Impact Evaluation of the Graduate Practice Intervention in Slovakia with the Application of the CART Method

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Abstract: In Slovakia, the contribution to graduate practice is one of the active labour market policy interventions, the main goal of which for young school-leavers is to gain first job experiences and contacts with potential employers. Among the young jobseekers, it is one of the most used interventions. This study aims to provide a counterfactual impact evaluation of this contribution on the employability of its participants and also on their monthly wages. The total period under review is 2014–2017, during which the treated individuals participated in the graduate practice during 2014–2015. Then, their course of employment and average monthly wages were monitored over a two-year impact period, covering the period 2015–2017. The study was carried out using a database of 12,953 treated eligible participants of graduate practice and 83,907 non-treated controls. The data used in the study is managed by the Central Office of Labour, Social Affairs and Family of the Slovak Republic (COLSAF SR) and the Social Insurance Agency (SIA). For the evaluation, propensity score matching was used, where the propensity scores were estimated using classification and regression trees. The results of the study show that the participants of the graduate practice were employed on average three months longer during the two-year impact period after the end of the intervention as full-time employees or self-
employed, and their average salary was almost 217 euros higher than that of the control group of non-participants.

**Keywords**: active labour market policy, counterfactual impact evaluation, graduate practice intervention, unemployment, young jobseekers

1. Introduction

Young people could be considered a disadvantaged group for several reasons. The fact that school graduates have very little or even no experience with the labour market and employment, and that they often lack sufficient qualifications and education, are just some of the reasons why young people are considered disadvantaged in this respect. Youth unemployment is not only a problem for young people, but also for individual countries. Currently, more than 10 million young people in the European Union are categorised as neither in employment nor education (NEET) (Youth Employment Policy Conference, 2022). Youth unemployment has therefore become a major policy challenge for governments as well as employers (Grinevica & Rivza, 2018).

To improve the situation of unemployment, various programs have been implemented in individual countries within the framework of labour market policy (LMP). These labour market measures are usually active and passive (Zieliński, 2015). Active LMP measures are aimed at helping people to find a job (Fossati, Liechti & Wilson, 2021), while passive LMP instruments are rather protective in nature and are designed to reduce the risk of a sudden drop in income in the event of unemployment (Zieliński, 2015; Krasnopjorovs, 2020).

The aim of active labour market policy (ALMP) interventions is to reduce unemployment and thus increase employment (Rotar, 2018). This goal can be achieved through a variety of measures, ranging from counselling and individual guidance to various activating and training programs, either generally oriented or focused on some disadvantaged group of jobseekers.

It can be said that countries worldwide spend a lot of money on ALMP programs, but not all of them are helpful and effective, as the problem is that even too much support for the unemployed from the state can lead to a loss of motivation to work. Determining the effectiveness of programs
designed for the unemployed is therefore very important (Rotar, 2021). The magnitude of ALMP expenditures and their effectiveness should be monitored from a temporal, economic, integration, institutional, and policy perspective (Bánociová & Martinková, 2017). One of the key tools for improving ALMP is their ongoing evaluation (Mueller, Gaus & Rech, 2014). This evaluation could be done as an ex-ante, ongoing, or ex-post evaluation. The ex-post evaluations are very useful, providing information about the participants’ course of employment or other outcomes during the defined impact period after the end of the program. In recent years, counterfactual impact evaluation methods have recorded a growing interest to realise ex-post evaluations of ALMP instruments (Dutt & Nyman-Metcalf, 2021).

The main aim of conducting an impact evaluation is to determine the effect of social or economic programs. The primary purpose of this approach is to measure the causal effect of an intervention or program introduced by an external entity, which can be a national government or a local government, on a group of entities, that is, the people or businesses for whom the program was designed (Cerulli, 2015). The counterfactual evaluation approach considers “what would have happened if the individual had not participated in the intervention program.” Therefore, the impact evaluation compares the individual's outcome in the labour market if he or she participated in the intervention with the counterfactual situation if he had not participated in this intervention. In reality, however, an individual’s results can be measured in only one of these two situations: whether or not the individual participated in the intervention. Data on both situations cannot be obtained. Therefore, the counterfactual situation of non-participation in the intervention is only hypothetical for the participants (the treated group) and cannot be measured. In practice, this problem with missing data is solved by creating a comparison (or control) group of non-participants (non-treated group), who are as similar as possible to the participants in terms of their individual characteristics and other contextual variables. Using this comparison group, we create the counterfactual situation that provides missing data for the comparison with the treated group.

1.1 Literature review

In the literature, we come across studies that evaluate the effectiveness of various ALMP instruments that target different population groups. The study by Caliendo and Schmidl (2016) examines ALMPs in Europe, discussing the advantages and disadvantages of different active policies.
They also provide an overview of recent evidence on the effectiveness of policies targeting young people living in Europe, focusing on a total of 37 already published evaluations. They highlight the factors that, according to them, support or hinder the effectiveness of these measures in practice. Kluve et al. (2019), in their meta-analysis, examine 113 already realised impact assessments of youth ALMP programs worldwide. The conclusions reached by the authors of this study provide practitioners with answers to questions regarding those elements that are essential and contribute to the success of youth employment programs.

Costabella (2017) discussed the evaluation of the effectiveness of intensive educational courses in Italy. These types of Italian educational courses are primarily intended for young high school graduates. The impact of the training on its participants is estimated using a counterfactual approach, comparing the participants with a control group of individuals who did not participate in the training. The analysis focused on the monthly employment rate and the number of weeks that the individuals worked during one year. These indicators were measured four years after the beginning of the program. The results suggest that those individuals who participated in the program were approximately 10% more likely to get a job. Likewise, the treated group worked about 10–15% percent longer compared to individuals who did not attend the training courses. Similar results were achieved by Popescu and Roman (2018) in their study aimed at the impact evaluation of vocational education on employment in the Romanian labour market conditions. The authors found that participation in the training increased the chances of employment by 15%. The authors also identified the population groups where the program works best, especially women and people living in urban areas.

In Piedmont, the impact of vocational training on unemployment was investigated by Donato, Migliore and Poy (2018). In this study, the propensity score matching method was used to evaluate the impact. The authors concluded that this type of program has the greatest impact on the short-term unemployed, young people, and those who attended courses for a longer period. Cappellini et al. (2019) conducted a more in-depth analysis of the counterfactual evaluation of traineeships as one of the ALMP measures aimed at young people in Italy. The results of their study estimate that participation in a given intervention increases the probability of finding quality employment by seven percentage points.
In the study by Pirciog, Ciuca and Popescu (2015), the authors further evaluate the benefits of vocational education in Romania using the propensity score matching method. The results indicate that the measure was not effective during the monitored period because a year after the implementation of the measure, a treated individual is more than 8% less likely to be employed than a non-treated individual. The authors’ collective Bratti et al. (2021) analysed the effectiveness of vocational training aimed at unemployed young people in Latvia. However, even in this case, participation in the program did not lead to statistically significant positive effects on the observed outcome variables in the labour market.

Hora and Sirovátka (2020) use counterfactual impact evaluation methods for an apprenticeship program in the neighbouring Czech Republic. The study is based on data provided by the Czech Labour Office. Their results suggest that the program is successful for those groups of young people who are less disadvantaged in terms of their educational attainment and previous experience with unemployment. Based on the outflow of the unemployed from the register, it can be observed that the program had a low impact on groups of short- and medium-term unemployed, as well as on the groups of low- and highly-skilled youth. However, a stronger impact of this program could be observed in the group of moderately qualified youth and the group of long-term unemployed.

In the Slovak context, Štefánik, Karasová and Studená (2020) deal with the impact evaluation of the contribution to graduate practice. The evaluation results show that participation in this intervention increases the chances of employment during the period after participation. On the other hand, they found that the intervention had a negative impact on the income of employed participants. The same intervention was evaluated by Svabova, Kramarova and Gabrikova (2022). In this study, the authors concluded that graduate practice has a significant impact on the employability of young job seekers and their sustainability in employment, but the effect tends to be short to medium-term.

Recently, especially in foreign literature, we have noticed a growing interest among authors in the use of data mining methods in impact evaluations. It can be assumed that the propensity score could be estimated more precisely using the data mining methods, leading to a more accurate matching of treated and control individuals. However, in Slovakia, we have not identified this approach in existing studies aimed at the impact evaluation of ALMP programs. Therefore, with this study we aim to fill this research gap. At the
same time, only a few impact evaluations of ALMP intervention programs have been carried out in Slovakia so far, even though the graduate practice belongs to those that the authors are more focused on. The main goal of this study is to quantify the impact of this intervention on the employment of its participants during the two-year impact period after the end of the program by using the data mining method of binomial trees to create a model for propensity score. Our hypothesis is that the graduate practice intervention improves the employability of the participants after the end of the program, so we expect a positive impact of this program on its participants. We hypothesise that this impact is only short or medium-term; and we do not expect a long-term effect of this program. Moreover, we hypothesise that the intervention has a positive, but rather low, impact on the participants’ wages.

The rest of the article is organised as follows. The following section briefly explains the conditions for the provision and operation of the graduate practice intervention. Then, the second section aims to describe the methods and data used in this study. The results of this study are then described, followed by a discussion and conclusion.

1.2 Institutional background

The contribution to graduate practice in the context of the Slovak Republic is regulated by Section 51 of Act no. 5/2004 Coll. on Employment Services. The purpose of this contribution is to provide school graduates with professional skills and practical experience with an employer that will correspond to their level of education (Act no. 5/2004 Coll.). For the purposes of this contribution, a school graduate is understood as a citizen who is no older than 26 years, who has completed ongoing daily professional preparation at the relevant level of education less than two years before, and who has not had a regularly paid job since the end of professional preparation. The graduate practice may be carried out on the basis of the agreement on the graduate practice between the Central Office of Labour, Social Affairs and Family (COLSAF) and the jobseeker. Jobseekers must be registered in the COLSAF database of unemployed jobseekers for at least one month (COLSAF SR, 2022).

The graduate practice can be carried out for a minimum of three months and a maximum of six months. During the period of practice, the school graduate remains registered in the register of unemployed jobseekers. The graduate is obliged to perform a graduate practice with an employer who has signed an agreement with the relevant labour, social affairs and family office, that
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2. Methodology and data

In this study, we carried out an impact evaluation of the graduate practice intervention on the employability of its participants and their average monthly wages. This evaluation used the counterfactual approach, which provided highly rigorous results by applying econometric methods. As listed in Cerulli (2015), an impact evaluation is an analysis of causality, and its main aim is to answer the question of whether participation in the intervention led to the change in the value of the outcome variable that measures the participants’ employment. In other words, did participation in the program result in an improvement of the participants’ employability in the period after the end of the program.

In order to quantify this impact, we define the variable $D_i$ which indicates participation in the intervention. Let us mark the situation in the case of individual’s $i$ participation in the measure as $D_i = 1$ and the non-participation as $D_i = 0$. Moreover, we define variable(s) $Y$ as the outcome variable(s) measuring the individual’s employment or wages during the impact period. In this study, we used the following outcome variables, which are listed in Table 1.
Table 1. Outcome variables used in the study.

<table>
<thead>
<tr>
<th>Outcome variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wage</td>
<td>The average monthly wage during the 24-month impact period</td>
</tr>
<tr>
<td>Part-time employed</td>
<td>Duration of registration in SIA as part-time employed in days</td>
</tr>
<tr>
<td>Full-time employed</td>
<td>Duration of registration in SIA as full-time employed in days</td>
</tr>
<tr>
<td>Employed</td>
<td>Duration of registration in SIA as self-employed and full-time employed in days</td>
</tr>
</tbody>
</table>

Source: Authors’ elaboration.

These variables measure the employment process over the 24-month impact period which started after the end of participation in the intervention.

In the counterfactual approach, the employment situation of the intervention participants during the impact period after the program (in this study, 24 months after the end of the participation) is compared to the counterfactual situation of what would have happened if they had not participated in the intervention. Thus, to estimate the impact of the intervention, we need to find the difference in the mean values of the outcome variables:

\[
E(Y|X, D = 1) - E(Y|X, D = 0). \quad \{1\}
\]

We then mark as \(Y_{i0}\) the value of the outcome variable for the individual in case of non-participation, and \(Y_{i1}\) in case of participation in period \(t\) after the intervention. Thus, we can directly formulate the causal effect of the program on the individual’s outcomes as the difference \(Y_{i1} - Y_{i0}\). This difference expresses the treatment effect at the individual level. For simplicity, we can label the outcome variable for the situation of non-participation as \(Y_0\) and for the participation as \(Y_1\). Then, the impact of the intervention can simply be quantified as the difference \(Y_{i1} - Y_{i0}\) at the individual level, or just \(Y_1 - Y_0\) at the population level (Morgan & Winship, 2014).

The main problem of this approach is that the counterfactual situation of non-participation is only hypothetical; we cannot measure the individual’s employment in case he or she had participated in the intervention and the situation of the same individual in case he or she had not participated (Frondel & Schmidt, 2005). Every individual can either participate or not. Thus, we are not able to obtain data for the treated individuals in either of
these situations; thus, only one of the two values of outcome variables can be observed. This is called the “fundamental problem of causal inference” (Trivellato, 2011; Wooldridge, 2010). In fact, we can measure the outcomes \(Y_1\) for the intervention participants \(D = 1\), but the counterfactual outcomes \(Y_0\) are unobservable for them. Similarly, for the intervention non-participants \(D = 0\), only the values of \(Y_0\) are measurable, but \(Y_1\) are not. This means that only the value of the expected outcome \(E(Y_1 | D = 1)\) in \{1\} can be estimated from the observable data on the intervened individuals, but \(E(Y_0 | D = 1)\) cannot be.

This problem of non-measurability of the counterfactual situation cannot be solved by collecting more data on treated individuals or measuring suitable variables. It can only be solved by finding a suitable comparison (control) group of the intervention non-participants (called non-treated) (Frondel & Schmidt, 2005). For the intervention non-participants, we have the values of the outcome variables in the situation without the intervention. Thus, this group is suitable to compensate for the missing data if it is similar enough to the group of intervention participants. If the so-called conditional independence assumption (CIA) holds that there are no significant differences in the group of intervention participants (treated group) and non-participants (non-treated group), that would affect the impact of the program (the values of outcomes \(Y\)). That means participants of the measure and their counterparts are so similar in their characteristics that any difference in their outcomes can be ascribed to participation in the measure.

Under the validity of the CIA, we can express the total average treatment effect (ATE) as the difference

\[
ATE = E(Y_1 - Y_0) = \{P(D = 1) \cdot E(Y_1 | D = 1) + P(D = 0) \cdot E(Y_1 | D = 0)\} - \{P(D = 1) \cdot E(Y_0 | D = 1) + P(D = 0) \cdot E(Y_0 | D = 0)\},
\]

and the average treatment effect on the treated (ATT) as

\[
ATT = E(Y_1 - Y_0 | D = 1) = E(Y_1 | D = 1) - E(Y_0 | D = 1).
\]

If a CIA is valid, instead of the mean difference \{1\}, it is possible to estimate the intervention impact on the population by \{2\} and on the treated by \{3\} by replacing the unobservable values from the treated group with the values from the control group (Cerulli, 2015).

Then, the impact of participation in the intervention program is quantified using the values of the outcome variables (Table 2).
To ensure the validity of the CIA and to create the most accurate counterfactual situation for the treated individuals, the control group is usually created by matching the non-treated individuals to the treated ones based on their pre-intervention characteristics. This matching can be done using various techniques; the most accurate is exact matching, where the non-treated individual is matched with the treated one when they have exactly the same values of selected pre-intervention characteristics (Wooldridge, 2010). However, the problem with this method is its dimensionality and low degree of exact matches in both groups. Thus, the most widely used method for matching is propensity score matching, where the exact match of the pre-intervention characteristics is replaced by the matching of the so-called propensity score. This score represents the probability of participation in the intervention and is estimated using the observable characteristics of population units.

To estimate the individuals’ propensity scores, we used the method of classification and regression trees (CART). CART is a kind of decision tree that can provide a probability of treatment (Westreich, Lessler & Funk, 2010).

The difference between classification and regression trees is very simple. Classification trees are used in cases where the outcome variable is categorical, and regression trees are used in cases where the outcome variable is continuous (Breiman et al., 1984). CART is made up of nodes and branches (Künnapas, 2021). The tree starts with a single node (the root) to which the entire data file belongs, which is then binary divided into other nodes. In each node of the tree, a dividing variable is defined based on which the data set is divided into two groups, as well as the cut-off value of this dividing variable, which determines the value at which the division should take place (Shmueli & Mani, 2013; Berk, 2008). In our study, the root is a group of all individuals in the study, both treated and non-treated. Then, the first division is created using the variable that most significantly distinguishes the groups of treated and non-treated, and the division cut-off value of this variable is set as the criterion. This division leads to two groups (nodes), one in which prevails the treated group and the second in which prevails the group of non-treated. Both these nodes are then further divided according to the second variable and its cut-off value. The tree is complete when the set criteria for its creation are met. Each branch terminates in a node, which we call a leaf. Finally, the estimate of the propensity score for every individual is then calculated simply as the product of the probabilities, that is, the proportions of treated and non-treated individuals in each leaf.
For the CART model, and thus for the estimation of propensity scores, the variables listed in Table 2 were used.

**Table 2. Variables used in the study.**

<table>
<thead>
<tr>
<th>Variable name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treated</td>
<td>Participation in the intervention, i.e., identification of the individual’s inclusion in a treated group or control group</td>
</tr>
<tr>
<td>School</td>
<td>The last graduated school of jobseeker</td>
</tr>
<tr>
<td>Age</td>
<td>Age at entry into the database of jobseekers</td>
</tr>
<tr>
<td>Age shifted</td>
<td>Age at the beginning of the intervention</td>
</tr>
<tr>
<td>Previous registration</td>
<td>Cumulative time of previous registrations in the database of jobseekers</td>
</tr>
<tr>
<td>Profession</td>
<td>Last profession of the jobseeker before the registration</td>
</tr>
<tr>
<td>Duration of registration</td>
<td>Duration of the last registration in the database of jobseekers in days</td>
</tr>
<tr>
<td>Gender</td>
<td>Jobseeker’s gender</td>
</tr>
<tr>
<td>Marital status</td>
<td>Jobseeker’s marital status</td>
</tr>
<tr>
<td>Education</td>
<td>Degree of the highest completed education</td>
</tr>
<tr>
<td>Region</td>
<td>Region of permanent residence</td>
</tr>
<tr>
<td>Disadvantages</td>
<td>Jobseeker’s disadvantages according to Act no. 5/2004 on employment services, § 8 Disadvantaged jobseeker</td>
</tr>
<tr>
<td>Driving licence</td>
<td>Ownership of driving licences of individual categories</td>
</tr>
</tbody>
</table>

Source: Authors’ elaboration.

The tree was pruned to avoid the problem of overfitting. The propensity score of each individual, both treated and non-treated, was then estimated using the generated tree. These estimated propensity score values were then used to match the treated individuals with non-treated to create a counterfactual situation for them.

In this study, matching was performed with replacement using the radius matching approach (Khandker, Koolwal & Samad, 2009), with a maximum allowed difference in propensity scores between the matched individuals at 0.0004. Matching by replacement means that one non-treated individual can be matched to several treated individuals.

The matching resulted in samples of treated and non-treated jobseekers who were as similar as possible in terms of the probability of their participation.
in the graduate practice intervention. The groups thus created were then used to assess the impact of the intervention. This impact was quantified using the outcome variables listed in Table 2. The average treatment effect (ATT) on the treated is then calculated as the difference in means of outcome variables between the group of treated and non-treated individuals (Khandker, Koolwal & Samad, 2009).

Data on the unemployment of all registered jobseekers used in this study are from the database of jobseekers, managed by the COLSAF SR. Data on the employment and monthly wages of individuals come from the database of the Social Insurance Agency (SIA) of the Slovak Republic (SR).

Extensive preparation of the dataset preceded the creation of the propensity score model. First, it was necessary to carry out logical controls in the data, for example, the correct time sequence of the dates of registration in the database of jobseekers and the start of the intervention, eligibility controls of the participants for the intervention, such as the age and minimal duration of registration and, finally, controls about the course of the intervention. This database preparation resulted in the dataset of 83,907 non-treated and 12,953 treated individuals. Then, it was necessary to prepare and complete all the variables (listed in Table 1) in the required form.

Treated individuals participated in the intervention in the period between October 1, 2014 and December 31, 2015. Every individual was assigned an impact period that started after the end of the graduate practice and lasted 24 months. The impact periods of the treated participants cover the years 2015–2017. Thus, the whole study covers the period from October 1, 2014 to December 31, 2017. All these time limits were related to the availability of data from the COLSAF and SIA SR.

The gender composition of the sample is shown in Figure 1. It can be noticed that women predominate among the participants of the graduate practice, and men predominate among the non-treated. Based on this, we can say that women are more interested in this intervention.
Figure 1. Gender composition of the sample.

Source: Authors’ elaboration.

The composition of the sample in terms of highest education is shown in Figure 2.

Figure 2. Composition of the sample in terms of education.

Source: Authors’ elaboration.
The largest share of participants and also non-participants had upper-secondary vocational education. We see a strong interest in the graduate practice among individuals with a university education. On the contrary, individuals with low levels of education had very little interest in the intervention.

Figure 3 shows the composition of the samples according to the region of the jobseeker’s permanent residence. It shows that the Presov and Kosice regions have the highest number of unemployed individuals, which also applies to young people. In these two regions, the interest in participating in the analysed intervention was also the highest among all regions of Slovakia.

**Figure 3.** Composition of the groups in terms of permanent residence.

All calculations in this study were performed using the IBM SPSS Statistics software, version 26. A significance level of 0.05 was used in the hypothesis tests.
3. Results

After the first step of preparing the samples of treated individuals and their control individuals, the next step of the impact evaluation was the creation of the CART tree. This model classifies the individuals into the treated or non-treated group, with the classification based on the values of independent variables, and results in a prediction of the individual’s propensity score value. Due to the complexity of the model, we list it in the Appendix. The tree structure determines the branching according to the cut-off values of variables.

The first variable determining the tree branching is age shifted (individual’s age at the start date of the intervention) with a cut-off value of 20.675 years. In the following branches, the variables degree of education (with more values, i.e. degrees of education used in the tree structure), previous evidence (cut-off value 180.5 and 196.5 days), disadvantages (with values long-term unemployed and school-leaver) and age (individual’s age in the date of entering the jobseekers’ database) with cut-off value 19.5 years create the tree. These variables and their cut-off values determine the whole tree. Using this tree structure, we get the prediction of the classification of an individual with certain probability into a group of graduate practice participants or a control group. This probability of an individual’s classification into the treated group represents his or her propensity score.

The created CART model has the value of the risk estimate at the level 0.07, so it correctly predicts 93% interest or no interest in the intervention participation. Thus, it is incorrectly predicted in 7% of the cases. This fact is illustrated by the classification table in Table 3.

Table 3. Classification table of the created CART model.

<table>
<thead>
<tr>
<th>Observed group</th>
<th>Predicted group</th>
<th>Correct classification</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Non-treated</td>
<td>Treated</td>
</tr>
<tr>
<td>Non-treated</td>
<td>83,420</td>
<td>487</td>
</tr>
<tr>
<td>Treated</td>
<td>6,301</td>
<td>6,652</td>
</tr>
<tr>
<td>Overall percentage</td>
<td>92.6%</td>
<td>7.4%</td>
</tr>
</tbody>
</table>

Source: Authors’ elaboration.
With an overall percentage of correct classification at 93%, we consider the model a good classification model because it correctly classifies up to 93% of all cases. In any case, we have to say that it better predicts that the individual will not be interested in participating in the graduate practice, with a 99.4% correctness rate in the non-treated group. On the other hand, the correct classification of the treated group is 51.4%.

The created CART model served for the estimation of the propensity score for every individual in both groups. Subsequently, the propensity score values were used for matching the treated individuals with the controls. We used radius matching with the tolerance level of 0.0004, and the matching was done by replacement. By matching, we obtained 13,744 pairs of treated and control jobseekers. These have such similar propensity score values (and thus individual values of variables) that we can say that a change in their outcome variables is caused by their participation in the graduate practice intervention. The equality of means of the outcome variables for the matched groups was tested using the t-test. The results are presented in Table 4.

**Table 4.** Independent samples t-test.

<table>
<thead>
<tr>
<th>Variable / Test</th>
<th>Levene’s test for equality of variances</th>
<th>t-test for equality of means (equal variances not assumed)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>F</td>
<td>Sig.</td>
</tr>
<tr>
<td>wage</td>
<td>36,245.20</td>
<td>&lt; 0.05</td>
</tr>
<tr>
<td>employed</td>
<td>51,642.60</td>
<td>&lt; 0.05</td>
</tr>
<tr>
<td>part-time employed</td>
<td>8,199.10</td>
<td>&lt; 0.05</td>
</tr>
<tr>
<td>full-time employed</td>
<td>38,227.10</td>
<td>&lt; 0.05</td>
</tr>
</tbody>
</table>

Source: Authors’ elaboration.

According to the p-values, the means of the outcome variables (wages, employed, part-time and full-time) of the matched treated and control groups are significantly different. The average monthly wage of the treated individuals was almost 217 euros higher than that of the matched controls during the impact period. Moreover, the employment of the treated individuals (as full-time employees or self-employed) lasted on average more...
than 97 days longer than that of non-treated controls during the impact period. Part-time employment of the treated group was on average almost 16 days longer, and full-time employment was on average more than 76 days longer than that of matched controls.

4. Discussion

In this study, we focused on the impact evaluation of graduate practice intervention on the employment of young school graduates and their average monthly wages. Studies by other authors in Slovakia have focused more on ALMP measures but have also analysed the graduate practice intervention (Borik et al., 2015; Harvan, 2011). Among these, the study by Štefánik et al. (2014) found that the graduate practice intervention proved to be one of the most effective measures. Štefánik et al. (2020) address a similar issue in their study. The authors evaluated the impact of graduate practice using an instrumental variable method, with the instrumental variable being travel time to the nearest COLSAF office. They used propensity score nearest neighbour matching and kernel matching. According to the authors, this intervention had a long-term positive impact on the participants’ employment. However, they also found a negative intervention impact on the income of the participants. Svabova and Kramarova (2021) investigated the same intervention graduate practice in 2016–2017 and found a positive impact on employment, but it did not turn out to be statistically significant. Unlike the previous study, the impact of the intervention on the wages of the treated participants was positive and significant.

Among the studies pointing to the positive effect of a similar instrument of active labour market policy carried out in the countries of the European Union, one could mention the study by Costabella (2017), who found a positive effect of vocational training on the probability of employment in Italy, especially for young people who participate immediately after leaving school. The positive effect of vocational training in Italy was also evaluated by Bazzoli et al. (2018). Traineeships also have a positive effect on youth employment in Italy (Cappellini et al., 2019). A positive effect can also be observed in Romania, where participation in a vocational training program increases the chances of employment by 15% (Popescu & Roman, 2018). However, it should be mentioned here that the programs for young people vary across the EU countries, as do the conditions for their implementation and the eligibility of participants.
It can be said that the studies aimed at the impact evaluation of the graduate practice intervention in Slovakia showed a positive impact, where the evaluations were carried out using different methods and focused on different periods. We dare to say that this intervention certainly has a positive impact on the participants’ employability and, according to several studies, also on their wages. The positive effect of similar types of tools can also be observed abroad, underlining the importance of such tools of an ALMP for young people. In the continuation of this study, we would like to use new data from the period up to 2020 to update and validate the results. It would also be interesting to analyse the impact of the Covid-19 pandemic on the use of ALMP measures in Slovakia, as according to the already published data, there was a significant decrease in the use of the commonly used measures, among them also the graduate practice.

5. Conclusions

The study evaluated the impact of the graduate practice intervention as one of the ALMP instruments in the Slovak Republic. This measure in Slovak Republic is offered on a voluntary basis to young jobseekers. The program’s primary goal is to assist young graduates in developing their professional abilities and getting their first real-world work experience. Young graduates under the age of 26 are eligible for this program. They must also be registered in the COLSAF SR database of jobseekers for a mandatory period.

To evaluate the allowance for graduate practice, we used the database of jobseekers, managed by the COLSAF SR, and the SIA SR database for tracking the employment history of the individuals involved in the study. After the data had been properly formatted, the database contained 83,907 non-treated control subjects and 12,953 participants of the graduate practice intervention. The impact of the intervention was quantified in the period from 2015 to 2017. Even though we followed the indicated period in our study, the findings are nevertheless relevant for several reasons. First of all, the legislation regulating this allowance’s provision has not undergone any changes from the monitored period until the present, and there have also been no significant changes in the Slovak labour market (with the exception of the Covid-19 pandemic, which affected the entire labour market in Slovakia and has an impact on the use of all ALMP programs, but the conditions for their use did not change due to the pandemic).
We used the propensity score counterfactual impact evaluation to assess the effects of the graduate practice intervention on the participants’ employability and wages. Using this approach, we calculated the propensity score values of each individual using the classification and regression tree. The classification ability of the CART is up to 93% for all cases; thus, it can be considered sufficiently strong to predict interest or lack of interest in participating in the intervention. After estimating the propensity score values of each participant, we used the radius matching technique to match treated individuals with non-treated counterparts.

Based on the results of the testing for differences in the means of the outcome variables, we can conclude that there are significant differences between the means of wages, employment (total), part-time employment, and full-time employment between the treated group and the matched non-treated control group. The monthly wage of the treated group was almost 217 euros higher than that of the non-treated group. Moreover, during the impact period, the employment of the treated individuals (as full-time workers or self-employed persons) lasted on average more than 97 days longer than that of the non-treated individuals. Compared to the matched controls, the full-time employment of the treated group lasted on average more than 76 days longer and the part-time employment more than 16 days longer. Thus, the results demonstrate the positive effects of the graduate practice contribution on participants’ employment and wages during the impact period.

In addition to the positive effects mentioned above, the intervention has provided considerable benefits to young people, which, however, cannot be quantified. The benefits are that young people acquire their first work habits and experiences as a result of this intervention, and can network with potential employers. In order to achieve the targeted outcome, which is to reduce youth unemployment rate, it is imperative to continue to rationalise the circumstances in which the given intervention operates, as reflected in the number of people treated.

Recent pressure from the European Commission has also increased the use of evaluation techniques for empirically assessing the effects of EU cohesion policies (Potluka et al., 2016). Additionally, as impact evaluations are required under EU Regulation no. 1303/2013, EU Member States must implement them.
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References


Appendix