The effects of training on Romanian migrants' income: a propensity score matching approach

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THE EFFECTS OF TRAINING ON ROMANIAN MIGRANTS' INCOME: A PROPENSITY SCORE MATCHING APPROACH[1]

Abstract:

Training programs are an important tool of human resource management, especially in case of technological and organizational changes inside a company. According to the human capital theory, trainings generally lead to increased post-training wages. Having this into consideration, this paper aims to evaluate the effects of trainings on the Romanian migrants' income by conducting propensity score matching, as a novelty in the field. Both the treatment group and the control group were selected from an online survey conducted in 2010 upon the Romanian migrants worldwide. The results confirmed the human capital theory, indicating that after attending trainings Romanian migrants should expect higher incomes.

Keywords: *Training, Migration, Income, Propensity Score Matching, Survey*

JEL Classification: R23, J61, J68

1. Introduction

Training programs are an important tool of human resource management in the case of technological and organizational changes inside a company. According to the human capital theory, both general and continuous trainings are likely to increase post-training wages. However, the wage effect of general training is expected to exceed the wage effect of firm-specific training, since generally-trained workers have transferable skills to other firms, while specifically-trained workers have skills that can only be used productively within the training firm.

Having this into consideration, this paper aims to evaluate the effects of trainings on the Romanian migrants' income by using propensity score matching

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technique. Since this approach of counterfactual analysis on the topic concerning Romanian migrants is quite new, this paper is assumed to bring novelty in the field. The structure of the paper is the following: in Section 2 a brief literature review of the topic is presented, while Section 3 is dedicated to the specific methodology of propensity score matching. In section 4 the data set is described, while the model and variables are presented in section 5. The results of the analysis are presented in section 6, while the conclusions are drawn in the last section.

2. Literature review

The literature review concerning the evaluation of the impact of training programs upon individual earnings is quite generous and most of the studies have focused on non-randomized cases. Starting with Rosenbaum and Rubin (1983) the propensity score matching (PSM) method was proposed in the evaluation problems, as a method to reduce the bias in the estimation of treatment effects with observational data sets. Since then, this method has become increasingly popular in the evaluation of both in medical trials and economic policy interventions.

For instance, LaLonde (1986) studied the possible effect of participation in a job training program on individual earnings in 1978 by using a dataset from the National Supported Work experiment (NSW), which was later on used in several other studies with similar results (Herryman, 2010; Becker and Ichino, 2002).

In LaLonde study (1986) the treatment variable consisted in the participation in the job training program, while the outcome was set as the earnings of the individuals in terms of 1978 dollars. The data set also included some information on pre-treatment, such as: age, years of education, real yearly earnings in 1974 and in 1975, the afro-american and the hispanic-american status, the marital status, education and unemployment rates. The results after applying PSM show that the training programs have a positive and significant impact on earnings.

Hollenbeck et al. (2003) proposed a quasi-experimental study of the net impacts of trainings provided under the Workforce Investment Act (WIA) in 1998 on the employment and earnings of participants in seven states of the U.S.A. The study focused on individuals who exited the program in 2000, in order to compare their labour experiences during the first four quarters after exit to those of comparable individuals who were registered for WIA but did not receive training services. The results once again confirmed that the treatment had a positive impact on quarterly earnings for adults, but with considerable variation across participant subgroup (i.e., adults and dislocated workers) and across states.

In a similar study, Heinrich et al. (2013) estimated the impacts on earnings and employment of the two primary adult workforce support and training programs under the U.S. WIA using administrative data on 160000 participants from 12 states for up to four years following program entry. Their main findings suggested that participants in the WIA Adult program improved employment levels and increased average quarterly earnings of several hundred dollars.

Moreover, Lauringson et al. (2011) tried to find out if the labour market training measure provided by the Estonian Unemployment Insurance Fund in 2009 and 2010 had an impact on the labour market outcomes of the participants in the training. The results indicated both a significant positive impact of trainings on wages and on employment when assessing it through the PSM method. Besides that, when broken down by the various socio-demographic characteristics (gender, age, unemployment duration, education) the results indicated that training was more useful for women, for elderly persons with a lower level of education and for those who had been unemployed for a shorter period of time. Moreover, the cost-effectiveness of the training program was confirmed by the cost-benefit analysis conducted on the basis of the 2010 estimations.

In another recent study, Wordofa and Sassi (2014) studied the impact on farm income of the Farmer Training Center (FTC) implemented by the government of Ethiopia to improve smallholder farming systems. Thus, a household survey was conducted on a sample of 250 household heads in FTC and non-FTC in 2013 and propensity score matching procedure was conducted to estimate the causal effect of an FTC-based training on farm income. The results of the investigation indicated a positive and statistically highly significant gain of farm income by the participants of the training.

When considering program evaluation of longer-term job training programs, Card et al. (2009) discovered that longer-term job training programs tended to have small or even negative impacts on employment or on earnings in the first year, but positive in the second or third years. This fact could presumably reflect the "lock-in" effects due to withdrawal from the labour market during training.

In contrast to the vast majority of empirical studies, Muehler, Beckmann and Schauenberg (2007) focused on the wage effects of continuous training, separated by general and firm-specific training programs. Using data of the German Socio Economic Panel (GSOEP) they applied nonparametric matching estimators to explicitly account for observed and unobserved differences between training participants and non-participants. Their main findings consisted in the fact that general training yields a significant 5% to 6 % increase in wages, whereas the effects of firm-specific training are mostly insignificant. These results are consistent with standard human capital theory as general training is associated with larger wage increases than firm-specific training.

PSM was also successfully applied for identifying the effects of training on migrants' income. Most of the studies have compared migrants with natives. Therefore, Aldashev et al. (2010) evaluate the effects of some short-term off-the-job programs, such aptitude tests, job search training, skill provision and combined training programs. The research was conducted separately for natives and immigrants living Germany and the authors find that aptitude tests and skill provision have positive treatment effects for all participants and immigrants benefit more than natives.

3. The methodology

The matching process actually involves pairing treatment units with comparison units that are similar in terms of observable characteristics. According to Dehejia and Wahba (2002) matching methods can generate unbiased estimates of the treatment impact only if the relevant differences between any two units are captured in the pre-treatment covariates.

Propensity score matching (PSM) is a semi-parametric estimation that first implies a parametrical estimation of the propensity scores y, followed by a non-parametric comparison of these propensity scores. After the matching is conducted based on distinct algorithms, finally the matching quality is checked and the medium impact of the treatment can be determined.

In the classical binary treatment case of treatment versus non-treatment, the propensity scores are normally estimated by either a logit or a probit model. The logit model is described below:

$$\Pr(T_i = 1 \mid X_i) = \frac{e^{\lambda h(X_i)}}{1 + e^{\lambda h(X_i)}}$$

where T_i is the treatment status (equals 1 in case of treatment and 0 in case of no treatment) and $h(X_i)$ is made up of the covariates that influence the participation to treatment.

On the other hand, the probit model has the following general form:

$$\Pr(T_i = 1 \mid X_i) = \int_{-\infty}^{X_i} \varphi(t)dt = \varphi(X_i)$$

where $\varphi(X_i)$ is the normal density function:

$$\varphi(X_i) = \frac{\exp(-\frac{X_i^{\,2}}{2})}{\sqrt{2\pi}}$$

Next, the matching between treatment units and non-treatment units according to their scores is conducted through a matching algorithm. There are several matching methods proposed in the literature, out of them the most widely used are: the Nearest-Neighbour Matching (with or without caliper), the Radius Matching, the Stratification Matching and the Kernel Matching.

The nearest-neighbour method (NN) selects the comparison units with the propensity scores closest to a specific treated unit. In the context of matching on the propensity score, the simplest distance metric is:

$$d(i,J) = \left| p(X_i) - \frac{1}{|J|}\sum_{j \in J} p(X_j) \right|$$

where i is typically a treated unit, J is a set of control units ($|J|$ denotes the cardinality of J), while $p(X_i)$ is associated to the probability of a unit i having been assigned to treatment.
The objective then would be:

$$\min_{m(\cdot)} D = \frac{1}{n}\sum_{i=1}^{n} d(i, m(i))$$

where $m(i)$ denotes the set of control units matched with the treated unit i, and where we sum over the n treated units since we are estimating the treatment effect for the treated population. If the treated units are exactly matched to controls, then D=0.

NN Matching actually involves a trade-off between bias and variance since matching just one nearest neighbour minimizes bias at the cost of larger variance, while on the contrary matching using additional nearest neighbours increases the bias, but decreases the variance. A downside of the NN matching is that the difference in the propensity scores of a treatment and its closest matched neighbour may still be very high, resulting in poor matches.

One way out of such a problem consists in imposing a tolerance level on the maximum propensity score distance (called a caliper or radius). The caliper matching uses all of the comparison units within a pre-defined propensity score radius and has the benefit of using only as many comparison units as are available within the calipers. This way it allows for the use of extra units when good matches are available. However, it can be difficult to estimate a priori a reasonable tolerance level (Dehejia and Wahba, 2002).

The Stratification method consists of dividing the range of propensity scores in intervals so that within each interval, treated and control units have on average the same propensity score. On the other hand, Kernel matching and local linear matching are nonparametric matching estimators that use a weighted average of all individuals in the comparison group to construct the counterfactual outcome. Hence, a key benefit of these methods is the use of more information which leads to lower variance. However, some of the subjects might still be poor matches.

The choice between these algorithms can generally be seen as a trade-off between bias and variance, though these strategies should normally lead to the same estimation results.

After matching, an analysis of the matching quality is required in order to check for differences between the two groups after conditioning on the propensity score (Caliendo and Kopeinig, 2008). One way will be to check balancing, including mean comparisons between treatment and comparison groups, standardized bias and overall measures of covariate imbalance. In terms of mean comparisons, according to Rosenbaum and Rubin (1983) a two-sample t-test before

and after matching can be used to check the existence or lack of significant differences in covariate means between the treated and comparison groups.
However, to what extent the different matching procedures reduce the original bias cannot be visible from t-test results only.

4. The data set

For empirical analysis we use data from Romanian Emigrants Survey, conducted during August-December 2010. The survey was performed by a research team from The Bucharest University of Economic Studies in order to provide valuable information on Romanian migrants worldwide. The data were collected through an online survey and the respondents were asked to answer on a variety of topics including income, employment, graduated studies both in Romania and in emigration country, length of migration, remittances and intention to return to Romania. The dataset consisted of 1514 respondents from more than 20 countries. Although according to the data of the Romanian National Institute of Statistics there are about 2.7 million Romanians abroad, if we were to consider only the employed migrants, the figure would be smaller. Because there is no complete information about structure, precise volume and dispersion of the migrant population of Romania, the issue of representativeness of the sample is relatively difficult to prove through classical survey methods.

The collected data was responsive to the purposes of the present research, containing relevant information on education of Romanian migrants. The migrants were asked to specify the highest level of education graduated in native country and for comparability reasons International Standard Classification for Education (ISCED) was used. The respondents were also asked to specify the institution they graduated and, in the case of students, the number of years studied in Romania before graduation. Eventually, the respondent was asked to specify if he/she has taken any courses in destination country and the education level of the courses. The "other professional training courses" refers to the professional training the migrant received abroad, without detailing the type of the courses, the length or the institutions that provided the courses. In our research we aim at analyzing the effects of taking this kind of training on migrants' economic performance.

The economic performance of migrant could be captured by migrants' economic status (see Heinrich et al., 2013) or by the income, such in Wordofa and Sassi (2014). Both variables are available in the dataset, and they are strong candidates for measuring the effect of the treatment.

The dataset also provide information on the personal characteristics of migrants and the country of residence. One of the important advantages of using the RES dataset is that data concerning treatment receivers and non-receivers are collected in the same manner, and in the same manner- the online survey-is also collected the outcome variable. This is a valuable argument for an increased accuracy of our results.

5. The variables

The starting point in applying Propensity Score Matching is to define the groups of treated and non-treated migrants and also to decide what is the outcome variable. The population of interest in this study is defined by those migrants who took professional training courses while living abroad and they constitute the treated group.

The Romanian migrants in the sample were asked if they have followed any form of education abroad. Out of the 1514 respondents, 819 have followed courses in destination country, while the other part (695 persons) did not take any kind of training aboard. The question was further detailed by asking the respondent to specify the kind of education he/she has received abroad: vocational school, high school, college, master program, doctoral studies and professional training courses. The subgroup of the respondents that have taken professional training courses in destination country is therefore the group of treated persons and amounts 391 migrants, as presented in the descriptive statistics (Table 1).

The control group consists in respondents that did not take any kind of education abroad gathering all the education and training in the country of origin. They amount 695 persons.

The relevant outcome variable for the treatment and the control group is the income after the treatment or non-treatment, therefore the income in the moment of the interview for the persons belonging to the two groups. The income is an interval variable, having 11 values corresponding to 11 equal intervals ranging from less than 500 USD to more than 5000 USD. The indicator is expressed in USD, for the comparability reasons. The average income of the total sample is 5.622, corresponding to an average of 2811 USD. We have also considered the employment status as a potential outcome, but the variable proved to be irrelevant due to a small variation, since the largest share of migrants (86%) were working as employers, employees, workers in own household or in agriculture, self-employed.

After having defined the treatment group, the control group and the outcome variable, the propensity of receiving treatment or the propensity of having followed courses abroad is estimated based on a number of observable characteristics that affect both the treated and the control group. These are introduced as the supporting covariates in a binary regression model.

According to Caliendo and Kopeinig (2008), when selecting variables into the binary model in order to estimate the propensity scores, it is advisable to include all the variables which simultaneously affect both the participation in treatment and the outcome variable of interest. Therefore, the challenge in developing the model was to find all those observable characteristics that affect both the participation in training programs, as well as the outcome.

For selecting the covariates, we rely on economic theory and prior research results concerning the program participation in order to find the best selection of variables. We have considered several types of characteristics: demographic characteristics, regional characteristics and characteristics that counts for migrant's integration in receiving country. Taking this into account and in order to control for background information which could possibly influence the labour market performance of an individual, the following demographic variables are used for the calculation of the propensity score: age, gender, the highest education level attended and marital status.

As most of these variables are nominal, dummy variables were created for all of the above characteristics except for age. These dummies are indispensable for a reasonable interpretation, but they also lead to problems of multicollinearity and drop outs as described later in the analysis section. The variable education contains eight dummies according to the Romanian school system. Human capital of Romanian migrants was evaluated through the last level of education attended (EDU). Education is a scale variable ranging from 1 to 8 and coded as follows: 1-primary school, 2- vocational school, 3-secondary education (high school), 4-second level of secondary education, 5-first level of tertiary education, 6- higher education, 7-master degree, 8-doctoral studies. Socio-demographic predictors used as regressors include age (AGE), gender (GENDER), coded 1 for males and marital status (MARR), coded 1 for married persons and 0 for other situations: single, divorced, separated or widowed.

Integration in the destination country and in the host labour market was approached by taken into account the number of years since the first arrival in the destination country (TIME ABROAD) and was expresses as integer. Our hypothesis is that migrants better integrated abroad prove a higher income, and also have a higher probability to take professional training courses compared to new arrivals.

Since the respondents were living in a large number of countries, there could be heterogeneity in the definition of professional training courses, depending on education system or labor market regulations in destination country. At the same time, some linguistic courses could be also considered as professional training courses by some respondents. We have no information regarding the length of the courses or the moment when these courses were taken after the migrant's arrival in destination country. We accept such biases, due to the data limitations.

At the same time, we consider that the group of recent Romanian migrants working abroad is quite homogenous in respect with their personal characteristics and economic behavior (Roman, 2012): on average they are young, medium trained, most of them are married and they are mostly recent migrants, with a medium length of migration time of less than 10 years. The differences in treatment effects could be also explained by the differences existing in labor market regulations. The European Union aims at harmonizing the European labor markets and the "Single market act" established in 1992 states the necessity of a single European labor market. Despite the strong efforts that were and still are made for the increased harmonization of European labor markets, there are barriers that need to be overcame. On the other hand, there are clear differences between the European situation and the labor market in the United States, where mobility is much higher. (Krausse et al., 2014). In such circumstances, the regional differences between destination countries were employed with the dummy variable REGION that takes 1 for European countries and 0 for the rest of the world, since most of the Romanians outside Europe live in the United States and Canada.

6. Results and discussion

Table 1 presents the descriptive statistics for the entire sample and separately for the treatment and the control group. The full sample consists of 1086 individuals. 391 individuals meet the requirements of the treatment group, which is an important value in consideration of the full sample size. The entire control group includes 695 individuals, referring to the control group before matching. Male individuals form the biggest part of the full sample with 65%. Among the participants of training program the share of males is similar: 66,5%. The Romanian migrants are young, well educated, most of them are married and with a short migration history.

Table 1. Descriptive statistics

Variable abrevioation	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Total sample					
TREATMENT	1086	0,3600368	0,4802319	0	1
INCOME	1086	5,622468	3,083360	1	11
AGE	1086	36,63996	9,890098	17	76
GENDER	1086	0,6528545	0,4762818	0	1
TIME ABROAD	1086	6,773481	6,076189	1	61
EDU1	1086	0,0211786	0,1440459	0	1
EDU2	1086	0,0451197	0,2076623	0	1
EDU3	1086	0,2265193	0,4187718	0	1
EDU4	1086	0,0561694	0,2303547	0	1
EDU5	1086	0,0349908	0,1838411	0	1
EDU6	1086	0,4373849	0,4962924	0	1
EDU7	1086	0,1436464	0,3508924	0	1
EDU8	1086	0,0349908	0,1838411	0	1
MARR	1086	0,5699816	0,4953064	0	1
REGION	1086	0,6602031	0,4738589	0	1
TREATMENT=0					
INCOME	695	5,1525180	2,990338	1	11
AGE	695	35,1870500	9,590137	17	76
GENDER	695	0,6460432	0,4785404	0	1
TIME ABROAD	695	5,8474820	5,581959	1	61

EDU1	695	0,018705	0,1355788	0	1
EDU2	695	0,057554	0,2330658	0	1
EDU3	695	0,2388489	0,4266873	0	1
EDU4	695	0,0633094	0,2436939	0	1
EDU5	695	0,028777	0,1672995	0	1
EDU6	695	0,4100719	0,4922007	0	1
EDU7	695	0,1553957	0,3625424	0	1
EDU8	695	0,0273381	0,1631842	0	1
MARR	695	0,5223022	0,4998621	0	1
REGION	695	0,6892086	0,4631509	0	1
TREATMENT=1					
INCOME	391	6,4578010	3,073065	1	11
AGE	391	39,2225100	9,900226	17	73
GENDER	391	0,6649616	0,4726086	0	1
TIME ABROAD	391	8,4194370	6,559239	1	60
EDU1	391	0,0255754	0,1580672	0	1
EDU2	391	0,0230179	0,1501524	0	1
EDU3	391	0,2046036	0,4039285	0	1
EDU4	391	0,0434783	0,2041924	0	1
EDU5	391	0,0460358	0,2098312	0	1
EDU6	391	0,4859335	0,5004425	0	1
EDU7	391	0,1227621	0,3285844	0	1
EDU8	391	0,0485934	0,2152918	0	1
MARR	391	0,6547315	0,4760649	0	1
REGION	391	0,6086957	0,4886676	0	1

The propensity score was estimated through *pscore* command in STATA12, which employs a Probit regression model in this purpose. Table 2 shows the results for the Probit regression.

The results are highly significant, but the pseudo R^2 is modest (6,36%) and it is obvious that more variables are needed to overcome unobserved influences. This number shows to what extent the included covariates explain the participation probability and in this case it suggests a rather poor specification. Variable EDU8 was dropped from the model because of multicollinearity, but the remaining results are fairly significant and show the expected sign of coefficients. Age and time spent in destination country are significant variables that increase the probability of taking training courses. The married migrants also have a greater propensity compared to those with other marital status.

On the contrary, the education gathered in the country of origin is decreasing the probability for all the considered education levels. The highest coefficient is noticed in the case of migrants with vocational education, the probability of these migrants being to follow training courses being the lowest. This is connected with the profile of the Romanian migrants that are mostly involved in low and medium skilled jobs so as to qualification attended in home country is satisfactory.

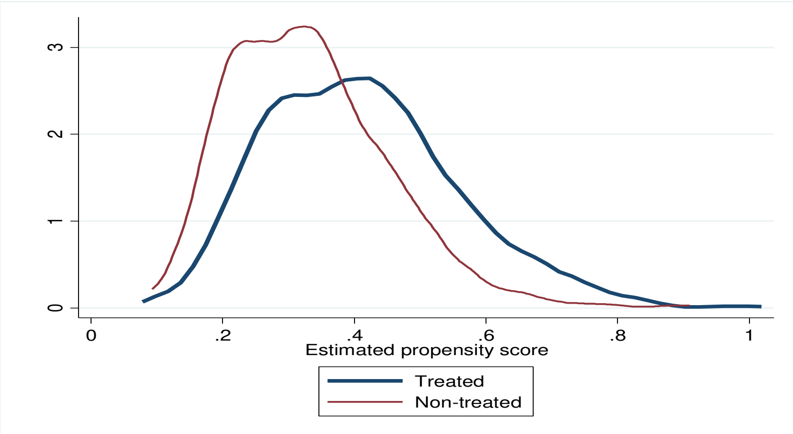
Table 2. The results of the Probit regression model

	Coef.	**Std. Err.**	**z**	**P>z**	**[95% Conf. Interval]**	
AGE	**.0138593**	.004958	2.80	0.005	.0041417	.0235768
GENDER	.0125672	.0850107	0.15	0.882	-.1540507	.1791852
TIME	**.0316994**	.007567	4.19	0.000	.0168685	.0465304
EDU1	-.0847064	.3417385	-0.25	0.804	-.7545016	.5850888
EDU2	-.902424	.2972158	-3.04	0.002	-1.484.956	-.3198916
EDU3	-.4289028	.2245771	-1.91	0.056	-.8690658	.0112602
EDU4	-.7386991	.2705306	-2.73	0.006	-1.268.929	-.2084688
EDU5	-.0073611	.2918654	-0.03	0.980	-.5794067	.5646845
EDU6	-.2698661	.2155213	-1.25	0.211	-.6922802	.1525479
EDU7	-.4627587	.2333912	-1.98	0.047	-.920197	-.0053203
MARR2	**.1803498**	.0876935	2.06	0.040	.0084736	.352226
REGION	**-.1561092**	.0862589	-1.81	0.070	-.3251735	.0129552
constant	-.7445008	.2753497	-2.70	0.007	-1.284.176	-.2048254
Number of obs. = 1086						
LR chi2(12) = 90.27						
Prob. > chi2 = 0.0000						
Log likelihood =-664.5						
Pseudo R2 =0.0636						

Gender is not significantly affecting the probability to take training courses, but REGION is a significant variable. As expected, the Romanian migrants living in Europe have a lower propensity compared to those living outside Europe (mostly in The U.S.A. and Canada). Due to similar requirements for accessing the European labor market and also due to the harmonization of the Romanian education and training system in respect with labor market policies with EU (after Romania entering the EU in 2007), the migrants living in Europe have a lower incentive for taking professional courses abroad compared to migrants living in the rest of the world.

The *common support* option has been selected. The common support condition is valid, as persons with the same characteristics cannot be observed in both the treatment and the control group. The region of common support is [.11751442, .97923002]. Description of the estimated propensity score in region of common support by percentiles is presented in Table A1 from the Annex.

Figure 1. Kernel densities estimates for propensity score.



The optimal number of blocks for propensity score is 7, which in this case ensures that the mean propensity score is not different for treated and controls in each blocks.

The PSM method requires that the distribution of the propensity scores for the treated and untreated groups overlap sufficiently, implying overlap in the distribution of observed characteristics. Actually, this is one of the major advantages of PSM, because it provides an ability to force a direct test of the extent that the distribution of characteristics in the treated and untreated groups overlap.

In figure 1, the Kernel densities estimates are represented for both the treated and control groups. The overlap region is large enough to ensure the strong similarities existing between the two groups in respect with observable characteristics considered in the model. The Epanechnikov Kernel function was employedand the bandwidth was 0.0391.

Test of balancing property of the propensity score was automatically run in STATA12. The balancing property is satisfied and table A2 in the Annex shows the inferior bound, the number of treated and the number of controls for each block.

The next step of our research is to estimate the treatment effects on migrants' income. The estimated average treatment effects of the professional training for immigrants are shown in Table 3, where the average treatment effect on the treated (ATT) is mostly suited for measures on specific groups. The differences in the estimated average income between treated and control groups are statistically significant, as it is proved by the t statistics values reported in the table below. The result obtained with radius matching method has the highest significance, and also provide the highest magnitude of the effect.

Table 3. Average treatment effects on the treated

Mathcing method	n. treat.	n. contr.	ATT	Std. Err.	t
ATT estimation with Nearest Neighbor Matching method	391	267	0.769	0.278	2.767
ATT estimation with radius	391	684	1.188	0.196	6.061
ATT estimation with the Kernel Matching method	391	684	0.786	-	-
ATT estimation with the Stratification method	391	684	0.755	0.210	3.600

As described in section 3, different matching methods were used to ensure that the best identification strategy is employed. It is noticeable that the Nearest Neighbour method, the stratification method and the Kernel matching method yield similar results: having followed training courses leads to an increase in monthly income of migrants with less than 500 USD; on the other hand the Radius method yield to a significantly higher effect.

Taking the results of the stratification method as a basis, the ATT connotes the migrants that have taken professional courses abroad had a higher net monthly income with 375 USD than they would have had if they had not participated in the training programs. Considering ATT estimation with radius, the effect of professional training is larger, leading to an increase in migrants' income of 560 USD.

Different matching methods confirm our research hypothesis: the migrants that have followed training professional courses in receiving countries have a higher income compared with migrants that have not taken any courses abroad. The discussed results are consistent with the human capital theory and they demonstrate that after attending trainings the Romanian migrants should expect higher incomes.

7. Conclusions

As we could conclude from our research is that training programs do play an important role in human resource management, and according to the human capital theory, trainings are likely to increase post-training wages.

This paper evaluated the effects of trainings on the Romanian migrants' income by using a propensity score matching approach. Both the treatment group and the control group were selected from an online survey conducted in 2010 upon the Romanian migrants, in order to compensate for the lack of official statistical data on Romanian working migrants. The final sample consisted in 1086 Romanian migrants, out of which the treated group contains 361 respondents.

By applying different matching methods we conclude that the Romanian migrants that have followed training professional courses in destination countries have a higher income compared to migrants that did not take any courses abroad. The results are consistent with the human capital theory, indicating that after attending trainings the Romanian migrants should expect higher incomes.

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Annex A.

Table A1. Estimated propensity score

	Percentiles	**Smallest**
1%	.1423186	.1175144
5%	.1795863	.11928
10%	.2074736	.1224816
25%	.2593095	.1260727
50%	.343185	
		Largest
75%	.4414569	.8357991
90%	.5419522	.8805373
95%	.6140825	.9094639
99%	.7643861	.97923

Table A2. Propensity score by blocks

Inferior of block of propensity score	Number of observation: control	Number of observation: treated	Total
.1	8	5	13
.15	66	7	73
.2	432	178	610
.4	159	159	318
.6	17	38	55
.8	2	4	6
Total	684	391	1,075