. (2022) pay attention to the substantial leeway of PES caseworkers in the distribution and implementation of ALMP programs. Dividing Swiss ALMP programs into supportive (carrots) and restrictive (sticks), the above authors estimate "regime" effects in addition to program-level treatment effects, showing a positive income effect of supportive carrot-type programs. In contrast, quick placement and, thus, a shorter unemployment period might send a less stigmatizing signal in future job searches. For example, Belle et al. (2018) reveal that employers use job candidates' unemployment duration as a sorting criterion. Caseworkers must also consider any potential lock-in effects associated with sending an employable client to an intensive and lengthy ALMP program in an early stage of her/his unemployment (Rosholm, 2014; Wunsch, 2016).

Especially in less regulated employment service models (e.g., that in Slovakia), caseworkers relatively more independently decide whether to prolong the employment counselling phase with an individual job search or to suggest a more intensive (and expensive) ALMP program for the client already in the earlier stages of her/his unemployment. The "stick" versus "carrot" juxtaposition is widely used in the empirical literature studying the strictness of caseworkers in managing the job search effort of JSs (see, e.g., Arni et al. (2022); McGuinness et al. (2019)). Available evidence suggests a trade-off between fast placement (job-first approach) and stable placement into a better-paying job.

The duration of unemployment benefits also plays a role in this situation. For example, Caliendo et al. (2013) demonstrate that job placements rushed by benefit exhaustion experience less stable employment patterns and receive lower reemployment wages compared to other job placements. Moreover, Lichter and Schiprowski (2021) estimate that one additional month of potential benefits reduces the number of early job applications by approximately 10 percent.

Therefore, although providing ALMP support in the earlier stages of unemployment appears to be desirable (Carling and Larsson, 2005; Arendt, 2022), it also needs to be considered against a relevant counterfactual situation. The composition of individuals with their job search effort in their first months of unemployment differs from the composition and job search effort of those remaining unemployed after one year. Furthermore, ALMP participation is associated with a potentially costly lock-in effect, and client profiling is associated with a more positive ALMP impact (Kluve et al., 2019). Bearing this in mind, PES caseworkers make an initial assessment of each client, sorting each based on his/her employability. In comparison to the convention in the ALMP impact evaluation literature, we take an extra step in aiding PES caseworkers and generate evidence on the long-term impact of ALMP program participation, estimated for the following two counterfactual situations:

- the less employable client is assumed to be unemployed for more than 6 months, and
- the more employable client is expected to find a job within 6 months.

3 Identification and estimation strategy

Our identification strategy rests on the recent research on the use of a DML-based estimator in impact evaluation (Chernozhukov et al., 2018). We employ the dynamic treatment effects estimator that uses DML to control high-dimensional confounders (Bodory et al., 2022). Instead of a causal impact of a single treatment, we study the causal impacts of *sequences* of different treatments on employment. The identification scheme relies on the unconfoundedness property: we need to have a rich set of information about JSs so that conditioning on this information makes the treatment in different periods independent of potential outcomes. We make use of the following notation in a two-period setup: D_1, D_2 denote treatments in periods 1 and 2, respectively; X_0, X_1 denote covariates measured before periods 1 and 2, respectively; and $Y_2(d_1, d_2)$ is a potential outcome for a sequence of treatments $d_1, d_2 \in \{0, 1, \cdots, Q\}$, where 0 encodes no treatment, 1 means the JSs left the unemployment database for various reasons and $2, \cdots, Q$ represent different ALMPs. We use information about X_0 to predict the probability of an individual receiving treatment in the first period, D_1, and information X_0, X_1, D_1 to predict program participation in the second period, D_2.

Our object of interest is the differences between potential outcomes for two different treatment sequences—(d_1, d_2) and (d_1^*, d_2^*):

$$E[Y_2(d_1, d_2)] - E[Y_2(d_1^*, d_2^*)]$$

or the difference between these sequences for a particular subgroup, defined by an indicator variable, S:

$$E[Y_2(d_1, d_2)] - E[Y_2(d_1^*, d_2^*)|S = 1],$$

which could, for instance, denote whether JSs received treatment d_1 or d_2 in the first period ($S = I(D_1 \in \{d_1, d_2^*\})$), thus allowing us to evaluate the impact of treatment in the second period.

In this study, we follow the identification and estimation strategy outlined in (Bodory et al., 2022). More concretely, we make the following identifying assumptions:

Assumption A1

$$\forall d_1, d_2 : \; Y_2(d_1, d_2) \perp\!\!\!\perp D_1|X_0,$$

Assumption A2

$$\forall d_1, d_2 : \; Y_2(d_1, d_2) \perp\!\!\!\perp D_2|D_1, X_0, X_1.$$

Assumptions A1 and A2 present unconfoundedness assumptions applied in two sequences of the two-period setup. Assumption A1 rules out the existence of any unobserved confounders that would jointly affect D_1 and $Y_2(d_1, d_2)$, and Assumption A2 rules out the unobserved confounders that jointly affect D_2 and $Y_2(d_1, d_2)$ given information on D_1, X_0 and X_1. The plausibility of these assumptions rests on the richness of information encoded by X_0 and X_1, which is why the DML setup that can handle possibly high-dimensional data, where the number of parameters is large relative to the sample size, is particularly appealing in this application. Note that X_1, the information about the JS measured prior to D_2, could be influenced by both X_0 and D_0, and thus, we allow for *dynamic confounding*. Caliendo et al. (2017) test the unconfoundedness assumption in a data context comparable to ours and conclude that the usually unobserved variables do not threaten the validity of those estimates acquired when using unconfoundedness-based estimators, especially if a comprehensive set of control variables is used.

Among the set of observable characteristics, we include, in addition to individual characteristics and skills, a rich set of regional characteristics, individuals´ unemployment history, benefit claims and caseworkers' assessment of clients´ employability. In the Slovak context, with highly-pronounced regional differences in economic performance, the structure of the labour supply as well as PES implementation, regional characteristics acquire particular importance. Here we use variables available at various levels of granularity, also including municipality-level[5] information. Especially the share of Roma population in the municipality of client´s permanent residence is a strong predictor of PES programme participation.

To make the estimation feasible, we also need to make assumptions about common support so that we have a sufficient number of units for appropriate comparison:

Assumption A3

$$\forall d_1, d_2 : P(D_1 = d_1|X_0) > 0, P(D_2 = d_2|D_1, X_0, X_1) > 0, P(S = 1|X_0) > 0.$$

3.1 Description of the DML estimation technique

The propensity scores in Assumption A3, together with the models for the conditional mean of the outcome variable (also called nuisance functions), are estimated via ML algorithms and thus

[5]We use the information at the LAU 1 level of the international classification NUTS. At this level, Slovakia breaks down to almost 3 000 municipalities, with a median population of 890 persons.

can handle high-dimensional data.[6] These ML-estimated nuisance functions are then plugged into moment condition functions (p.633 and p.635 in Bodory et al. (2022)) to estimate mean potential outcomes $E[Y_2(d_1, d_2)]$ and $E[Y_2(d_1, d_2)|S = 1]$. These moment condition functions are insensitive to local perturbations of the estimated nuisance functions (a property called Neyman orthogonality), which removes the regularization bias introduced by the ML algorithms, as such algorithms trade an increase in bias for a decrease in variance. In addition, the cross-fitting technique reduces the overfitting bias that stems from the fact that the same data are used for both nuisance function estimation and moment function estimation (Chernozhukov et al., 2018). These are the two sources of bias from which a naive plug-in estimator would suffer (see Chernozhukov et al. (2018) for a detailed discussion).

The estimator that we use (Bodory et al., 2022) possesses a number of convenient properties; it is (i) doubly robust (Robins et al., 1994) and thus is sufficient if the outcome model *or* propensity scores are correctly specified, (ii) asymptotically normal under weak conditions on the quality of the ML estimators (Chernozhukov et al., 2018) and (iii) semiparametrically efficient Robins (2000). We use a random-forest-based estimation technique to estimate both the propensity scores and outcome models.[7]

3.2 Addressing the caseworker's dilemma

We address the caseworker's dilemma by considering the following two situations: having a client who is less likely to find a job and having a client who is more likely to find a job. Here, we use two different comparison (control) units to contrast the outcomes of participants to those of nonparticipants. Please be aware that we report the average treatment effects for the population of treated together with their respective control group.

As a first control unit, we consider a client who is unlikely to find employment within the first 12 months of being unemployed. Thus, we estimate the impact of participation in one or multiple ALMP programs against a counterfactual situation of a twelve-month-long unemployment period. Under this counterfactual situation, we also refer to the "less employable" type of client.

Alternatively, we consider a situation in which a client is likely to find a job after 6 months of unemployment. Here, our quantification builds on a comparison to a counterfactual situation of six-month-long unemployment followed by an exit from the database between the seventh and twelfth months of the unemployment period. Note that in this case, identification relies on Assumption A2 with D_2 being an employment indicator, meaning that the variables in X_0 and X_1 are rich enough to capture any dependence between this variable and the outcome of interest.

We argue that distinguishing between these two counterfactual situations yields relevant information from the perspectives of policy design and implementation. By deciding on the placement of two alternative types of PES clients into an ALMP program, the cost of the potentially associated lock-in effect can be assessed. To consider this to the full extent, we should also look at the long-term effects of "not suffering" a longer unemployment period on the two types of clients. By looking at the "benefit" of ALMP participation in the long run, we also consider the "benefit" of choosing the alternative "work-first" approach over ALMP participation. In line with this reasoning, we estimate the average treatment effects (ATEs) for the entire population of treated together with the control group defined by the considered counterfactual situation.

[6] Regularity conditions (Assumption 4 in Bodory et al. (2022)) also require that these functions are estimated using ML methods "well enough", which is satisfied for a wide range of ML algorithms under relatively weak conditions, namely, that the rate of convergence is of order $n^{-1/4}$ or better.

[7] To improve the finite sample properties of the random forest estimator, we follow (Borup et al., 2022a) and remove those variables with little variation and that are almost colinear with other predictors.

4 Data and sample

We explore administrative data provided by the Slovak PES - Central Office for Labour Social Affairs and Family of the Slovak Republic (COLSAF)[8]. These data cover the total population of unemployed persons in Slovakia registered from January 2014 to December 2020. We are able to reconstruct information on their i. unemployment history; ii. individual characteristics declared during registration; iii. behavior during their unemployment period, including participation in ALMP programs; and iv. high-granularity regional information. We select a sample of individuals registered as unemployed JSs during 2016. The data allow for us to trace their absence from the unemployment register up to 48 months after the start of their unemployment. We focus on estimating the impact of youth activation in the long run, that time when it should be more pronounced (Kluve et al. (2019), (Caliendo and Schmidl, 2016)). We restrict our sample to the age group between 15 and 29 years. Only unemployment periods longer than 3 months[9] and shorter than 3 years are considered. Individuals with more than one unemployment period during 2016 are also dropped. The most substantial trimming of the sample (approximately 20 percent; see Table 1) is linked to dropping all those observations with the ALMP participation of more than 12 months of individuals after the start of their unemployment. In the case of PW, the share of dropped participants climbs to 40 percent.

Table 1: Number of observations dropped due to late participation

ALMP program	0-6 months	7-12 months	Dropped N	Dropped Perc.
EIs	1,067	2,005	1,187	0.279
GP	3,810	411	67	0.016
TR	1,646	711	815	0.257
PW	670	150	546	0.400

Note: Individuals with ALMP participation taking place later than 12 months after the start of unemployment are dropped.
Source: COLSAF database.

The restriction of our sample to ALMP participation taking place in the first 12 months enables a straightforward interpretation with recommendations drawn for casework during the first twelve months of the unemployment period[10]. The total size of the sample, after cleaning, includes 57,716 PES clients, out of which 49,854 (86 percent) do not participate in any ALMP program during the first 12 months of their unemployment period.

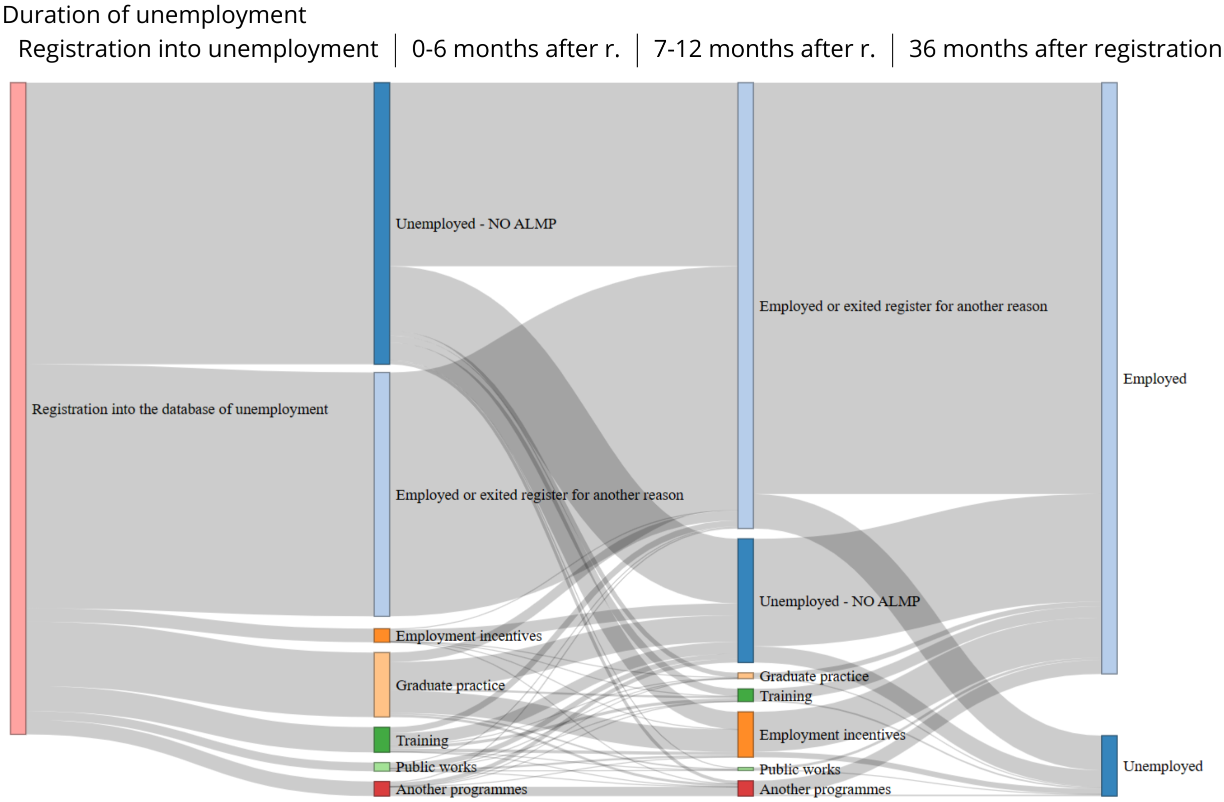
After the first six months following unemployment registration, the 2016 inflow cohort (sample) is broken into approximately equal thirds. One-third of such individuals find employment, and another third of individuals remain unemployed without participating in any ALMP program. The last third participates in some of the ALMP programs within the first six months following unemployment registration (Figure 1). Our outcome variable is a binary indicator of individual presence/absence from the PES register, measured three years after the original registration in 2016. The proportions of individuals present/absent from the PES register correspond to the proportions of unemployed/employed individuals in the very right bar of Figure 1. Distinguishing between participation taking place in the first half of the year from that in the second half of the year of unemployment leaves us with 36 theoretically possible combinations of treatment sequences, namely, participation in one of the four ALMP programs and presence or absence from the register. Of the

[8] https://www.upsvr.gov.sk/.

[9] The application of this condition drops approximately half of the sample of unemployment periods.

[10] Our results are not sensitive to extending the second period from 7-12 to 7-24 months. In such cases only, the reduction in the sample of participants is only marginal; 0.4 percent of participant observations are dropped (1.76 percent of PW participants). The results for such a variant can be found in Table A.3 in 6.

Figure 1: Flows of the sample between periods: 0, 1-6, 7-12 and 36 months after registration



Source: COLSAF Database.

possible combinations, we decide not to consider those for which we observe fewer than 40 PES clients in our sample. The final list of eighteen considered combinations of treatment sequences with their numbers of observations is available in 6 Table A.1.

The data allow for us to control for a rich set of covariates, including individual-level characteristics, such as clients' (un)employment history, skills or caseworker assessment of client´s employability. Individual characteristics are complemented by a long list of regional-level characteristics at various levels of granularity, ranging from the municipality level to the district level. Regional characteristics include regional unemployment or average wage, commuting times, the municipality's population or the share of Roma individuals. A complete list of covariates, with their mean values, can be found in the Online Annex (Table 3.1)[11] `http://www.lmevidence.sav.sk/data_uploads/DML_Online_Annexe.html`. Following the instructions of Borup et al. (2022b), we exclude weak predictors and check for the collinearity and concentration of the dummy variables. As indicated in Table 2, after cleaning, we are left with 239 variables observed at the moment of client registration (X0), complemented by 10 additional variables observed during the first 6 months of registered unemployment (X1).

5 Results

We estimate the average treatment effects (ATEs) of participation in various ALMP programs with respect to the timing of participation on the long-term chances of individuals being absent from the PES register, observed three years after the start of the initial unemployment period. Due to the flexibility of the applied ML estimation technique, we are able to distinguish the effect of participation taking place in the first six months of unemployment from that of participation taking

[11] `http://www.lmevidence.sav.sk/data_uploads/DML_Online_Annexe.html`

Table 2: Number of control variables entering the estimation

Variables	X0	X1
Before cleaning		
dummy	255	10
numeric	8	0
total	263	10
After cleaning		
dummy	231	10
numeric	8	0
total	239	10

place between the seventh and twelfth months of unemployment. Additionally, to provide information tailored to the caseworker´s dilemma, we estimate our effects in contrast to the following two alternative counterfactual situations:

- a twelve-month-long unemployment without any ALMP participation and
- a six-month-long unemployment without any ALMP participation.

First, we report the estimated effects quantified against a situation of unemployment of at least 12 months (Table 3). The composition of clients remaining unemployed for such a long period of time is biased towards the less educated and attached to the labour market; therefore, we consider this situation as a proxy for a less employable client. Comparing the outcomes of programme participants to this counterfactual situation reveals results that align with internationally observable patterns or previous empirical studies on Slovak ALMP programs.

Regardless of the type of ALMP program, its impact is higher when applied earlier in the unemployment period, which is observable for EI (treatment sequence 2-0 versus 0-2), GP (treatment sequence 3-0 versus 0-3) and TR (treatment sequence 4-0 versus 0-4). Participation in EI after 6 months of unemployment yields a 3-percentage-point-higher probability of an individual being absent from the PES register after three years. In contrast, if EI participation happens within the first 6 months of unemployment, then the probability of absence after three years is 12 percentage points higher (see Table 3, treatment sequences 0-2 vs. 2-0). In the case of training, the gain from early intervention appears to be relatively smaller, 4 versus 6 percentage points (see Table 3, treatment sequences 0-4 versus 4-0). A higher impact of interventions offered earlier in the unemployment period aligns with earlier studies (see, e.g., Martin and Grubb (2005); Carling and Larsson (2005)).

In the case of PW, the estimated coefficients are not significantly different from zero, regardless of the timing of PW participation (Table 3, treatment sequences 0-5 and 5-0). This finding is in line with those conclusions drawn from meta-studies on the impact of youth-oriented ALMPs (Caliendo and Schmidl, 2016; Kluve et al., 2019). Additionally, we observe that if PW participation is followed by an individual exiting the PES register or by participation in EI, then it might increase the probability of him/her being absent from the PES register after three years. Note that the ATEs estimated for treatment sequences with PW participation in the first period followed either by employment (5-1) or employment supported by employment incentives (5-2) are higher than if EI participation is preceded by six months of unemployment without any ALMP participation (treatment sequence 0-2). This finding suggests that PW programs might work as a stepping stone, enabling the further collection of workplace experience for clients in the most urgent need of employment activation.

Additionally, in line with the extant meta-studies (e.g., Kluve et al. (2019); Vooren et al. (2019)), we see evidence of an increased impact of participation in combined ALMP programs. In addition to the above-mentioned combination of PW and EI, this result is particularly observable in combinations of training with other types of ALMP programs. TR followed by EI (treatment sequence 4-2

Table 3: ATE estimates against a counterfactual situation of 12 months of unemployment, outcome: Absence from the unemployment register after 3 years

Treatment sequences		Results					Observations	
Treated	Control	y0	Effect	SE	p-value	sig.	N	Trimmed
0-1	0-0	0.84	**0.06**	0.01	0.00	***	27320	87
0-2	0-0	0.83	**0.03**	0.01	0.00	***	27320	4155
0-3	0-0	0.84	0.02	0.02	0.35		27320	20151
0-4	0-0	0.83	**0.04**	0.02	0.06	.	27320	10976
0-5	0-0	0.79	-0.05	0.06	0.40		27320	25208
1-1	0-0	0.84	**0.07**	0.01	0.00	***	51863	21223
2-0	0-0	0.84	**0.12**	0.03	0.00	***	28501	21971
2-1	0-0	0.84	**0.13**	0.01	0.00	***	28501	13200
3-0	0-0	0.86	**0.08**	0.01	0.00	***	33025	20011
3-1	0-0	0.86	**0.10**	0.01	0.00	***	33025	15582
3-2	0-0	0.86	**0.06**	0.01	0.00	***	33025	22989
4-0	0-0	0.84	**0.06**	0.02	0.00	***	29607	17899
4-1	0-0	0.85	**0.11**	0.01	0.00	***	29607	7239
4-2	0-0	0.83	**0.13**	0.02	0.00	***	29607	24782
4-4	0-0	0.84	**0.14**	0.01	0.00	***	29607	28124
5-0	0-0	0.80	0.06	0.05	0.21		28165	22889
5-1	0-0	0.82	**0.08**	0.01	0.00	***	28165	15725
5-2	0-0	0.80	**0.07**	0.02	0.00	***	28165	26794

[0] 0: Not participating in any program
[1] 1: Employed or exited register for another reason
[2] 2: Employment incentives
[3] 3: Graduate practice
[4] 4: Training
[5] 5: Public works

in Table 3) increases the probability of an individual being absent from the PES register by 13 percentage points. In contrast, two periods of participation in short-term training programs increase this probability by 14 percentage points (treatment sequence 4-4), yielding the highest impact of all the considered treatment sequences.

Finally, while evaluating the particular types of ALMPs, one should consider the possibility of pushing the JS out of the register by applying the “work-first" approach to job search monitoring and penalizing. We observe a clear impact of exiting the PES register after six months compared to twelve months in registered unemployment among individuals. After accounting for the observable differences among individuals, the net impact of exiting the register in the first six months is six percentage points in terms of the probability of an individual being absent from the PES register after three years (treatment sequence 0-1 in Table 3). In magnitude, this effect is comparable to that observed for training participation taking place in the first six months of unemployment, which is not followed by an exit from the PES register (treatment sequence 4-0 in Table 3).

A different result is observed for ATEs quantified against a counterfactual situation of six months of unemployment followed by an exit from the unemployment register (see Table 4). Basically, all of the ALMP programs, if applied later than six months after the start of unemployment, show negative effects on the long-term chances of an individual being absent from the PES register after three years. If such programs are applied in the first six months of unemployment, then ALMP participation (with the exception of PW programs) shows positive and significant ATEs (treatment sequences: 2-0, 3-0, 2-1, 3-1 and 4-1 in Table 4) [12]. GP programs show only a moderate ATE if unemployment continues after program participation (treatment sequence 3-0).

Table 4: ATE estimates against a counterfactual situation of 6 months of unemployment followed by an exit from the register, outcome: Absence from the unemployment register after 3 years

Treatment sequences		Results					Observations	
Treated	Control	y0	Effect	SE	p	sig.	N	Trimmed
0-0	0-1	0.90	**-0.06**	0.01	0.00	***	27320	87
0-2	0-1	0.90	**-0.03**	0.01	0.00	***	27320	4096
0-3	0-1	0.92	**-0.05**	0.02	0.00	***	27320	20136
0-4	0-1	0.90	**-0.03**	0.02	0.10	.	27320	10944
0-5	0-1	0.87	**-0.13**	0.05	0.02	*	27320	25208
1-1	0-1	0.91	**0.01**	0.00	0.00	***	51863	538
2-0	0-1	0.90	**0.07**	0.03	0.02	*	28501	22040
2-1	0-1	0.91	**0.06**	0.00	0.00	***	28501	13260
3-0	0-1	0.92	**0.02**	0.01	0.00	***	33025	20173
3-1	0-1	0.93	**0.04**	0.00	0.00	***	33025	15736
3-2	0-1	0.93	0.00	0.01	0.90		33025	23149
4-0	0-1	0.90	0.00	0.02	0.86		29607	18056
4-1	0-1	0.92	**0.04**	0.01	0.00	***	29607	7362
4-2	0-1	0.92	**0.04**	0.01	0.00	***	29607	24841
4-4	0-1	0.92	**0.06**	0.01	0.00	***	29607	28229
5-0	0-1	0.85	0.00	0.05	0.95		28165	23004
5-1	0-1	0.89	0.01	0.01	0.23		28165	15834
5-2	0-1	0.89	-0.02	0.02	0.30		28165	26895

[0] 0: Not participating in any program
[1] 1: Employed or exited register for another reason
[2] 2: Employment incentives
[3] 3: Graduate practice
[4] 4: Training
[5] 5: Public works
Note: Observations with the estimated propensity score probabilities close to 1 (above 0.99) or zero (under 0.01), were trimmed to avoid over-weighting or potential common support issues.
Source: COLSAF Database.

The most interesting finding of this study is that combining TR with workplace experience (EI) or other training increases its impact. Our evidence, here, aligns with the finding of Kluve et al. (2019). Moreover, a sequence of two short-term training participations (treatment sequence 4-4 in Table 4) yields the highest gain, even if compared to a counterfactual situation of a shorter (6-month-long) unemployment period. Although we provide evidence showing that there is some benefit to shortening the unemployment period with a “work-first" type of approach to casework, we also provide evidence that intensified training increases the long-term probability of an individual being absent from the PES register and, thus, of being unemployed. This finding supports the idea that training if adequately chosen and designed, may lead to more sustainable employment. Note that the training programs evaluated here are short-term (approximately 4 weeks) and chosen by the JSs themselves. In other words, youth JSs are able to choose the training specialisations that outperform the impact of the scarring career effect of unemployment potentially prolonged

[12] In the case of EI participation in the first period, followed by unemployment in the second period (treatment sequence 2-1 in Table 4), unemployment in the second period (7-12 months) is indicated because of the extensive EI duration.

by the lock-in effect.

It is also the case that training works for those more employable and skilled PES clients. The Y0 column indicates the estimated potential outcome of the control group. A value of 0.9 indicates that 90 percent of the control group is expected (in terms of estimated potential outcome) to be out of the register of JSs after three years. Note that in Table 3, the Y0 values are slightly lower, approximately 84 percent, indicating that considering the composition of the JSs remaining in registered unemployment for at least twelve months, their expected absence from the register after three years is lower than that expected for those leaving the register after six months (Y0 in Table 4). The differences in ATEs reported in Tables 3 and 4 present the differences when applying the same level of support to less and more employable types of clients.

Looking at the share of trimmed observations, we may observe how the model deals with the common support problem. The share of trimmed is extraordinarily high in two instances. In the first one (treatment sequences 0-5 and 5-0) treated are less employable compared to both control groups (0-0 or 0-1). PW presents the last-resort program, sheltering the least educated individuals furthest from the labour market, with a high fraction of Roma participants. In contrast, the treatment sequence (4-4) covers the most motivated clients acting actively in applying for a sequence of two client-picked training courses. The DML estimation technique was able to correctly identify the instances with the most pronounced differences and address them by a more severe trimming. Note that even in these most extreme instances, after trimming, we remain with numbers of observations exceeding 40 in the case of each group the treated as well as controls[13].

6 Discussion

In our analysis, we describe the impact of various types of ALMPs available to unemployed youth in Slovakia. Our empirical strategy allows for comparisons across program types and periods of participation. We design our analysis to generate relevant information from a caseworker perspective, distinguishing between more and less employable clients and assessing their chances of finding a job without ALMP participation. Thus, we draw a complex picture of the impact of support provided under various types of ALMPs. Our analysis yields findings comparable to those yielded by popular impact evaluation meta-analyses (e.g. Caliendo and Schmidl (2016); Card et al. (2018); Kluve et al. (2019)). Reflecting on the above studies, specifically in relation to the activation of unemployed youth, we confirm a number of their findings:

- The impact of ALMPs is higher if the intervention takes place earlier in the unemployment period (Martin and Grubb, 2005; Carling and Larsson, 2005).
- Workplace experience collected under "PW" types of programs has a smaller impact than does that collected in the private sector or regular employment (Kluve et al., 2019; Card et al., 2018; Caliendo and Schmidl, 2016).
- Combinations of various interventions appear to increase the impact of some program types (Kluve et al., 2019).

In addition to the well-discussed findings of the meta-analyses, we also observe the following:

- The shortening of the unemployment period is associated with an impact on the long-term probability of an individual´s absence from the unemployment register (aligns with the findings of Schmillen and Umkehrer (2017)).
- The shortening of the unemployment period, by itself, without any ALMP participation, outperforms ALMP support provided later in the unemployment period.

[13] The number of observations for each of the sequence and each of the models can be found in the Online annexe - Tables 5.1 and 6.1 (`http://www.lmevidence.sav.sk/data_uploads/DML_Online_Annexe.html`).

- Sequences of at least two short-term trainings outperform the shortening of the unemployment period in terms of impact on the long-term probability of an individual being absent from the unemployment register.

The design of our empirical analysis allows us to draw conclusions based on inter-program comparisons. The identified ATEs are based on a difference in potential outcomes estimated for the joint sample of the treated and control groups. While doing so, we have to assume that the information we observe sufficiently covers the differences between the groups of treated and eligible controls (uncounfoundedness assumption). At the same time, we have designed our identification strategy with a sufficiently long time elapsed between observing our covariates with the treatment assignments and the period when we observe the outcome of interest. As a result, we believe that the estimated ATEs present the impact of the different paths taken by individuals during their unemployment period rather than of the different compositions of participants and the control group.

Furthermore, we have explored the heterogeneity of the estimated ATEs across subpopulations of participants, namely, for different genders, educational levels, shares of the Roma population and sizes of permanent residence settlements. The main conclusions of our analysis hold across these subpopulations. The most interesting finding from the heterogeneity analysis is that sequences of training have an even greater impact on medium-educated (lower secondary) individuals and on individual residents in municipalities with a higher share of Roma individuals[14]. We believe this finding opens numerous pathways for future research.

[14]Please refer to the Online Annex for further details: `http://www.lmevidence.sav.sk/data_uploads/DML_Online_Annexe.html`

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Appendix

Table A.1: Sequences of binary treatments

Treatment sequence 0-6 months	7-12 months	N
0	0	3,790
0	1	11,150
0	2	341
0	3	97
0	4	750
0	5	149
1	1	19,061
2	0	1,239
2	1	104
3	0	2,307
3	1	808
3	2	96
3	4	87
4	0	1,826
4	1	1,650
4	4	137
5	0	241
5	1	47
NA	NA	167

[a] 0: Not participating in any program
[b] 1: Employed or exited register for another reason
[c] 2: EIs
[d] 3: GP
[e] 4: TR
[f] 5: PW

Table A.2: Mean outcome conditional on treatment sequence; OUTCOME emplm36

Treatment sequence		Absence from the PES register
0-6 months	7-12 months	mean
0	0	0.7807
0	1	**0.893**
0	2	**0.8814**
0	3	**0.8839**
0	4	**0.8315**
0	5	0.7182
1	1	**0.9107**
2	0	**0.8975**
2	1	**0.9356**
3	0	**0.8822**
3	1	**0.9421**
3	2	**0.8998**
3	4	**0.8504**
4	0	**0.808**
4	1	**0.8875**
4	4	**0.9319**
5	0	**0.8044**
5	1	**0.843**

[a] 0: Not participating in any program
[b] 1: Employed or exited register for another reason
[c] 2: EIs
[d] 3: GP
[e] 4: TR
[f] 5: PW

Table A.3: Effect estimates with a trimming threshold of 0.01, employment after 3 years

Treatment sequences		Results					Observations	
Treated	Control	y0	Effect	SE	p-value	sig.	N	trimmed
0-1	0-0	0.84	**0.06**	0.01	0.00	***	27,312	80
0-2	0-0	0.83	**0.04**	0.01	0.00	***	27,312	4,052
0-3	0-0	0.84	**0.01**	0.02	0.65		27,312	20,077
0-4	0-0	0.83	0.06	0.02	0.00	***	27,312	10,921
0-5	0-0	0.79	**0.00**	0.03	0.93		27,312	25,204
1-1	0-0	0.85	**0.07**	0.01	0.00	***	51,855	21,158
2-0	0-0	0.85	0.09	0.03	0.01	**	28,529	21,629
2-1	0-0	0.84	**0.13**	0.01	0.00	***	28,529	12,923
3-0	0-0	0.86	**0.08**	0.01	0.00	***	33,045	19,914
3-1	0-0	0.87	**0.09**	0.01	0.00	***	33,045	15,368
3-2	0-0	0.86	0.07	0.01	0.00	***	33,045	22,867
3-4	0-0	0.85	**0.04**	0.03	0.14		33,045	29,472
3-5	0-0	0.88	-0.09	0.07	0.19		33,045	31,479
4-0	0-0	0.83	0.08	0.02	0.00	***	29,595	17,871
4-1	0-0	0.85	**0.10**	0.01	0.00	***	29,595	7,171
4-2	0-0	0.85	**0.12**	0.01	0.00	***	29,595	24,820
4-4	0-0	0.86	**0.13**	0.01	0.00	***	29,595	28,118
5-0	0-0	0.79	**0.06**	0.04	0.14		28,199	22,637
5-1	0-0	0.82	**0.09**	0.01	0.00	***	28,199	15,254
5-2	0-0	0.80	**0.09**	0.02	0.00	***	28,199	26,807

[a] 0: Not participating in any program
[b] 1: Employed or exited register for another reason
[c] 2: EIs
[d] 3: GP
[e] 4: TR
[f] 5: PW