WORKING PAPERS

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Miroslav Štefánik

EXPLORING THE DOSE RESPONSE FUNCTION FOR PARTICIPANTS OF A TRAINING PROGRAMME BEFORE AND AFTER THE HIT OF THE ECONOMIC CRISIS (EVIDENCE FROM SLOVAK ADMINISTRATIVE DATA)

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AUTHOR
Mgr. Miroslav Štefánik, PhD., *Institute of Economic Research SAS*

REVIEWERS
Ing. Mária Širaňová, MA., PhD., *Institute of Economic Research SAS*
Ing. Marek Radvanský, PhD., *Institute of Economic Research SAS*

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ABSTRACT

Exploring the dose response function for participants of a training programme before and after the hit of the economic crisis (evidence from Slovak administrative data)

Submitted article presents evidence for a particular training measure in Slovakia. This measure was implemented with positive impact in 2008 and negative impact in 2011 – 2012. Here we apply a routine to estimate the dose response function, considering the continuous nature of the treatment, by following the length of the trainings in days. Working income during 2 years after the training is used to construct the outcome indicator. Results are estimated separately for male training participants of 2008 and 2011 – 2012. A rich administrative dataset is employed in the analysis. Estimations rely on the concept of generalized propensity score and take advantage of recently introduced estimation methods. The results show substantial differences in the dose response function between the two selected periods. For 2008 participants the function has a U shape, while for 2011 – 2012 participants an inverted U is clearly observable.

KEYWORDS
dose response function, training programme evaluation, propensity score matching, counterfactual impact evaluation, active labour market policy

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Intitute of Economic Research SAS/ Ekonomicky ústav SAV, Šancová 56, 811 05 Bratislava, www.ekonom.sav.sk

CONTACT: miroslav.stefanik@savba.sk

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INTRODUCTION[1]

Evaluation of policy interventions has gained some additional importance as a consequence of the economic crisis. Providing trainings to unemployed under the active labour market policy (ALMP) presents a textbook example of a policy intervention. In this article we are going to analyse the impact of a particular training measure in operation in Slovakia since 2004. In terms of content, the measure covers various training activities; dominantly providing low skill training. Trying to explore related heterogeneity further we try to estimate the dose response function of the duration of the trainings on the income of participants. Moreover, previous studies bring evidence on the differences in the impact the measure had on income of participants when the treatment was operationalized as a binary variable. In 2008, before the hit of the economic crisis, overall impact of participation in the measure on income of participants appeared to be positive. In the post crisis period the impact of the measure showed to become negative.

Thus we have an example of one measure implemented with opposite impacts in different periods of time. Our question in this paper is how this is reflected in the shape of the dose response function when looking at the length of the training as a continuous treatment.

Our methodological approach is rooted in the so called Rubin Causal Model. Under the unconfoundedness assumption observational data are processed in order to identify causal relations between a policy intervention (training) and an outcome (working income of participants). Moreover, the continuous nature of the treatment is considered, specifically looking at the length of the training, measured in days. Comparable methodological approach applied to estimate a dose response function to the length of a training programme was applied in (Kluve, et al. 2012) and (Flores et.al., 2012).

In order to employ a continuous treatment variable, we estimate a generalized propensity score for male participants and consequently apply two non-parametric methods of estimating the dose response function of the length of the training on working income of participants in the period of two years after the training. For this purpose we use rich, country specific, administrative data on registered unemployed provided by the public employment service provider in the country. These are linked with social insurance data obtaining detailed information about working income and employment history of training participants.

Acquired results confirmed the differences in the impact of the measure between pre and post crisis period. The dose response function seems to be U shaped in the pre-crisis period and inverse U shaped in the post crisis period. This suggests that it could be longer trainings (between 30 and 50 days) actually driving the difference in the overall impact of the measure. Yielded estimates are relatively homogenous for both applied estimators as well as robust to selected changes in the identification.

[1] Author would like to acknowledge the great support he received from Michela Bia. She was guiding him through the methodological and data related problems while preparing this paper.

1 MOTIVATION AND DESCRIPTION OF THE TRAINING MEASURE TO BE EVALUATED

The measure whose impact is being evaluated in this paper is one of the measures within the portfolio of active labour market measures provided by the Central Office of Labour, Social Affairs and Family of the Slovak republic (COLSAF). COLSAF is the implementation agency of the Ministry of Labour, Social Affairs and Family and thus the centralised provider of publically funded employment services. The name of the measure is “Education and preparation of the job seeker to find a job on the labour market[2]” and it was implemented since 2004. In this paper we are focussing on two periods of implementation:

- from April to December 2008,
- calendar years 2011 and 2012.

Evaluation periods were selected in order to identify periods homogenous in terms of implementation rules, one before the hit of the recent economic crisis and the other after the hit of the economic crisis. Štefánik (2015) reports positive impact on income of participants before the crisis and negative effects after the crisis.

During these periods the evaluated measure was, the only training measure in the portfolio of ALMP in Slovakia. In this setting, training was provided to all types of registered unemployed. There are no further restrictions neither related to the target group (eligibility), or the thematic focus of the trainings provided. This means that the same trainings could be provided just the day after registration, as well as to a long term unemployed. It also means that the content of the trainings provided could be on several levels of skill complexity and related to various fields. No academic training, or training corresponding to any level of formal education, was provided under this programme. The content of the trainings is strictly applied, as the thematic portfolio is designed based on the assessment of the needs of employers in the particular region. This is done with respect to the qualifications of individuals registered by COLSAF office as unemployed in the region. As a result, mostly low skilled applied trainings are provided. For men it is dominantly trainings on: driving and manipulating a forklift card, private security service employee trainings, welding or elementary skills required in construction. These trainings on focused applied skills are mixed with more general activating trainings, such as how to write a CV, or prepare for a job interview.[3]

1.1 Previous evaluations of the measure

There are few previous evaluations of this particular measure. (Bořík, et al., 2013) evaluated the outcome of participants finishing the trainings before the end of 2009. They conclude that

[2] More details about the programme is available in Slovak at: http://www.upsvar.sk/sluzby-za mestnanosti/nastroje-aktivnych-opatreni-na-trhu-prace/vzdelavanie-a-priprava-pre-trh-prace/vzdelavanie-a-pri prava-pre-trh-prace-uchadzaca-o-zamestnanie-46.html?page_id=291685.

[3] Moreover, in some periods of time and in some regions, also trainings provided under a different measure (support of self-employment start-ups) are coded in the database as being provided also under this measure.

this measure has positive impact on employment as well as income of participants two years after finishing the training. This study used the same administrative data, but different methodological approach exploring aggregate descriptive statistics on income and employment status quantifying gross effects of the measure. No counterfactual technique was applied.

The results of the study are in contrast with later evaluations published in (Štefánik, et al., 2014) and (Štefánik, 2014). These studies showed negative effects of the measure provided during 2011 on the chances of unemployed to find a job. Using propensity score matching, they observed a negative impact of participation in the trainings on the chances of exiting the unemployment status.

The study Štefánik (2015) brings a little consensus into the evidence, providing evidence from two PSM models, as well as OLS estimates, for the whole period between 2007 and 2013. Findings point at the decline in the impacts of the measure after 2010. This is observable on both outcome indicators, income as well as employment status.

Štefánik (2015) is pointing at a rapid decline in the impact of the trainings in the crisis and post-crisis period. Various factors played a role behind this decline, not only the hit of the economic crisis. The number of provided trainings declined sharply after 2010, resulting into a decline[4] in the accessibility of the trainings provided. A centralized procurement procedure was introduced and became obligatory for regional COLSAF offices when contracting training providers. This has resulted into a long and complicated process in answering regional labour market skill needs with implemented trainings.

Regardless of the reasons behind the different impact of the same measure, we have an example of one measure implemented with opposite impacts in different periods of time. Our question in this paper is how this is reflected in the shape of the dose response function of the measure when looking at the length of the training as a continuous treatment.

1.2 Description of the dataset

Estimations will be done on an administrative data set, merging two autonomous countrywide registers:

- the central register of unemployed persons in Slovakia administrated by COLSAF
- the register of social security entries (social security registration is obligatory for all individuals in employment and self-employment in Slovakia).

The register of unemployed persons was made available together with the information about the participation in all active labour market measures provided by COLSAF (the only Public employment service provider in the country). The information about unemployment registrations is available for the period of 2007 – 2014. The information about active labour

[4] While in 2008 the ratio of the number of training participants versus the total number of newly registered unemployed (yearly average) was 5.3 %, in 2011 it was only 0.7 %.

market measures participation is available for 2004 – 2014. For each unemployed registration form we have information about:

- Duration of unemployment (date of entering, length of the evidence, ...)
- Individual characteristics (gender, age, region, level and field of education, ...)
- Family background (kids, marital status, ...)
- Declared skills (PC skills, languages, driving licence)
- Previous participation in any ALMP measure since 2004 (type of the measure, date of start and end of the participation)
- Previous working experiences (days of previous working experience, economic sector and occupation, ...)
- Spatial indicators (estimated time of travel to the closest COLSAF regional office, regional unemployment rate).

Out of this database, we identify the group of participants. For participations in the evaluated measure we know only the real start and end of the participation. More detailed information about the content of the trainings is missing. No information about the planned duration of the training or a successful completion of the training is provided.

Furthermore we are able to complement this information with income and employment status (including type of the working contract) of each individual appearing in the register of unemployed. Linking with the social security database thus adds an additional area of information:

- Monthly evidence on past and future earnings and type of the working contract.

Here we are able to follow our target group during the period of 2007 – 2014 with information provided on a monthly basis.

Because these are administrative data released at individual level, we are able to follow each one of the participants as well as each individual in the group of eligible. No sampling has to be applied. By merging these two databases we will get a very rich dataset, including many observable pre-treatment characteristics. Propensity score matching techniques have in the past proved to provide reliable results when applied in this data setting (Štefánik, 2014) (Štefánik et al., 2014) (Štefánik, 2015a) (Štefánik, 2015b).

1.3 Description of the evaluated group of participants

We focus on two periods which showed a different impact of the training programs on various labour market outcomes of participants. We would like to see how this difference, observable when considering the treatment as a binary variable, is reflected in the dose response function of the same treatment when its continuous nature is considered.

In order to identify these two periods we select:

- First period – from May 2008 until December 2008
- Second period – from January 2011 until December 2012.

The first period starts with the implementation of a new amendment to the Act on Employment, based on which the measure is provided. It ends up before the main impact of the economic crisis was observable on the Slovak labour market. The second period starts in the post-crisis period, after the turbulent impact on the main LM indicators has faded away, starting a period of stagnation in the employment and unemployment rate. The period is also homogenous in terms of implementation rules. In comparison to the first period, the number of trainings provided is lower because of a shift to a new national project under which the measure is implemented. Under new rules, regional COLSAF offices are no longer autonomous in selecting the training providers. Providers are procured by the central office of COLSAF. The topics of the trainings procured are collected in regular reports of regional offices assessing the regional labour market skill needs. The procedure of the centralized procurement has prolonged the whole process of delivering the trainings to more than one year after the need was reported. Based on interviews with COLSAF representatives (Štefánik, 2015b), the obligation to procure via a centralized public procurement system was one of the main reasons of the decline in the overall impact of the measure.[5]

Defining and cleaning the group of participants

Based on the differences in the length of the training participation between male and female participants, as well as based on the responses of COLSAF representatives discussing the implementation of the measure, we assume a strongly gender differentiated portfolio of trainings to be provided. Male participants attend mostly trainings related to manual, low skilled professions in construction, industry and storage and transportation. Trainings attended by female participants are more often targeting professions in personal care and services. Because of this heterogeneity in topics, we assume that estimating one joint dose response function for male and female participants could lead to clouded results. In this paper we therefore focus purely on male participant in the training measure. Here we only focus on the impact of different levels of exposure of male participants.

More in general, training measures show to have specific impacts on extreme ends of participants´ age spectrum. Hence we have excluded all participants which are younger than 20 and older than 54.

In order to further increase the homogeneity in the population of participants we have also excluded all the participants, who have participated in trainings provided by the regional office in Bratislava. Bratislava, being the capital city of the country, is economically

[5]When considering the binary nature of the treatment.

performing not only above the average of the country, but also highly above the EU average.[6] For this reason it presents a labour market picture which is totally different from the rest of the country. Moreover the regional COLSAF office of Bratislava was the only regional office which was free from the obligation to procure training providers via the central office. It also has a lot of specific differences in the implementation rules and procedures in comparison to other regions. Because we are not able to control for these specific differences, we have decided to exclude all participants from this region from the analysis.

Table 1
Loss of observation of participants because of narrowing the target group

		Period 1		**Period 2**	
		Included	Excluded	Included	Excluded
Defining the target group in steps	Total	7 537	0	2 780	0
	Male	3 064	4 473	1 309	1 471
	Age group 20-54	2 609	455	1 193	116
	Not from Bratislava	2 535	74	872	321

Source: Authors´ calculations.

In order to keep the evaluated population clear from possible biases, several further layers of cleaning were applied. First of all we have excluded all participants being coded as participating in the evaluated measure and simultaneously in the programme for supporting self-employment start-ups.[7]

As repeated participations in the trainings were possible during the period since 2004, we have taken into account only one-time participations to avoid possible interference between the effects of various participations and to avoid heterogeneity in the dose response linked to repeated participation in the measure.[8]

Finally we have decided to deal with the cases of extreme values of the treatment variable. As the distribution of the treatment variable becomes scattered above 50 days of training, we are dropping all the participations in the training longer that 50 days.[9, 10]

[6] Based on the 2013 figures was Bratislava region the sixth best performing region in the EU, with 184 % of the average EU GDP per capita. Outperforming Prague or Vienna. Source: http://ec.europa.eu/eurostat/documents/2995521/6839731/1-21052015-AP-EN.pdf/c3f5f43b-397c-40fd-a0a4-7e68e3bea8cd.
[7] The trainings provided under the later programme are of a specific content on how to start a business. In some regions these trainings were coded both, under the programme for supporting self-employment as well as under the evaluated measure. To avoid biases linked with this, we exclude all participants simultaneously participating in both these measures.
[8] Repeated participations presented rather limited proportion, approximately 12 % of the observations. Results were not sensitive to the exclusion repeated participations, but we have decided to exclude them to keep the data as homogenous as possible.
[9] This is necessary also in order to be able to draw the dose response function in a continuous form.
[10] Here also 8 cases of 0 days of training were considered as typos and dropped.

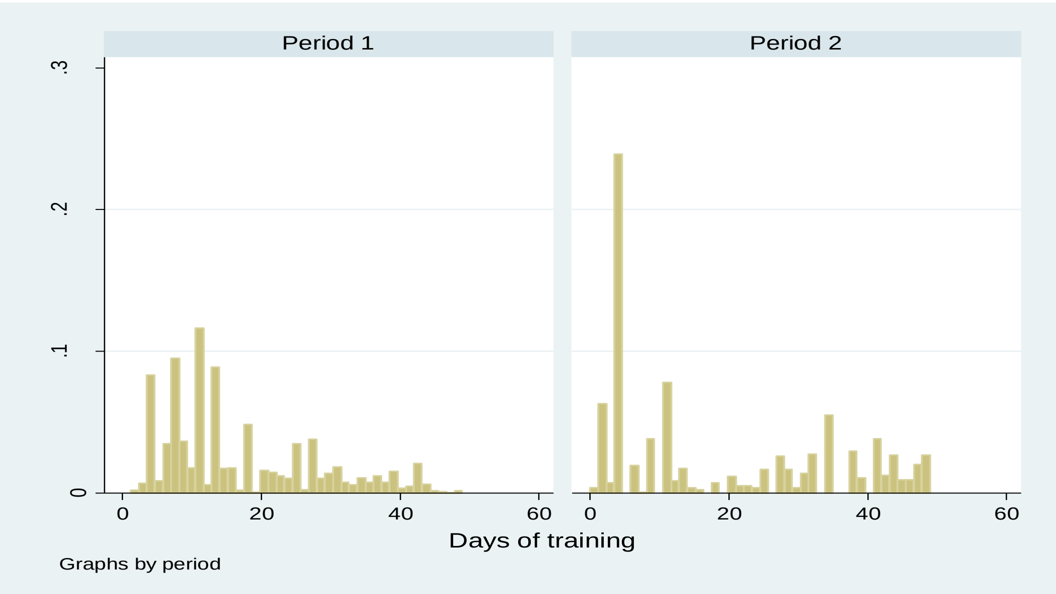
Table 2
Loss of observation of participants because of further cleaning of the target group

		Period 1		Period 2	
		Included	Excluded	Included	Excluded
Further cleaning of the target group	Total	2 535	0	872	0
	Self-employment programme participants	1 729	806	814	58
	Repeated training participations	1 524	205	718	96
	Extreme values of the treatment variable (>50)	1 485	39	627	91

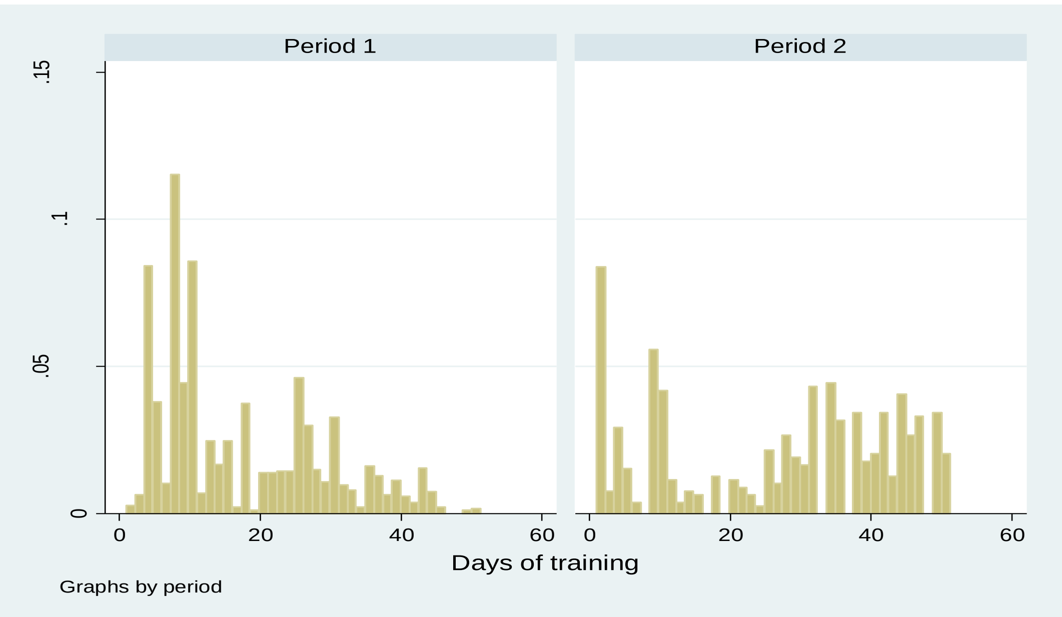
Source: Authors´ calculations.

Figure 1
Distribution of the treatment variable for male participants (for the interval 0-50 days)

Before cleaning



After cleaning



Source: Authors´ calculations.

Table 3
Main descriptive statistics of male participants before and after cleaning

	Before cleaning				After cleaning			
	Period 1		Period2		Period1		Period2	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Age	37.347	12.522	36.565	11.448	35.743	10.983	33.764	10.228
Region Trnava	0.092	0.289	0.017	0.129	0.101	0.301	0.026	0.158
Region Trenčín	0.081	0.273	0.104	0.305	0.093	0.290	0.153	0.360
Region Nitra	0.134	0.341	0.148	0.355	0.158	0.364	0.190	0.392
Region Žilina	0.117	0.321	0.038	0.192	0.112	0.316	0.061	0.239
Region BanskáBystrica	0.171	0.376	0.210	0.408	0.194	0.396	0.225	0.418
Region Prešov	0.170	0.376	0.147	0.355	0.147	0.355	0.258	0.438
Region Košice	0.175	0.380	0.057	0.231	0.172	0.378	0.088	0.283
Elementary education	0.262	0.440	0.199	0.400	0.255	0.436	0.233	0.423
Lower secondary education	0.336	0.473	0.209	0.406	0.350	0.477	0.244	0.430
Upper secondary education	0.333	0.471	0.395	0.489	0.339	0.473	0.427	0.495
Tertiary education	0.069	0.253	0.197	0.398	0.057	0.231	0.096	0.294
Income in 2007	2 573.87	5 142.98	4 405.67	9 260.41	2 315.41	3 517.15	2 139.96	3 505.57
Income in 2008	1 133.94	2 606.84	5 066.52	11 048.44	1 197.17	1 956.88	2 572.65	3 852.31
Income in 2009	1 433.37	2 691.21	4 794.18	9 841.09	1 905.48	2 865.39	2 223.78	4 105.29
Income in 2010	1 727.02	3 068.77	4 071.53	9 232.70	2 324.11	3 294.12	2 084.58	4 527.05
Income in 2011	2 049.48	3 486.87	1 782.44	4 538.89	2 671.32	3 696.17	1 484.48	3 083.22
Income in 2012	2 237.47	3 872.04	1 559.68	4 075.10	2 785.83	3 956.25	1 288.39	2 620.97
Income in 2013	2 235.15	4 020.13	2 410.82	5 253.61	2 774.76	4 151.41	2 052.08	3 357.36
Income in 2014	2 879.51	4 300.13	3 424.13	6 393.93	3 215.96	4 501.68	2 653.44	3 871.73
Number of days in the training	18.70	14.75	23.06	19.84	17.11	11.50	26.79	16.07
Number of days between entering unemployment and the start of the training	194.81	177.19	398.94	385.35	190.28	180.49	433.07	419.36
N	3 064		1 309		1 485		627	

Source: Authors´ calculations.

2 DOSE RESPONSE ESTIMATION

While the trainings provided under the measure of interest are of various content, length, as well as targeting various types of participants, high heterogeneity in the treatment effects has been encountered by previous evaluation studies. Following on these studies, our goal is to reduce this heterogeneity of estimated treatment effects. In order to add to the existing evidence the ambition of this paper is to provide evidence on the dose response related to the length of the participation in the training. Namely we are going to estimate the dose response function by taking advantage of the concept of generalized propensity score (Hirano and Imbens, 2004) and consequently applying the nonparametric inverse-weighting estimator introduced in (Flores, et.al., 2012), and a semiparametric estimator based on additive penalized spline techniques described in (Bia, et.al., 2014). In order to perform the estimation a Stata package specifically developed for this purpose and introduced in (Bia, et al., 2014) will be employed.

2.1 Previous studies on dose response of a training programme

At least two applications of similar methodology in the context of a training programme impact evaluation are at hand to be confronted with the evidence presented here. First Kluve et al. (2012) estimated a dose response function of training programmes implemented in Germany between 2000 and 2002. Authors obtains the dose response function by estimating the average potential outcome for each level of the treatment, when looking at employment status 2 years after entry into the programme and 1 year after the exit from the programme. They report flat and bimodal shape of the dose response function.

Flores et al. (2012) evaluates the US Job Corps programme, taking advantage of the rich National Job Corps Study dataset, operationalizing the length of the training as the treatment variable. The study reports results for several estimators, concluding that semi parametric estimators, one based on nonparametric partial mean and the other on the inverse weighting approach (introduced in Hirano et al. (2003)) are behaving in a similar way especially in regions with limited numbers of observations. In these areas important differences in comparison to parametric estimators (OLS and an estimator based on parametric partial mean) can be observed. Authors´ report an increasing dose response function to the length of the trainings provided, with mostly declining marginal impact of the trainings on future income of participants.

In terms of methodological approach, both of these studies take the same alley in adopting the propensity score approach introduced in Rosenbaum and Rubin (1983) adjusted into the so called generalized propensity score approach in Hirano and Imbens (2004). From this point they introduce different variations of estimators of the dose response function.

2.2 Methodological framework

Our methodological framework is rooted in a standard quasi-experimental setting, to employ observational data in order to infer to a causal relation between a treatment and its outcome. Rosenbaum and Rubin (1983) pointed that after balancing on a set of individual characteristics, for which a balancing score can be used, the treatment assignment is strongly ignorable. We are thus able to control for possible biases in selection into treatment, related to the set of considered individual characteristics. Furthermore they show that the propensity score is a balancing score with some attractive attributes. After the balance on observable characteristics (covariates) between the group of participants and non-participants is assured a difference in average outcomes of these groups can be considered as the average treatment effect. This is because after balancing, the level of outcome is independent of observable covariates. Moreover, we condition that, there are no unobservable characteristics influencing neither the selection into the treatment, nor the outcome. These conditions summarize the well-established unconfoundedness assumption. The balancing score is supposed to eliminate all factors confounding the outcome either through selection into treatment or directly. Rosenbaum and Rubin (1983) consider a binary treatment framework, where balance has to be assured separately for both levels of the treatment; participants as well as the control group of non-participants.

Hirano and Imbens (2004) elaborate on this reasoning by considering a framework involving a continuous treatment. They point out that under a continuous treatment variable setting, the uncofoundedness assumption does not have to be applied separately to all levels of the treatment, but only conditional independence is required. Based on this, they reformulate the unconfoundedness assumption into a *weak unconfoundedness assumption*. This can be formalized as follows.

$$Y_i(t) \perp T_i \mid X_i \text{ for all t } \in \tau \tag{1}$$

Where in a sample of units *i=1...N*, X refers to the vector of observable characteristics (covariates); T refers to the level of treatment and Y(t) is the potential outcome conditional on X. Applying this assumption together with the balancing score property, a generalized propensity score can be estimated as a score balancing the covariates, conditioning them on the level of treatment. When r(t, x) is the conditional density of the treatment given the covariates:

$$r(t,x) = f_{T|X}(t \mid x) \tag{2}$$

Following (Bia et.al., 2014) the generalized propensity score may, in a general way, be formalized as follows:

$$g(T_i \mid X_i) \approx \psi(h(\gamma, X_i), \theta) \tag{3}$$

Where *g* is a link function, ψ is a probability density function, *h* is a flexible function of the covariates depending on an unknown parameter vector γ, and θ is a scale parameter.

The generalized propensity score is estimated for each level of the treatment, in our case each day of training duration. A two stage estimation is used. In the first stage, the equation (4a or 4b) is estimated at each level of treatment. In the second stage, estimates acquired in the first stage are used to produce partial means of potential outcome at treatment level *t*, conditioned on the level of propensity score.

In this paper two alternative non-parametric estimators are used in the estimation of partial means. Namely the Inverse-Weighting estimator assuming a normal kernel distribution (IW kernel) originally described in Flores et al. (2012, p. 161) and later adopted in Bia et al. (2014).

$$\widehat{\mu}(t) = \frac{D_0(t)S_2(t) - D_1(t)S_1(t)}{S_0(t)S_2(t) - S_1^2(t)} \tag{4a}$$

Where $S_j(t) = \sum_{i=1}^{N} \tilde{K}_{hX}(T_i - t)(T_i - t)^j$ and $D_j(t) = \sum_{i=1}^{N} \tilde{K}_{hX}(T_i - t)(T_i - t)^j Y_i$, j = 0 ,1 , 2

As an alternative to this estimator we will report results obtained by an additive penalized spline estimator (PSPLINE) introduced in (Bia et al. 2014, p. 584).

$$E(Y_i \mid T_i, \widehat{R}_i) = a_0 + a_t T_i + a_i \widehat{R}_i + \sum_{k=1}^{K^t} u_k^t (T_i - k_k^t)_+ + \sum_{k=1}^{K^r} u_k^r (\widehat{R}_i - k_k^r)_+ \qquad (4b)$$

In order to run the spline estimator we rely on the routine on space-filling location selection described in (Bia and van Kerm, 2014).

To summarize, in this paper we apply the generalized propensity score approach, originally developed and described in Hirano and Imbens (2004) and adopted in the Stata package for the application of semi-parametric estimators of dose-response functions (Bia, et al., 2014). Assuming Gaussian distribution of the dependent variable and using a log link function we parametrically estimate the generalized propensity score. Afterwards we rely on two non-parametric techniques to estimate the dose response function of the number of days spent in the training on the income of participants.

2.3 Empirical strategy

Designing the main indicators

By applying this methodological framework, the impact of the measure will be quantified on income of trained individuals after finishing the training. Income of participants will be followed during two years after the end of the evaluation period. The indicator is constructed as an aggregate income in the period of 24 months after the evaluation period ends. In the first period the total working income of participants is considered during the period between January 2009 and December 2010. In the second period, the values of the indicator present the sum of working incomes reported to the social insurance database in the period between January 2013 and December 2014. If a participant was not observed in the social insurance database for a particular month his income was imputed as being zero. Let us from here refer to this indicator as to the indicator of outcome.[11]

[11] Data and the methodology applied allow us to construct the indicator of income also in relative time, for 24 months after the end of the training participation. In that case, for a substantial part of the first period participants, the period when outcome would be followed would start in the pre-crisis period. The main impact of the crisis on labour market indicators in Slovakia could be observable from the end of 2009. This could potentially become a source of bias of the outcome variable. Therefore we are favouring the outcome indicator constructed based on evidence from two calendar years after each of the evaluated periods. Results employing the outcome indicator in relative time are reported in the sensitivity analysis.

In the methodological framework chosen in this paper we consider the continuous nature of the treatment. In particular we assume that the level of dose related to the participation in the measure can be quantified by the number of days actually spent in the training. No information about the supposed duration of the training participations or about the success in finishing the trainings is available in the data. We therefore have to rely on the number of days counted as the difference in reported date of starting and finishing of the training participation. Calendar days are being reported, with weekend days biasing the information provided by the indicator.

Estimation of the generalized propensity score (GPS)

In the first step, the generalized propensity score (GPS) is estimated in order to deal with selection into the length of exposure to the training. GPS is estimated by using generalized linear models incorporated in the DRF Stata command via the GLM Stata command. Based on the results from the Modified Park[12] test we are assuming a Gaussian distribution of the treatment variable with a log link function.

The GPS was estimated separately for duration of trainings under and over 15 days of trainings.[13] This additional condition was implied as the shorter trainings differ in terms of topics covered, so we assumed that they could differ also in terms of the characteristics of participants. But imposing this additional condition did not significantly change the results of the estimation.

The list of the explanatory variables was basically the same for the first as well as for the second evaluated period. All information observed in the data was considered for being included in the estimation of the propensity score. Variables not referring to the period before the programme participation were excluded. As well as collinear variables and in some cases also variables with extremely low association to the treatment variable and thus low contribution to the model were excluded. Included explanatory variables cover all the areas listed in the description of the dataset (section 1.2). A complete list of the explanatory variables can be found in the annex. Complete results of the estimations can be found in the web annex.

Table 4
Diagnostics of the GPS model for the two evaluated periods

	2008	2011/12
AIC	7.741912	7.956242
BIC	168577.4	75639.56
Log likelihood	-5664.37	-2406.28
N	1485	627

Source: Authors´ calculations.

[12] Detailed output for this test can be found in the web annex.
[13] Using the "cutpoints" option under the DRF command in Stata.

Among the strongest explanatory variables we can find the participation in a public works programme. Individuals who have participated in the public works programme in the past have a significantly higher average duration of the trainings. Also a higher number of days previously in unemployment and past working experience in the sector of Repairing and installing of devices (NACE 33) prolongs the number of days in the training. Including dummies referring to detailed fields of education contributed significantly to the explanatory power of the GPS model, thus fields of the highest level of acquired education are probably associated with the type and as well the length of the trainings provided.

Satisfying the common support assumption

1 485 observations were used to estimate the GPS for the first evaluated period. Less than a half, 627 observations, were available for the estimation of the GPS in the second evaluated period. The common support condition was imposed by dividing the sample into three equally sized subgroups, based on the quintiles of the treatment variable distribution.

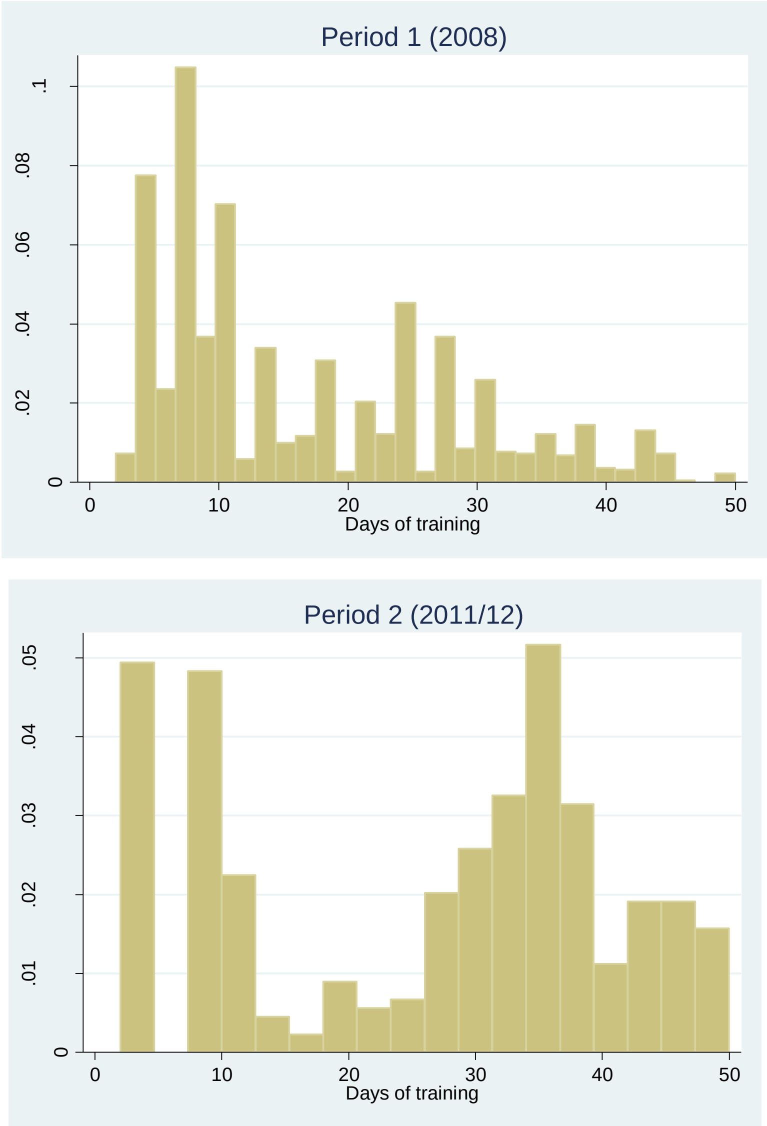
Table 5
Descriptive statistics of the GPS variable and the common support condition

		2008	2011/12
Observations dropped because of the common support condition		61	293
Observations included into the DRF estimation		1424	334
Mean		0.0246	0.0206
St.Dev.		0.0087	0.0095
Percentiles	1%	0.0020	0.0016
	5%	0.0051	0.0038
	10%	0.0115	0.0083
	25%	0.0200	0.0125
	50%	0.0266	0.0201
	75%	0.0314	0.0305
	90%	0.0343	0.0326
	95%	0.0351	0.0329
	99%	0.0353	0.0329
Skewness		-0.9258	-0.1924
Kurtosis		3.1143	1.8002

Source: Authors´ calculations.

The values of the estimated GPS range from values close to zero (0.0003) up to values over 0.035. Range of the GPS variable are alike for the first as well as for the second evaluated period, nevertheless in case of the first period a higher share of the observations seems to satisfy the common support condition.

Figure 2
The treatment variable distribution, for training participants included in the common support



Source: Authors´ calculations.

Assessing the balancing property

To assess the balancing property of the GPS we use the likelihood-ratio test proposed by Flores et al. (2012) and incorporated in the DRF Stata command. Here the explanatory power of an unrestricted model (including the GPS together with covariates) is compared to the explanatory power of a model restricted only to covariates and a model restricted purely to GPS and its products. The explanatory power is measured in terms of the Log-likelihood score of the model. In case of both periods the unrestricted model was not statistically significantly stronger than the model restricted only to covariates. The covariates thus have little additional explanatory power after balancing for the GPS. Moreover the model restricted only to GPS terms is less powerful in comparison to the unrestricted model. This is true for both of the evaluated periods.

Table 6
Results of the Likelihood-ratio tests

		LR-test	T-Statistics	p-value	Restrictions
Period 1 (2008)	Unrestricted	-5051.06	.	.	.
	Test restriction that X's can be excluded from the unrestricted model	-5097.00	91.892	0.057	72
	Test restriction that GPS coefficients can be excluded from the unrestricted model	-5444.66	787.203	0.000	3
Period 2 (2011/12)	Unrestricted	-1323.32	.	.	.
	Test restriction that X's can be excluded from the unrestricted model	-1355.96	65.271	0.571	68
	Test restriction that GPS coefficients can be excluded from the unrestricted model	-1334.03	21.423	0.000	3

Source: Authors´ calculations.

3 RESULTS

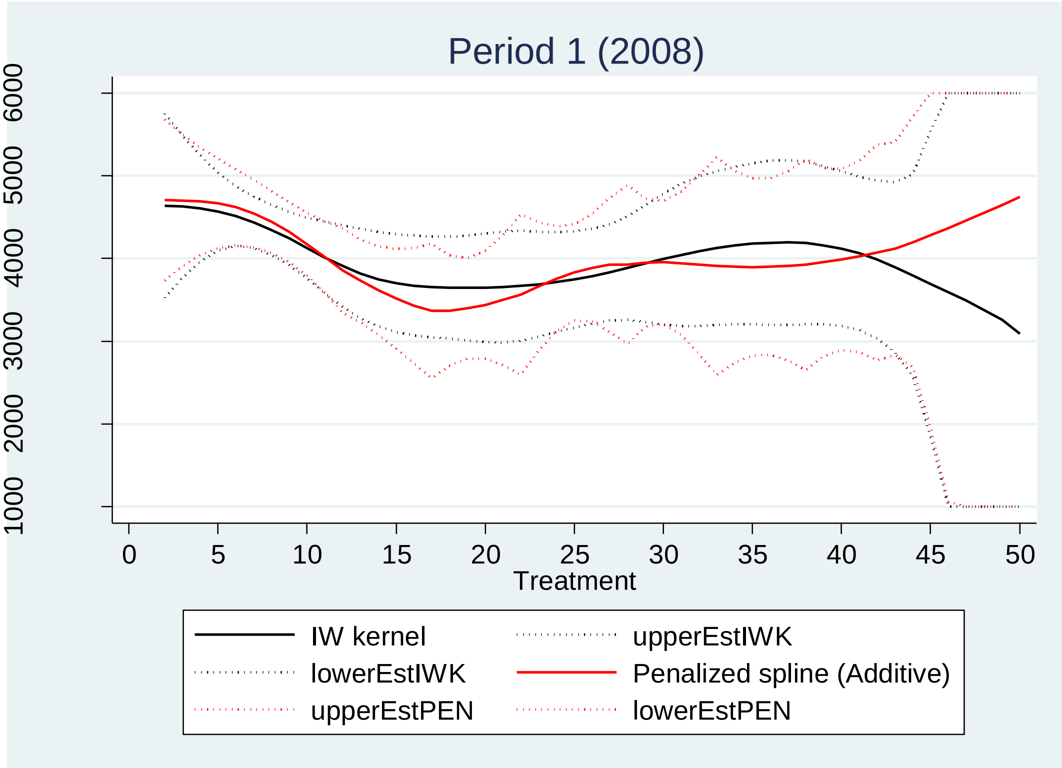
Based on the methodological framework described above, we have yielded the following estimations of the dose response function of income on the length of the participation in training, for the two evaluated periods. When looking at the overall shape of the dose response function of income on days spend in training, similarly shaped functions have been acquired by both selected estimation methods (IW kernel, PSPLINE). Chosen estimators thus bring homogenous results. In contrast, observed shapes of the function differ substantially between the evaluated periods. While in the pre-crisis period (2008)[14] the dose response function of the trainings provided appears to be U shaped. During the post-crisis period (2011 – 2012)[15] the shape of the dose response function draws an inverted U.

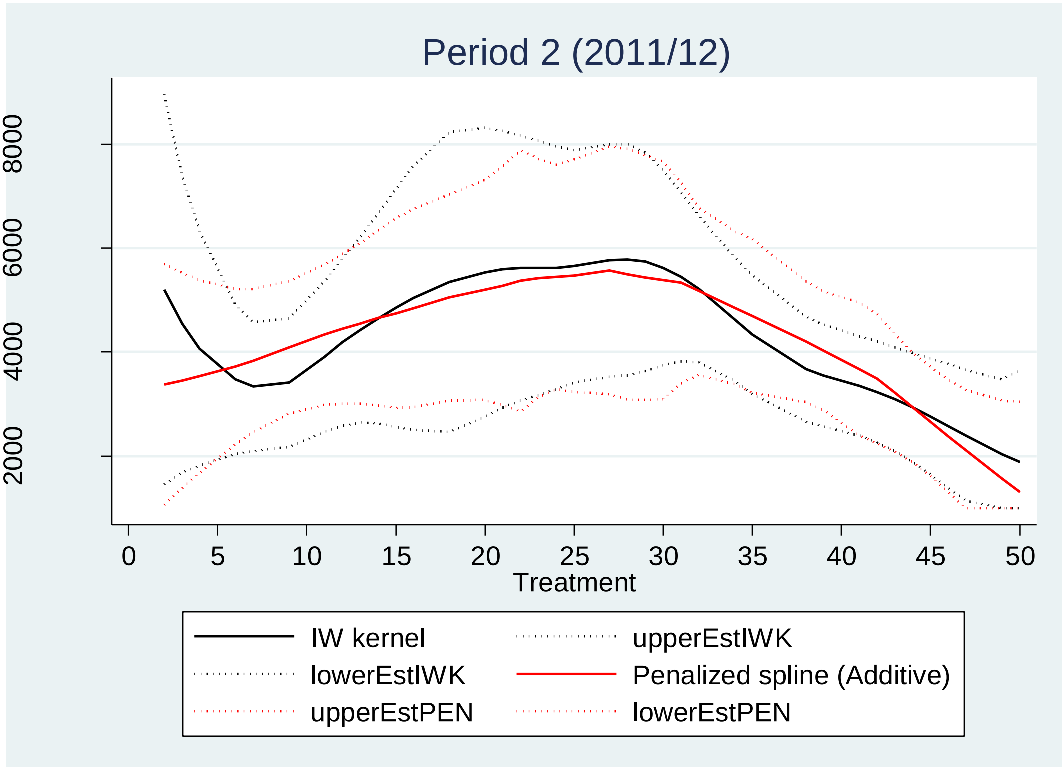
While in the first period the U shape is rather moderate, ranging from 3.6 thousand euro for 19 days spent in training up to 4.6 thousand euro in the beginning of the training participation. The inverted U in case of the second period is carved with a higher range of values ranging from maximum values up to 5.8 thousand euro after 28 days of training to minimum values bellow 1.9 thousand euro at the end of the observed spectrum of the treatment variable.

[14] When positive impact of the trainings has been reported when measured on a binary treatment variable.
[15] When negative overall impact of the training when measured on a binary treatment variable was reported.

Figure 3

Estimated dose response function (CI values trimmed to fit the range 1000 – 6000 in case of Period 1 and 1000 – 9000 in case of Period 2)





Note: 95 % CI values trimmed to fit the range 1000 – 6000 in case of Period 1 and 1000 – 9000 in case of Period 2.

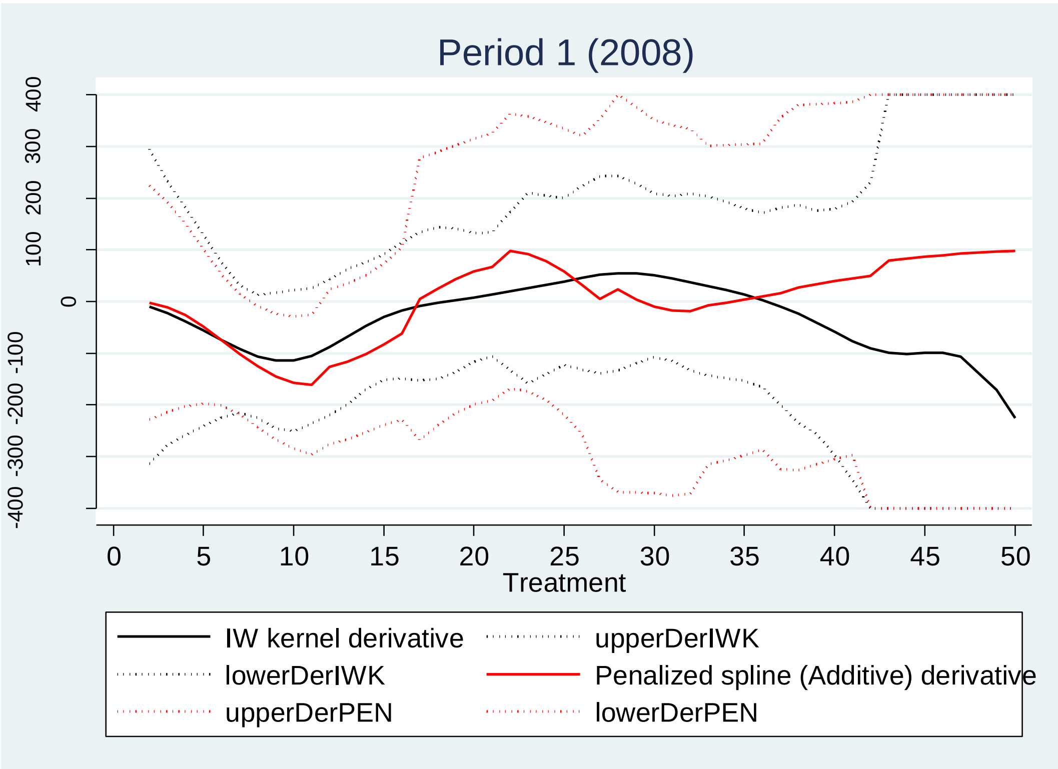
Source: Authors´ calculations.

The shape of the estimated dose response function sheds some light into the heterogeneity of the trainings provided. In both periods a difference between shorter and longer trainings can be observed. In case of the first period the minimum of the dose response function is somewhere between 15 and 20 days of training. For participation in shorter trainings in 2008 each additional day spend in training was related to a loss in future income. This is observable also when looking at the derivative of the function. The only derivative significantly different from zero was acquired by the penalized spline estimator for this period between the 8th and 11th day of training. Longer training implemented during the first evaluated period (2008) started to pay off later approximately after the 25th day of training. But here the results acquired by different estimators differ, with inverse weighting kernel (IW kernel) expecting a decline in the dose response function after 40 days of training and additive penalized spline estimator (PSPLINE) expecting an increase up until 50 days of training. Except those between 8th and 11th day of training, all other values of estimated derivatives (based on one day delta) are not statistically significantly different from zero.

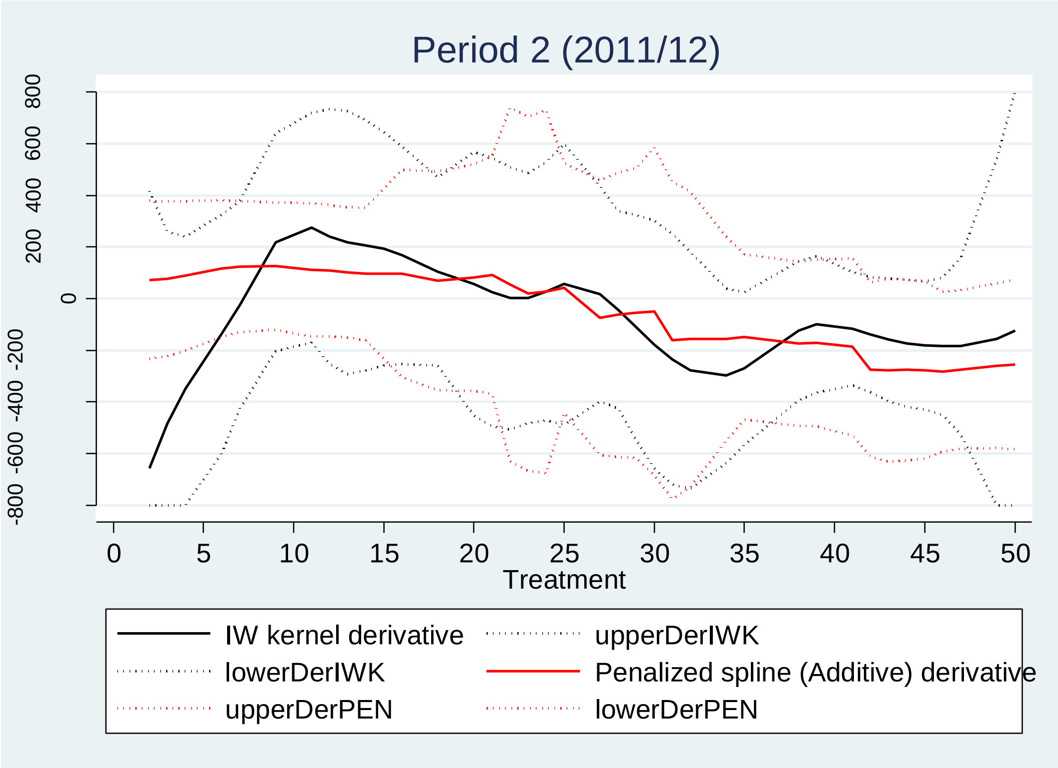
For the second period the results show a positive gain from trainings approximately up to 25th day of the training. After a the 25th day of training the dose response function starts to decline sharply with negative marginal gains from an additional day of training on income of participants. No estimated derivatives for the second period are significantly different from zero. The closest to zero are negative estimates after 30 days of training.

Figure 4

Estimated derivatives of the dose response function[16]



[16] Maximum and minimum various set for the 95 % confidence interval to.



Note: 95 % CI values trimmed to fit the range -400 – 400 in case of Period 1 and -800 – 800 in case of Period 2.
Source: Authors´ calculations.

The limited information about the content of the trainings provided sets rather narrow borders for the interpretation of the results. Based on information provided in the interviews with some of the COLSAF representatives, we could expect that training provided in the later, post-crisis period are dominantly low skilled, but they were not significantly shorter. On the contrary the average number of days spent in trainings was higher in the second period. The evidence, we present here, suggests that it could be the difference in the trainings with longer duration which could make the difference when confronting the results with overall impact of the measure.

For the first period, based on previous studies, we expect a positive overall impact of the measure on income of participants. Additionally, we present evidence on a U shaped dose response function for this period. In contrast we present a dose response function in the shape of an inverse U for the supposedly negative, post-crisis period. In the U shaped period, longer trainings (over 25 days) are showing a slightly increasing pattern suggesting the additional day spent in training not to be related to a decline in earnings.

In the inverse U shaped period, longer trainings (over 30 days) are showing a clearly declining pattern suggesting that an additional day spend in training is not related to positive gain in terms of yearnings. In this case, longer trainings seem to be the source of difference, playing a role in determining the overall impact of the programme.

CONSLUSIONS

The evidence presented here is rather a first look at the shape of the dose response function of the length of trainings on earnings of participants. More information about the content of the training, or evidence from a more homogenous training programme, could shed some light necessary in order to interpret, understand and generalize the results properly.

Despite its limitations, yielded evidence certainly brings information relevant from the perspective of policy makers responsible for implementing the measure during the period of evaluation. In this context, the sensitivity of the results to changes in the methodological settings of the analysis was considered. Here a different definition of the outcome indicator was considered constructing the indicator in relative time starting not after the end of the evaluation period, but after the end of training participation of each training participant, following for 24 months after the training. Here the U shaped dose response function for the first period was clearly confirmed. The inverse shaped dose response function observed for the second period has its maximum shifted towards more days of training in case of PSPLINE estimates and more breaks in the pattern in case of IW kernel estimates. The results are not sensitive when changing from evaluating the dose response function at each level of the treatment to its evaluation per each three levels of treatment (three days of training). The results of the sensitivity analysis can be found in Annex 2.

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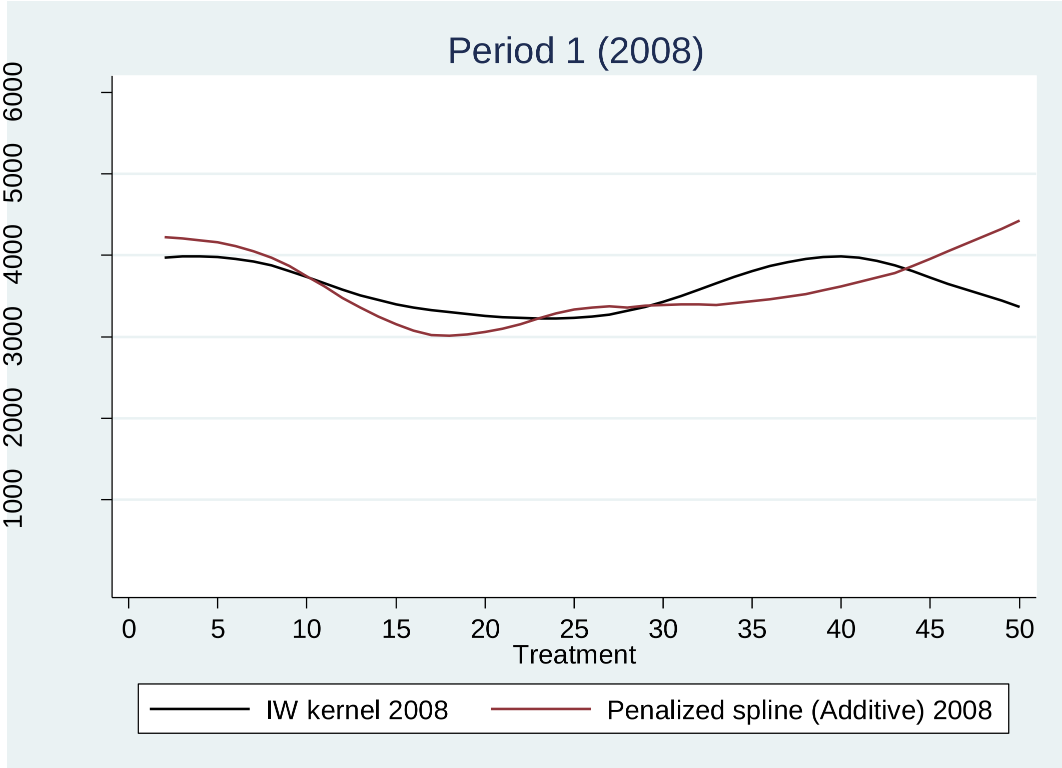
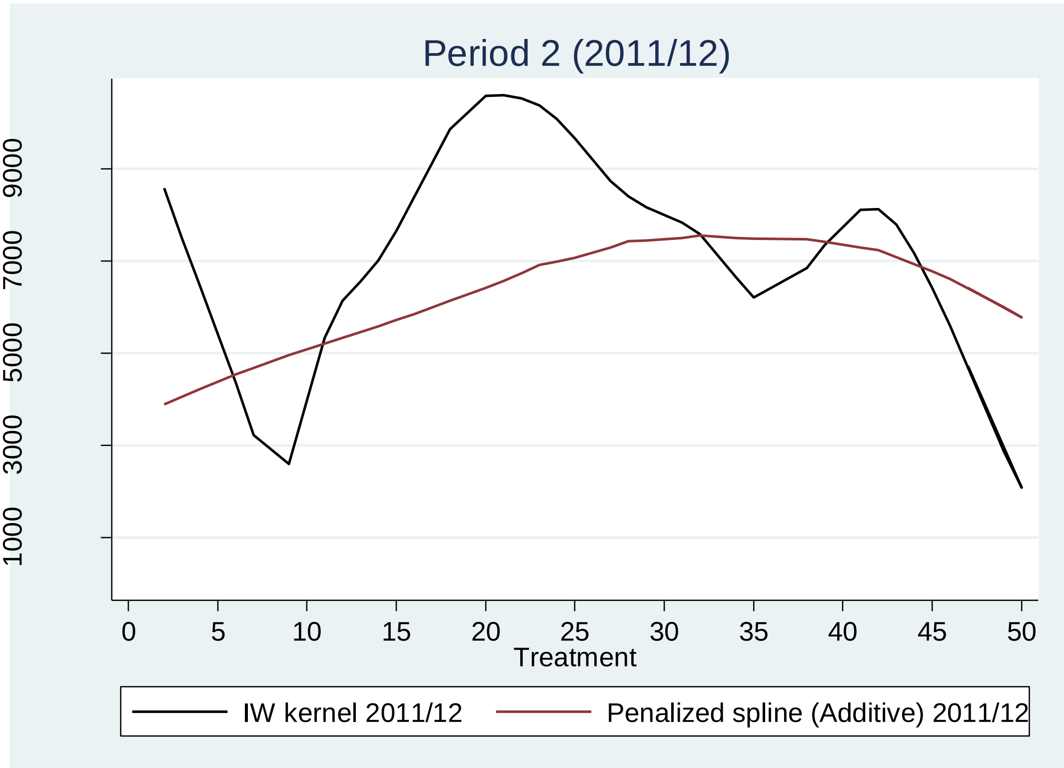
ANNEX

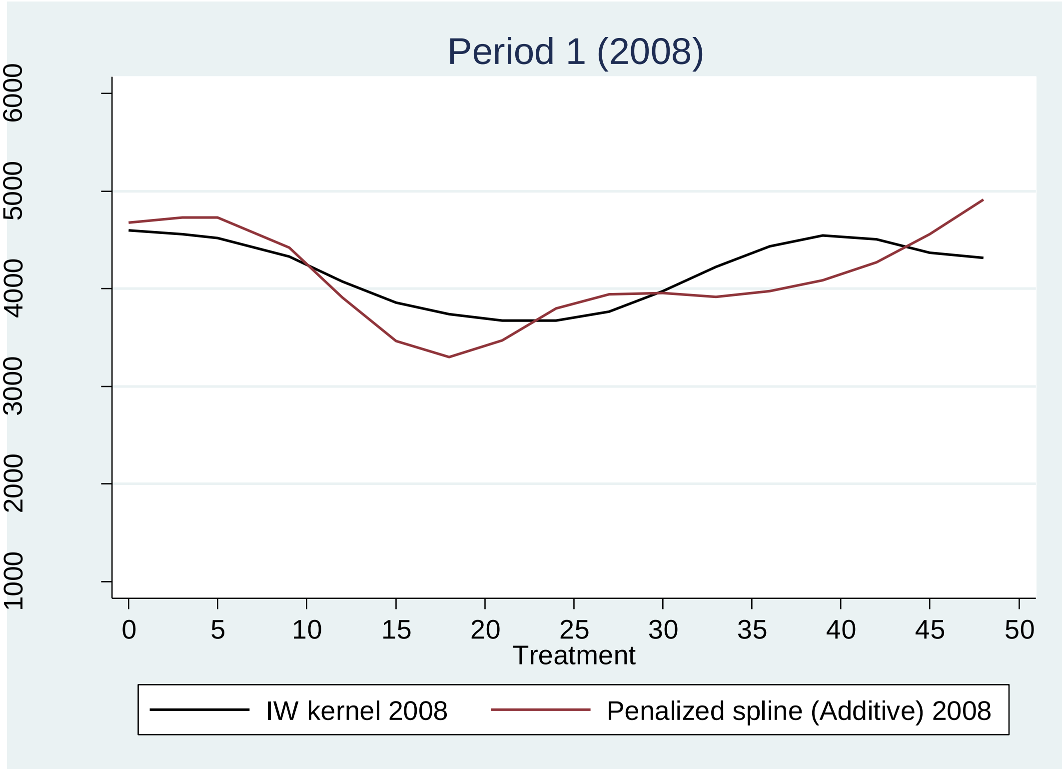
Annex 1: Complete list of the explanatory variables used in the GPS model
Average annual income (inc2007, inc*)
Monthly income in particular month (vz200701, vz200703, vz200704, vz200707, vz200709)
Number of unemployments proceeding the unemployment in which training was provided (pocevpred)
Number of total days in unemployment since 2007 (doev)
Number of days before last unemployment and the start of the unemployment in which training was provided (dni_predev)
Dummy_Employed before unemployment (zam_predE)
Dummy_ Employee before unemployment (zam)
Dummy_Registered as unemployed ever before (minev)
Number of minutes in travelling to the nearest COLSAF regional office (cas)
Subjective assessment of the obstacles he has to face in order to find a job (prekazka)
Dummy_for being a detached from the labour market based on the Law on employment (neznev)
Participated in any ALMM before (ucast_aotp)
Participated in ALMM_supported employment (p50)
Participated in ALMM_on job training for youth (p51)
Participated in ALMM_public works (p52)
Date of entering current unemployment in which training was provided (zaradenie)
Age (vek)
Square of age (vek2)
Married (zenaty)
Slovak citizenship (sk)
Slovak nationality (slovak)
Hungarian nationality (madar)
Dummy_not phisically disadvantaged (zdravy)
Dummy_speaking a foreign language (cj)
Dummy_driving licence (vp)
Dummy_able to operate a computer (pc)
Sectoral dummies (nace29, nace30, nace50, nace*)
Dummies for regional offices (dumurad23, dumurad*)
Dummies for field of education (eduf1-eduf58)
Dummies for level of education (edul1-edul10)
Average unemployment rate in the region (kraj_mn)

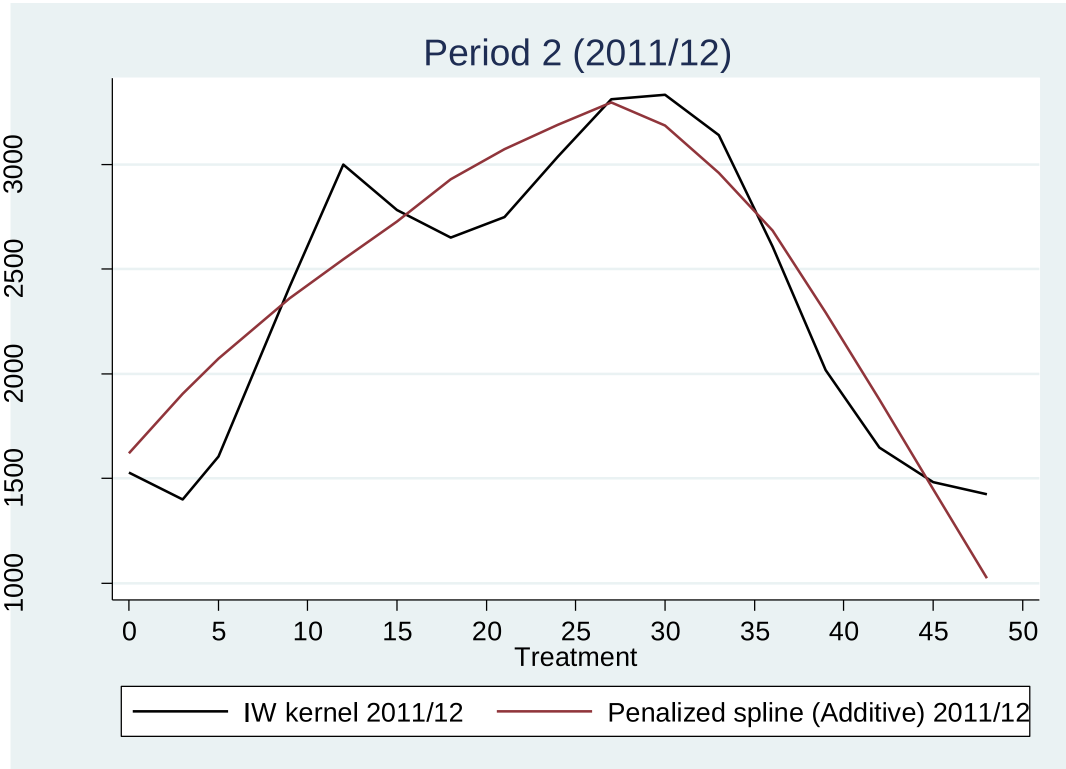
Annex 2a: Results for outcome indicator defined in relative time





Annex 2b: Results for DRF estimated for treatment variable levels per 3





Note: tp = (0\3\5\9\12\15\18\21\24\27\30\33\36\39\42\45\48).