XV Public Economics Meeting
University of Salamanca, Spain
February 7-8, 2008

A COMPREHENSIVE MICROECONOMETRIC EVALUATION OF AN ACTIVE LABOUR MARKET POLICY

APPLICATION TO THE PORTUGUESE ECONOMY

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October 2007
(Preliminary Draft)

Abstract: The traditional evaluation literature, where the subject of the evaluation is the participation in an exclusive treatment, does not capture the reality of the active public interventions in the European labour markets. That is the case of the Portuguese economy characterized by the heterogeneity of ongoing programmes that are available for the universe of potential unemployed participants. So, this paper presents a comprehensive evaluation of the Portuguese active labour market policy in a multiple treatment context. Our approach to assess the effectiveness of the Portuguese active labour market policy, to the improvement of the employability of participants, combines propensity score matching techniques with the conventional difference-in-differences estimation to construct the relevant counterfactual under the hypothesis of selection on unobservables. The results are very heterogeneous among participants in the different active programmes in the short-run but that diversity of results tends to converge in the long-run.

JEL Classification: C10, C50, J68
Keywords: Active Labour Market Policies, Multiple Treatments, Social Programme Evaluation, Propensity Score Matching, Difference-in-Differences

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1. INTRODUCTION

The focus of the evaluation literature of Active Labour Market Policies (ALMPs), which is vast and is becoming technically sophisticated, is traditionally the evaluation of a single programme. However, stimulated by the work of Imbens (1999) and Lechner (2001), who extended the matching methodology for a single treatment - under the Conditional Independence Assumption (CIA) – to the case of multiple treatments, the evaluation literature of labour programmes is being extended to the evaluation of the set of programmes that are running simultaneously in a particular labour market.

The traditional microeconometric evaluation literature, where the subject of the evaluation is the participation (or not) of individuals in a particular programme – that is in a exclusive treatment – does not capture the reality of active public interventions in the European labour markets characterized by the heterogeneity of ongoing programmes that are available for the universe of potential participants in ALMPs.

The Portuguese labour market is an example of an institutional framework where several ongoing active labour market programmes are available for those unemployed individuals who register in the public employment service looking for an employment solution. So, the evaluation of the labour programmes offered to the unemployed, independently of each other, could not explain satisfactorily the effect of the public intervention in the labour market for the registered Portuguese unemployed. A comprehensive microeconometric evaluation of the Portuguese ALMPs is a way to understand fully the effect of the public intervention on those who are unemployed and are potentially eligible to participate in the full range of programmes offered.

Indeed this is the major contribution of our present work. In Portugal we do not know any work which addresses a comprehensive evaluation of the active labour market policy in a multiple treatment context and even in the international literature those kind of empirical studies are not very common. Still our work will follow some international empirical applications of the matching estimator for a multiple treatment context proposed by Imbens (2000) and Lechner (2001). Mainly, we will have as reference the work by Gerfin and Lechner (2002) since the authors evaluated the active labour market policy adopted in Switzerland, which described labour market institutional framework as very similar to the Portuguese one, using an administrative database as we intend to. However other evaluation applications can be referred. Brodaty et al. (2001) evaluated, for the period 1986-1988 and using administrative data, the effects of youth employment programmes that were set up in France to improve the labour market prospects of the most disadvantaged and unskilled young workers. Also for a youth population, Larsson (2003) evaluated, jointly, the effects on the employment of two Swedish active programmes and Dorsett (2001) evaluated the relative effectiveness of the New Deal's option in reducing the male youth unemployment in the United Kingdom.

As with the above international empirical evaluations, we will use administrative data. Our study uses the administrative records of *Instituto de Emprego e Formação Profissional* (IEFP) – the Portuguese public employment service – to assess the effectiveness of the Portuguese active labour market policy in the improvement of the employability of participants. The raw dataset contains the individual records collected by all local offices of IEFP. It includes a substantial number of individual labour market characteristics and, in particular, very detailed information on participation in a set of ALMPs over a period of six years (1998-2003).

Also like the above referred empirical applications we will use a matching methodology but, unlike those works, we will extend the econometric multiple treatment evaluation framework to apply a nonparametric conditional difference-in-differences methodology. This approach combines propensity score matching techniques with the conventional difference-in-differences estimation, to construct the relevant counterfactual under the hypothesis of selection on observables and on unobservables.

The paper is organized as follows. In the next section, we describe the Portuguese institutional context for the active labour market policy and the programmes we will evaluate. Section 3 presents the microeconometric framework to a multiple treatment evaluation. The dataset and the modelling strategy are described in Section 4 followed by Section 5 where the empirical analysis of participation on one of the selected treatment states is discussed and Section 6 where the matching procedure is presented. Results from the selected econometric conditional difference-in-differences methodology are reported in Section 7.

2. - PORTUGUESE ACTIVE LABOUR MARKET POLICY

2.1 - Institutional Context

The Portuguese ALMP, like the ones evaluated by the papers referred to above, are applied through a wide range of different programmes which we aggregate in five different major groups of intervention like the areas of intervention identified by the Portuguese public service: (i) Direct Placement, (ii) Job Counselling, (iii) Employment Programmes, (iv) Training Programmes, and (v) Professional Rehabilitation Programmes designed, specifically, to disabled individuals.

Some of these major groups of intervention, like the group of Employment programmes or the group of Training Programmes, comprise ample sort of heterogeneous programmes. So, the major division presented above can be further divided in some main aggregation of programmes that share general characteristics, aims and are addressed to the same individuals.

In practice, the set of distinct operational programmes of ALMP is wide, sometimes running continuously over time, and are potentially available for all the recorded unemployed individuals. On the other hand, the individuals can be recorded repeatedly (and the data show they actually are) having the right to participate in different periods of time and in different patterns in their observed unemployment spell.

After the participation in a programme, there are several destination states for the participant. However, the main objective of the Portuguese ALMPs is to improve the (re)employability of the unemployed recorded individuals and so employment (including self-employment) represents the main policy outcome.

Although this institutional framework does not fit into a standard traditional evaluation process, where a programme is administered at a fixed point in time and where it is easier to distinguish the individuals by their participation, or no participation at all, in the programme, this is an institutional framework commonly found, in practice, in the European economies (see, for instance, Sianesi, 2004) where one has ongoing programmes and any unemployed individual can potentially become a participant.

2.2 – Treatment States

The major group of Employment Programmes can be divided into (i) Training/Employment Programmes, (ii) Private Employment Incentives for those who want to create their own employment and (iii) the Social Employment Market (which includes, as the key group of programmes, the Public Employment Programmes). Concerning the Training Programmes it is important to make a distinction between two main groups: (i) the vocational training and (ii) the professional training programmes (which we will call basic training, since is an international recognized designation for this kind of training)[1].

We will compare the above mentioned programmes among them and also with the absence of participation in any ALMP. So, we will consider six different states of participation, which we will call treatment states and we will identify them by the initials to help the reading: 1) No participation (NP); 2) Direct Placement (DP); 3) Job counselling (JC); 4) Training/Employment (TE); 5) Social Employment Market, which we will associate with the Public Employment Programmes since these programmes are the ones which collected almost all the participants in Social Employment Market Programmes (PEP); and, 6) Basic training (BT).

The NP treatment state will be defined as the treatment state where a participation in any of the programmes offered by the public employment service is not observable.

The DP treatment state is considered in this analysis as a treatment state since it is one of the major groups of intervention identified by the Portuguese public employment service and because, although it is not a real active labour market programme, the register individual benefits from the active efforts of the public employment service to match the supply and demand for a job. Indeed in the Portuguese institutional context even the non-participants are, in some way, "treated" because, since the moment they register in a public employment office, they can benefit – even if they do not – from the available

[1] In our work we will not consider the Private Employment Incentives and the vocational training programmes since their specificity creates practical problems of comparability.

general services like counselling, guidance or placement. To participate in the DP treatment state only requires registration in the public employment service as the participation in the JC treatment state.

The JC treatment state consists of technical services offered by the public employment service aiming to support the development of programmes of active and organised employment demand by the registered unemployed individuals. These technical services intend namely to promote the acquisition of effective job demand skills like the ability to find and explore labour market opportunities, the ability to present an appealing CV and cover letter or the capability to represent themselves at a job interview. In short we can define the JC programmes as programmes which promote the self-knowledge of labour skills to enable an easier (re) admission and ability to fit in the labour market.

TE programmes are characterized by the offer of training to registered unemployed individuals (looking for a first employment or with former employment experiences) and, simultaneously, by allowing the contact with a real labour market experience. The ultimate goal of the TE treatment state is to increase the opportunities of labour marker (re)absorption. Among theses programmes we can find programmes for individuals with different levels of education but all of them are directed at unemployed individuals registered in a public employment office and have a maximum duration of one year.

PEPs, best known in Portugal as *Programas Ocupacionais,* are mainly targeted to unemployed individuals in families with a per capita monthly income lower than the national minimum wage and to unemployment beneficiaries. Participants in these programmes are required to perform non market-oriented activities (i.e. activities which do not directly compete with existing labour market vacancies). Although participation is not intended to exceed a maximum of twelve months, renewals with the same maximum duration are frequent. Any job or vocational training offered by the public employment service prevails over participation in *Programas Ocupacionais*. A refusal immediately ends entitlement to unemployment benefits and other income support schemes. In addition, participants must be involved in active and confirmed job searching for which they have a free day per week.

To conclude, among the BT Programmes it is possible to find a large extension of different programmes with particular characteristics. However all of them share the same type of beneficiaries – unemployed individuals with no, insufficient or non-adequate labour market qualifications concerning the needs of the labour market[2] – and possess a duration that does not exceed one year.

The selected treatment states present differences and could be classified as heterogeneous. Indeed we admit that they are not strictly comparable but we argue that they share features which make their comparability not only possible but also very interesting to assess the performance of the active labour market policy in the Portuguese labour market.

Our arguments are: (i) all the treatment states are potentially available for all the registered individuals; (ii) all of the selected treatment states, except the NP treatment state, involve a participation period which does not exceed one year of duration; (iii) the characteristics, which could decide the entry on a particular treatment state according to the legislation regulating the programmes, are observable characteristics captured by the administrative data – the educational level of the registered individual in one example – and; (iv) the aim of all the treatment states, again with the exception of the NP treatment state which does not have a particular aim, is to improve the employability of the unemployed participants.

So assuming six heterogeneous, but comparable, treatment effects we will present a comprehensive empirical evaluation of the Portuguese public active intervention on the labour market within a multiple treatment econometric framework.

3. - Framework to the causal Evaluation Model with Multiple Treatments

To evaluate the Portuguese active labour market policy, assuming the coexistence of heterogeneous multiple treatments for the registered unemployed individuals, we will apply the extension of Imbens(2000) and Lechner(2001) to the Rubin (1974) model of causality with a binary treatment framework.

[2] Some of the basic training courses have also employed individuals as beneficiaries but they are not considered in the database used in the empirical application.

Following the notation of Lechner (2001) let us assume that a random individual, i, could participated in $(M+1)$ mutually exclusive treatments, denoted by $0,1,...,M$ [3]. The participation in treatment m is indicated by $D=\{0,1,...,M\}$. The potential results, associated with this $(M+1)$ possible treatments, will be defined by $\{Y^0,Y^1,...,Y^M\}$. The number of observations in the population is N, such that $N=\sum_{m=0}^{M} N^m$, where N^m is the number of participants in treatment N. For each participant individual only one component of the defined outcomes is observable being the others, M, the counterfactuals never observed. Under certain assumptions could be identified average causal effects of the treatment, though. The average treatment effect on the treated (ATT) is the parameter which receives more attention in the binary evaluation literature and is the typically estimated treatment effect in empirical evaluations (Lechner, 2002). For the multi-treatment version this parameter could be presented as a pairwise comparison of the effects of the treatments m and l for the participants in treatment m, this is:

$$ATT^{m,l} = E\left(Y^m - Y^l \middle| D=m\right) = E\left(Y^m \middle| D=m\right) - E\left(Y^l \middle| D=m\right), \tag{1}$$

where $ATT^{m,l}$ is the expected treatment effect for an individual randomly drawn from the population of participants in treatment m, comparing with treatment l.

The question is that the traditional model of causality (Rubin, 1974) assumes that in a non-experimental evaluation process it is not possible to identify the average causal effect of a treatment and so the identification of that effect must rely on strong, but normally non-testable, assumptions which plausibility should be argued case by case depending on the underlined economic problem and the available data. The extension of the traditional model of causality to the case of a multiple treatment context assumes the same problem and adopts the same most common assumption, the conditional independence assumption – CIA (or "strong uncounfoudness" as it as been called by Imbens, 2000). Under the multiple treatment context the CIA can be formalised as follow:

$$\{Y^0,Y^1,...,Y^M\} \perp D \middle| X = x, \forall x \in \chi \tag{2}$$

This is, all potential treatment outcomes are independent of the selection mechanism for any given value of a vector of characteristics, X, in a characteristic space, χ (Lechner, 2002a). This means that the researcher observes all the characteristics, X, which jointly influence the participation on a particular treatment and the consequently potential outcomes.

Additionally, the identification of the average causal effect requires that all individuals actually have the possibility of participation in all the alternative states of treatment, this is, it is required a support condition:

$$0 < P\left(D = m \middle| X = x, \forall m = 0,...,M, \forall x \in \chi\right) \tag{3}$$

Since conditioning on all relevant observable characteristics could cause a problem of dimensionality, Imbens (2000) and Lechner (2001) show that the properties of the particular balancing score, the propensity score, suggested by Rosenbaum and Rubin (1983) to overcome the "curse of dimensionality" also hold for the multiple treatment case. So, using the probability of participation in a treatment conditional on the observable characteristics, the $ATT^{m,l}$ can be presented as

$$ATT^{m,l} = E\left(Y^m \middle| D=m\right) - \underset{P^{l|ml}}{E}\left\{E\left[Y^l \middle| P^{l|ml}(X), D=l\right] \middle| D=m\right\}, \tag{4}$$

where $P^{l,ml}(x)$ is the conditional choice probability of a treatment given either treatment m or l, this is:

$$P^{l|ml}(x) = P^{l|ml}\left(D=l \middle| D\in\{l,m\}, X=x\right) = \frac{P^l(x)}{P^l(x)+P^m(x)} \tag{5}$$

The $ATT^{m,l}$ parameter is now identified from an infinitely large random sample because all participation probabilities, as well as $E\left(Y^m \middle| D=m\right)$ and $E\left(Y^l \middle| P^{l|ml}(X), D=l\right)$ are identified (Lechner, 2002a).

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[3] Generally, treatment 0 denotes the absence of participation in some kind of policy (treatment).

These results allow us to apply in the multiple-treatment context the appealing nonparametric propensity score matching methodology. A methodology not dependent of any functional form assumption and that allow us to correct two of the three important evaluation biases identified by Heckman et al. (1997, 1998). Indeed, the matching methodology eliminates the bias due to a different support of the vector of characteristics X (that is, the violation of the common support condition resulting from having a different range of X for treated and non-treated individuals) and the bias due to a different distribution of characteristics X over the region of common support. But, it does not however eliminate the third source of selectivity bias: the "selection on unobservables", or the bias arising from unobserved heterogeneity among potential participants, being the acceptance of the CIA very dependent of the richness of the available data.

The assumption that selection is driven only by observable characteristics is of course highly restrictive. For instance, some unobservable characteristics such as motivational differences across registered individuals, while known by public employment officers, are likely not to be observed by a researcher with no full access to the raw information. The implication is that the administrative data is likely to be insufficiently informative to make the CIA an acceptable assumption and in that case the presence of selection based on unobservable variables cannot be excluded. Admitting this could be the case of our present evaluation process we decide to extend the work of Imbens (1999) and Lechner (2001) a little further and apply, in the multi-treatment context, the Heckman et al (1997) proposal to eliminate the selection on unobservables.

Indeed, to eliminate the selection on unobservables, Heckman et al. (1997) proposed an extension of the difference-in-differences approach in which the behaviour of the treatment and comparison groups are compared in two moments in time. Since the control group is constructed using matching techniques, this approach is known as conditional difference-in-differences (CDiD) to distinguish from the standard difference-in-differences (DiD) approach.

The CDiD estimator assumes the Bias Stability Assumption (BSA) (Heckman et al., 1997), this is, that selection on unobservables is constant over time. It assumes, in particular, that the treatment has no impact in pre-treatment outcomes and therefore any observed difference in the pre-treatment period between participants and non-participants can be used to correct the observed differences in post-treatment outcomes.

Under BSA, and denoting t and t' as the time periods after and before the programme, respectively, Δ_{Mt}^{ATT} as the matching estimator for the effect of participation at time t and $\Delta_{Mt'}^{ATT}$ as the matching estimator at time t', the effect of treatment on the treated is then given by:

$$\Delta_{CDiD}^{ATT} = \Delta_{Mt}^{ATT} - \Delta_{Mt'}^{ATT} \tag{6}$$

Since we assume that everything not observable is constant over time, by differentiating twice over treated and non-treated individuals and before and after the event, one gets rid of the unobservable component present in both groups.

4 - Data

With the empirical evaluation carried out by this paper we pretend to assess the impact of the Portuguese Active Labour Market Policy on the participants in the main different ongoing programmes considering a multi-treatment framework. For that purpose, the paper's empirical evaluation relies on a dataset containing secondary information built from the information system of the *Instituto de Emprego e Formação Profissional (IEFP),* the public employment service in Portugal. This consists of an administrative dataset containing relevant information, as individual and labour market characteristics, related to all the individuals who had been registered by the public employment service. These records allow us to follow the registered labour history, including the participation on each ALMP and all (de)registration dates, normally connected to the reasons for it, on a monthly basis[4].

[4] The knowledge of all the registration and de-registration dates is an important issue because they allow us to understand the path of participation during the time period recorded by the public employment service. For instance, a registered individual recorded by *IEFP* as open unemployed, can change his labour market status due to the participation on an ALMP

The primary information is not suitable for scientific purposes, though. Since its main purpose is to be used in an administrative context, it became necessary to prepare the data in a way that makes possible its application in the econometric context discussed above. The construction of an identification variable, taking advantage of the existence of two original identification variables – for the individual and for the unemployment office – allow us to follow the individuals over their recorded labour history and, consequently, allow us to include the time component. Still the available data containing information about all the registered individuals in the period between January 1998 and December 2003 results in a dataset with a dimension difficult to deal with. Because it is not feasible to work with all these individuals the dimension obstacle was overcome using only part of the total amount of registered individuals during the above mentioned time period.

The sample population considered on this paper corresponds to all the individuals registered as unemployed at the beginning of January 2001 and who never participated in an ALPM before that period or will ever participate in another one after the analysed participation in one of the interest programmes. These restrictions to the sample construction try to avoid the contamination of the results for previous or subsequent participation in some kind of public employment programmes, which could lead to questions of sequential treatments which are not addressed by the present work.

The sample is further restricted to individuals aged between 16 and 60 years old to avoid bias caused by the legal impossibility to work and the abandon of the labour force due to retirement reasons, respectively. Apart from this age requirement only observations of those who change their register from one public employment office to another, were abandoned since data limitations do not allow us to follow them.

The interested unemployed population is then divided into different treatment sub-samples – which we will call treatment states –, according to the participation in a particular active programme, between January and December 2001, or the non-participation in any of the considered programmes[5]. Thus the treated individuals includes all individuals that participated in one of the possible considered treatment states between the period t' and t, with t' and t denoting points in time corresponding to periods of time before and after a particular treatment state participation, respectively.

The average treatment effect will be computed comparing the effects of participation in a particular programme with the participation in each of the other programmes and the non-participation case, that is, the outcome resulting of a participation in a treatment state will be compared with the outcome obtained by the alternative participation in each of the other treatment states.

The unemployment register at specific periods, t, after participation will be assumed as the outcome variable within our evaluation process. A positive average treatment effect on the treated will represent the maintenance of an unemployment register so it should then be considered as a failure of the programme, since the main official aim of the Portuguese active labour market policy is to help the unemployed individuals to find a regular employment[6].

5. EMPIRICAL ANALYSIS OF PARTICIPATION ON A TREATMENT STATE

5.1 – Descriptive Statistics

The propensity score matching literature supports the view that observable variables that might influence the decision of participation in one of the selected treatment states, as well as future potential employment outcomes, should be included in the conditioning set of characteristics, X, and, therefore, in the estimation of the propensity score for participation to avoid biased estimates of the causal effects. If we can include these available variables the question will be whether such important variables as motivation, ability or social contacts are missing so, the interest of applying a conditional difference-

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and become again openly unemployed before permanently, or just temporarily, de-registering due to a transition to a labour market status characterised by a regular employment.

[5] A non-participant is defined as a registered unemployed individual who has never been enrolled in any ALMP. However since we considered the non-participation as another treatment state, we will refer to all individuals as treated individuals.

[6] Other outcome variables, like wages for instance, could provide increased interest within an evaluation process but difficulties concerning the data source do not allow us to choose other feasible outcome variable.

in-differences estimator will be to try to capture the effect of these unobservable characteristics on the participants' results.

There is no algorithm to choose the set of characteristics X to include in the model used to estimate the propensity score and the economic theory – and, in this case, the nature of the institutional database – does not provide much guidance on how to choose it. For our empirical analysis were chosen, as factors that could be potentially important, socio-demographic variables like sex, age, regional location or the responsibility for others; qualification variables like the educational level, the previous occupational group, the qualification rank; and, labour market variables like the reason for being unemployed, the unemployment category or a previous register in a public employment office.

Details about the variables used in this paper, as well as their distribution between the treatment states are presented in Table 1. The predominant treatment state is undoubtedly the NP state with about 86% of the whole sample. Consequently only 14% of the selected unemployed population participated in a particular active programme during the year 2001. Among those who effectively participated it is important to note the participants in JC programmes – almost 8% of the whole sample – and the individuals directly placed in a job by the public employment service, which represent 3% of the sample. The remaining selected treatment states present a very similar size concerning the number of participants.

The whole sample is composed, by a bigger percentage, of women, no unqualified individuals or those with no previous occupation, with lower levels of education and under the age of 40. However, Table 1 also shows that there are differences related to gender, age, geographic location of participants, educational levels, reasons for the unemployment register and number of registers *per* individual at the public employment service and previous occupational groups among the individuals distributed by the six treatment states.

5.2 – Probability of Treatment State Participation

This section describes the results of the estimation of $(M+1)M/2$, with $(M+1)$ the number of treatment states, binomial *logit* models for the probability of individual participation in the selected treatment states. The results can be found in Table 2a), Table 2b) and Table 2c).

Lechner (2001) discusses whether the conditional participation probabilities should be estimated for each combination of states separately as binary choices or whether the process should be modelled simultaneously with a discrete choice model including all relevant states. Both alternatives present advantages, namely at a practical level[7]. If one chooses to estimate the binomial *logit* models, as did Larsson (2004) or Dorsett (2001), it could be preferable since it avoids the restrictions associated with simultaneous models, namely the IIA assumption associated with the multinomial *logit* model. At a practical level, such an option could be more robust to error since a misspecification in one model will have fewer consequences than in the simultaneous model in which case all results will be compromised. Arguments in favour of a multinomial option (using, for example, a multinomial *probit* model as Gerfin and Lechner (2002) and Frolich (2004) could stand up at a practical level since there is less output to consider.

The results of binomial *logit* models estimated show the probability of participation in one treatment state, compared with the remaining ones. For example, Table 2a) shows the results of the probability of being in the DP treatment state compared with each one of the other options – NP, JC, TE, PEP and BT.

Given the large number of models – fifteen binomial *logit* models – and variables the results are extensive and will not be discussed.

Table 3 presents the number of observations in the treatment (in row) and control (in columns) groups, for each binomial *logit* model, and several tests related to the estimation of these models. With

[7] Lechner (2001) argues that if $P^{l|ml}$ is modelled directly no information from sub-samples other than the containing participants in m and l is needed for the identification of equation (4) and we are basically back to the context of a single treatment. If all values of m and l are of interest, the whole sample is needed for identification. In that case either the binomial conditional probabilities could be estimated or a structural approach, where a complete choice problem is formulated in one model and estimated on the full sample, could be used.

the more common tests, as the Pseudo-R^2, the F-test ($LR\chi^2$, with degrees of freedom in brackets) and the value of the log-likelihood, we present also the correction prediction rate for participants in the treatment state (CPR_{TG}). Still since the dataset provides a full range of individual characteristics, we looked mainly at two aspects to obtain the preferred *logit* specifications: i) minimization of classification error[8]; and (ii) statistical significance of the included regressors.

The observation of Table 2a), Table 2b) and Table 2c) allow us to verify that the majority of variables are statistical significant in each *logit* model. To illustrate, variables like sex, age, educational levels and the reasons for the unemployment register perform particularly well in all models. In table 3 we can also verify that the variables in each model are jointly statistical significant. These results stress the findings that there are differences in the composition of the treatment states and represent a good indication that a matching procedure could produce effective results. Concerning the minimization of the classification error (Table 3) it is possible to find a within-sample correct prediction rate for participants in the treatment state in the 63-78% range.

6. THE MATCHING PROCEDURE

Given the choice probabilities, that is, the probability of being in a particular treatment state compared with another of the alternative states, it is possible to perform the matching on the propensity score.

For computational practical reasons, due to the dimension of the database, we chose to apply the nearest neighbour matching estimator, allowing the replacement of non-participant observations, within a common support region. This procedure is highly intuitive and not difficult to implement. It consists of a pairwise matching for every treated individual, obtained by choosing the closest non-treated individual given their propensity score. Although the choice of a nearest neighbour matching estimator might involve an efficiency loss (for each participant, this approach uses only its closest non-participant), it minimises the bias. The replacement option allows us to use the same non-participant individuals more than once if they prove to be good matches for participants.

However, before the matching procedure, it is necessary to guarantee the common support condition, that is, it is necessary to ensure that the observations from two different treatment states could be observed having a similar participation probability. In practice, this implies that some of the observations at the tails outside the common support region are excluded from the analysis if the propensity score distributions do not cover the exact same interval. Since we estimated pairwise effects between each of the different six treatment states *vs* the remaining ones, we used the criterion that all estimated probabilities in the particular sub-samples are smaller than the smallest maximum and larger than the largest minimum – the requirement is that all observations in the treatment state m for which there does not exist a comparison observation in treatment state l, $(m,l \in \{0,1,...M\}, m \neq l)$, are removed from the sub-sample.

After ensuring the common support condition and before showing the results of the propensity score matching procedure it is also important to verify the quality of the matching procedure to balance the relevant characteristics, since our matching procedure is conditional on the propensity score. In other words, the variables included in the propensity score model should guarantee that, for a given propensity score, the exposure to treatment is random. Table 5 shows the results of several tests performed in the matching procedure to verify the quality of its results.

The standardized bias suggested by Rosenbaum and Rubin (1985), for each characteristic in vector *X*, is a suitable indicator for testing the balancing property and it has been often used in the evaluation literature (e.g. Gerfin and Lechner, 2002; Larsson, 2004; and Dorsett, 2001). This indicator is defined as the difference in the mean of the two sub-samples (treated and control) as a percentage of

[8] Minimization of classification error was suggested by Heckman et al. (1998) and Heckman et al. (1999).

the square root of the average of the sample variances in both groups.[9] Due to the extension of the results the results for each variable are not presented. However the matching procedure achieved a significant reduction of the standardized differences among the variables, as it is possible to observe in Table 5 which presents the results for the mean standardized bias calculated as an unweighted average of the absolute standardized bias for each variable.

Another balancing test applied was the t-test on differences in means between the treated and comparison groups before and after matching, for each variable included in the matching procedure. Again practical reasons do not allow us to show the results. However we can guarantee that for most of the variables, this test yielded significant differences before matching but not after matching, indicating again the capacity of the matching procedure to balance the characteristics in the treatment and the matched comparison treatment states.

An alternative route, suggested by Sianesi (2004), consists of re-estimating the propensity score for the matched sample to compare the estimated pseudo-R^2 before and after matching. After matching there should be no systematic differences in the distribution of the covariates between both groups (participants and matched non-participants). In other words, the pseudo-R^2 after matching should be fairly low. As Table 5 shows, this is true in our case.

The results of the F-tests ($LR\chi^2$, with degrees of freedom in brackets) point in the same direction, indicating a joint significance of all variables before but not after matching for some of the estimated models.

7. RESULTS

Our goal is to measure the causal effects of participation in one of the selected treatment states compared with other options, in a multiple treatment framework, in terms of the employability prospects of participants, both in the short and long-run. So, the effect of the programmes' state participation will be measured adopting as the outcome the register in the public employment service.

Table 5 displays the results of the matching procedure on the average treatment effect of the programmes on their respective participants during two and a half years after the beginning of participation, Δ_{Mt}^{ATT}. The same table presents the mean differences concerning the unemployment register for the matched individuals before participation, $\Delta_{Mt'}^{ATT}$, which will be used to correct the bias due to selection on unobservables.

In the context of the econometric methodology presented in section 3, we will assume that the true effect of a treatment state before the beginning of participation is zero, so the differences among the registered unemployment rates of participants in the distinct treatment states, before treatment, are a good estimator of the unobserved differences among treated and comparison matched individuals. Being the individuals selected by the public employment service to engage in a particular treatment state it seems difficult for an individual to anticipate the participation in a programme and thus to change their labour market behaviour due to a potential participation. Furthermore the programme's target population are the unemployed so, in the Portuguese labour market, an individual must be registered at an unemployment office, as unemployed, in order to participate in the programme and it is not plausible that the individual abandons their labour market status, namely an employment status, to increase the probability of participating in a temporary occupational activity.

The former assumption allows us to estimate the bias due to incorrectly applied conditional independence assumption (CIA) and if we further assume that this bias is on average identical to the t and t' points in time chosen – the Bias Stability Assumption (BSA) – we can use the estimated bias to correct the estimate of the average effect of the treatment on the treated we get for t, assuming only the CIA

[9] Standardized Bias: $\dfrac{\left(\overline{X}_1 - \overline{X}_0\right)}{\sqrt{\left(V_1\left(X_1\right)+V_0\left(X_0\right)\right)/2}}$, where $\overline{X}_1\left(V_1\right)$ is the mean (variance) in the treatment group and $\overline{X}_0\left(V_0\right)$ is the analogue for the control group.

However, still in Table 5, each 6x6 square corresponds to the matrix of the comprehensive programme's effects in a selected point in time – one to five semesters (before and after the treatment). The programme effects are presented off the main diagonal. A positive number indicates that the effect on the participants of the programme shown in the column compared with the programme appearing in the row corresponds to a bigger amount of percentage points in the probability of being registered as unemployed. A negative number represents the inverse situation.

For example, six months after the beginning of participation (time period, t=1) in a PEP the participants have almost 22% more probability of being registered as unemployed compared with those non-participants (NP state). The percentage increases to 51% compared with those in the DP state, to almost 55% compared with the BT state and to 70% compared to the BT state. The bigger percentage of unemployment registers for PEPs participants is only reduced if we compare the PEP participation with the JC state – the percentage of unemployment rates is still bigger for the PEP state but now the difference is 4%, only. These results seem to improve over time. After two and a half years, the participation in PEPs still compares relatively badly except when compared with the NP treatment state. In the long-run the PEPs participants have 3% less probability of being registered as unemployed than the non-participants. Regarding the other treatment states, in the long-run a bigger probability of being unemployed decreases substantially and remains between 5 and 10 percent points.

On the other hand, we can find the results of the TE state. Six months after the beginning of participation, the average treatment effects on the treated show that the participation in TE has lower probabilities of having an unemployment register than all the other treatment options. The results, although remaining generally positive in terms of employability of TE participants, are reduced in the long-run and compared with the DP state the participants in the TE treatment state present a bigger probability of being unemployed.

Once more the results are obviously wide and a detailed description could be unpleasant reading so only some general remarks will be presented.

In the short-run PEP and JC treatment states seem to perform worse than DP, TE, BT and even NP treatment states. Between PEPs and JC, PEPs seems to perform the worst. The programmes which seem to perform better, in the short–run, are the BT and the TE, performing even better than the DP. We believe that the findings for the short-run, are not due directly to the performance of the programmes themselves but to administrative reasons – the participation in programmes like the BT and TE has the immediate result of unemployment's register cancellation, which does not happen, obviously, in the non-participation state or in the JC programmes. Another explanation concerns the locking-in effects due to a lower amount of free time to look for regular employment.

Indeed, in the long-run the average treatment results for the treated are not so clear. However is interesting to point out that all the treatment states seemed to produce better results than the non-participation treatment state, as is expected by an active labour market policy in the labour market. In a longer period of time the probability of having an unemployment register is lower for DP, JC, TE, PEP and BT treatments than for non-participants. However, among the effective participation in a particular active programme, the PEP is the programme that presents worse results followed by JC that performs only better than PEPs. In the long-run the programme that performs better is the DP – the participants directly placed in a job by the public employment service have a lower rate of unemployment registers than all the other participants in some treatment state.

The former analysis must be seen with careful, though. If we observe the unemployment's register rates among the state's participants before participation (this is, in time periods t=-1,-2,…,-5 in Table 5) we will see there are differences among participants that could, as we said above, indicate the existence of some unobserved heterogeneity not captured for the observed variables used to estimate the propensity score.

So, to estimate the unbiased average treatment effect on the treated we used the conditional difference-in-differences estimator, Δ_{CDiD}^{ATT}, in equation (6) above. Our application of the CDiD methodology was made considering two approaches to estimate the register unemployment effects of participation. The first approach uses t' symmetric to t, that is, given t_0 – the month where the program begins – the outcome variable is evaluated 1, 2, …, 5 semesters before and after t_0. The acronym $\left(t' = -t\right)$ denotes this case, for t = 1, 2,…, 5. The second approach considers t' fixed at one semester before t_0 and then t equal to 1, 2, …, and 5 semesters, respectively. This case is denoted by the acronym $\left(t^{'}=-1\right)$. The results for both approaches are presented in Table 6.

Having as reference the NP treatment state, the programmes present better results except for JC and PEP programmes. The explanation for the worse results of the PEPs could rest in a probable reduction of job search activities during participation, which can last for twelve months. The better results of DP, TE and BT could rest in administrative reasons – the individuals with participation in the last treatment states leave the unemployment register with the beginning of participation. Over time, however, the effects of all treatment states tend to converge and, even if the results for the t'=1 approach are more evident, in the long run all the treatment states seem to perform better than the non-participation.

Comparing each active programme with the others and with a state of non-participation is possible to observe the following conclusions.

When the DP is the reference treatment group TE and BT perform better in the short-run, only. The reason is probably due to the duration of the programmes. Those programmes can last for twelve months and their participants must leave the unemployment register during the participation time. Indeed if we observe the twelve months moment in time we find worse results for the BT and TE treatment states than for the DP treatment state. The better results of the DP treatment state over the others remains in the long-run. A possible explanation is that the individuals directly placed by the public employment service in a regular employment could be better adapted to the needs of the labour market and, because of that, it is easier to match their demands for a job with the available job offers;

Compared with the JC programmes only the PEP treatment state participants perform worse. The relative position of the JC programmes remains the same. In the long-run, only the BT treatment state seems to perform better if we compared it with the differences in the register unemployment rates closer to the beginning of participation and all the treatment states have similar effects if we compared with the opposite moment in time before participation;

Compared with the TE treatment state all the programmes perform worse in the short-run. The reasons were already presented. However in the long run they remain as the treatment state with better results only with the exception of the BT treatment state, only. The programmes of training seem to give to their participants permanent conditions to be more appealing to the labour market opportunities. In fact, when using the differences in the unemployment register rates for the period of time nearest to the beginning of participation it is clear that a participation on BT produces better results than a participation in another kind of active labour market programme. When using the differences in the unemployment register rates for periods of time more distant relating to the beginning of participation, the absolute better results of the BT treatment state are not so obvious and are quite similar to the results obtained to the TE treatment state;

As TE programmes have an important component of training, the conclusion that training induces an improvement in unemployed individuals' employability, in the long-run, is reinforced;

We can observe the PEP treatment state has worse results for participants in active labour market programmes. Indeed in the short-run the results for the PEP are even worse than the results for non-participants. Only in the long-run are the results of a PEP participation better than the non-participation results. The same conclusion was obtained by Gerfin and Lechner (2002) who admit that the additional amount of human capital obtained in these kinds of programmes is too small to compensate for the initial effects due to a reduced job search

Finally it is important to note that in the long-run all the treatment states' effects in the unemployment registers converge to the same relative values. This conclusion could indicate some sort of time dilution of the average treatment effects on the treated.

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Table 1: Number of Observations and Pre-Treatment Characteristics

VARIABLES (%)	NP	DP	JC	TE	PEP	BT
Number of Individuals	147548	5414	13581	1686	2550	1484
(%)	(85.65)	(3.14)	(7.88)	(0.98)	(1.48)	(0.86)
Sex (Men)	40.08	34.97	41.67	21.00	22.94	23.99
Age (Absolute value)	37.44	30.59	40.79	28.66	36.99	32.13
Persons at charge (yes)	47.58	42.93	49.91	33.63	60.00	52.63
Geographic location						
Norte	40.12	21.33	60.56	36.60	30.28	22.71
Centro	11.50	35.30	9.82	26.99	20.94	15.50
Lisboa e Vale do Tejo	40.04	23.68	26.03	23.07	27.41	43.26
Alentejo	5.29	4.71	1.84	7.59	17.37	16.11
Algarve	3.05	14.98	1.75	5.75	4.00	2.43
Educational level						
None	6.43	3.86	7.08	0.83	9.10	2.16
Primary (4 years)	34.07	23.68	41.30	17.97	36.16	19.95
Compulsory Secondary (9 years)	34.70	44.79	31.44	27.34	35.77	54.72
Secondary (12 years)	16.09	21.70	13.08	21.83	14.90	20.01
Superior (15 or more years)	8.72	5.97	7.11	32.03	4.08	3.17
Previous occupational group						
- None	11.24	17.64	8.67	45.02	8.98	13.34
- Management	1.43	0.35	1.23	0.53	0.39	0.20
- Scientific specialist	3.79	2.07	4.15	3.20	2.35	2.02
- Technical worker	6.78	4.17	7.63	2.85	3.80	4.25
- Administrative worker	13.22	10.79	13.70	8.96	14.00	13.88
- Seller	15.52	20.04	12.96	12.34	16.63	21.63
- Farmer	4.60	3.36	3.70	3.74	8.63	5.26
- Manufacturer's worker	14.87	11.95	18.28	6.94	10.71	11.12
- Machine's operator	9.64	8.52	11.43	2.37	6.71	6.13
- No-qualified worker	18.92	21.11	18.25	14.06	27.80	22.17
First employment (yes)	11.24	17.66	8.70	45.02	8.98	13.48
Re-application at IEFP (yes)	48.95	62.10	40.00	54.09	60.12	62.00
Reasons for unemployment register						
- End of formal education	9.95	15.87	7.14	38.14	5.96	12.33
- Dismissal	38.39	25.38	48.47	16.07	32.04	26.48
- End of temporary occupation	34.74	41.98	31.23	19.87	39.73	36.93
- Re-application	2.81	5.84	2.49	10.14	5.77	7.35
- Other	14.11	10.94	10.68	15.78	16.51	16.91

Table 2a): The Determinants of Participation on DP programmes comparing with the remaining ones

VARIABLES	DP (comparing with)				
	NP	JC	TE	PEP	BT
Sex	-0.058 (***) (0.032)	0.106 (**) (0.045)	0.548 (*) (0.076)	0.685 (*) (0.065)	0.511 (*) (0.076)
Age	-0.051 (*) (0.002)	-0.083 (*) (0.002)	-0.017 (*) (0.005)	-0.053 (*) (0.003)	-0.026 (*) (0.004)
Persons at charge (yes)	0.046 (0.033)	0.032 (0.045)	-0.239 (*) (0.082)	-0.238 (*) (0.059)	-0.250 (*) (0.073)
Geographic location					
Norte	-2.202 (*) (0.052)	-3.409 (*) (0.092)	-1.284 (*) (0.134)	-2.022 (*) (0.126)	-1.932 (*) (0.188)
Centro	-0.477 (*) (0.048)	-0.966 (*) (0.093)	-0.301 (**) (0.134)	-1.052 (*) (0.124)	-1.032 (*) (0.189)
Lisboa e Vale do Tejo	-1.992 (*) (0.050)	-2.207 (*) (0.091)	-0.786 (*) (0.135)	-1.609 (*) (0.123)	-2.438 (*) (0.181)
Alentejo	-1.744 (*) (0.077)	-1.355 (*) (0.133)	-1.203 (*) (0.171)	-2.860 (*) (0.143)	-3.147 (*) (0.200)
Algarve	(a)	(a)	(a)	(a)	(a)
Educational level					
None	0.579 (*) (0.105)	0.670 (*) (0.143)	3.590 (*) (0.310)	-0.382 (***) (0.204)	0.481 (0.297)
Primary (4 years)	0.549 (*) (0.080)	0.627 (*) (0.113)	2.172 (*) (0.142)	-0.243 (0.177)	-0.280 (0.223)
Compulsory Secondary (9 years)	0.520 (*) (0.073)	0.460 (*) (0.102)	2.138 (*) (0.115)	-0.207 (0.167)	-1.007 (*) (0.207)
Secondary (12 years)	0.552 (*) (0.072)	0.497 (*) (0.101)	1.726 (*) (0.108)	-0.132 (0.165)	-0.744 (*) (0.206)
Superior (15 or more years)	(a)	(a)	(a)	(a)	(a)
Previous occupational group					
- None	-0.031 (0.565)	1.330 (***) (0.784)	-0.206 (0.877)	-0.314 (1.429)	1.224 (0.970)
- Management	-0.886 (*) (0.238)	-1.231 (*) (0.280)	0.114 (0.474)	-0.251 (0.440)	0.597 (0.683)
- Scientific specialist	-0.491 (*) (0.116)	-1.136 (*) (0.152)	0.907 (*) (0.219)	-0.529 (**) (0.229)	-0.539 (**) (0.280)
- Technical worker	-0.275 (*) (0.080)	-0.586 (*) (0.106)	0.545 (*) (0.201)	-0.011 (0.152)	-0.004 (0.176)
- Administrative worker	-0.285 (*) (0.057)	-0.561 (*) (0.079)	0.230 (***) (0.137)	-0.364 (*) (0.103)	-0.168 (0.120)
- Seller	-0.143 (*) (0.046)	-0.159 (**) (0.068)	0.155 (0.112)	0.211 (**) (0.084)	0.056 (0.099)
- Farmer	-0.436 (*) (0.084)	-0.486 (*) (0.115)	-0.414 (**) (0.177)	0.074 (0.131)	0.045) (0.174)
- Manufacturer's worker	0.013 (0.053)	-0.161 (**) (0.071)	0.181 (0.130)	0.360 (*) (0.096)	0.142 (0.116)
- Machine's operator	0.044 (0.059)	-0.115 (0.081)	0.783 (*) (0.187)	0.400 (*) (0.113)	0.256 (**) (0.141)
- No-qualified worker	(a)	(a)	(a)	(a)	(a)
First employment (yes)	-0.131 (0.565)	-1.785 (**) (0.783)	-0.058 (0.874)	0.230 (1.427)	-1.032 (0.967)
Re-application at IEFP (yes)	0.342 (*) (0.031)	0.641 (*) (0.043)	0.117 (***) (0.069)	0.165 (*) (0.058)	0.121 (**) (0.068)
Reasons for unemployment register					
- End of formal education	(a)	(a)	(a)	(a)	(a)
- Dismissal	-0.128 (0.080)	-0.372 (*) (0.115)	0.511 (*) (0.143)	-0.739 (*) (0.151)	0.049 (0.158)
- End of temporary occupation	-0.058 (0.077)	-0.298 (*) (0.113)	0.729 (*) (0.138)	-0.726 (*) (0.148)	0.095 (0.154)
- Re-application	0.354 (*) (0.087)	0.336 (**) (0.132)	-0.050 (0.142)	-0.613 (*) (0.166)	-0.283 (0.174)
- Other	-0.073 (0.077)	0.085 (0.111)	0.005 (0.130)	-0.838 (*) (0.143)	-0.242 (0.152)
Constant	-0.523 (*) (0.122)	3.902 (*) (0.185)	0.145 (0.246)	4.728 (*) (0.262)	4.502 (*) (0.333)

Notes: (a) denotes the reference variable. *, **, and *** denote statistical significance at 0.01, 0.05, and 0.1. Standard errors are in parentheses.

Table 2b): The Determinants of Participation on JC programmes comparing with the remaining ones

VARIABLES	JC (comparing with)			
	NP	JC	TE	PEP
Sex	-0.073 (*)	0.447 (*)	0.583 (*)	0.464 (*)
	0.020	0.074	0.057	0.074
Age	0.024 (*)	0.062 (*)	0.031 (*)	0.051 (*)
	0.001	0.004	0.003	0.004
Persons at charge (yes)	-0.015	-0.225 (*)	-0.320 (*)	-0.232 (*)
	0.019	0.077	0.051	0.068
Geographic location				
Norte	0.948 (*)	1.635 (*)	1.575 (*)	1.328 (*)
	0.069	0.153	0.132	0.200
Centro	0.392 (*)	0.276 (***)	0.085	-0.160
	0.073	0.160	0.137	0.206
Lisboa e Vale do Tejo	0.050	0.936 (*)	0.718 (*)	-0.326 (**)
	0.070	0.157	0.133	0.197
Alentejo	-0.475 (*)	-0.056	-1.289 (*)	-1.777 (*)
	0.094	0.196	0.152	0.219
Algarve	(a)	(a)	(a)	(a)
Educational level				
None	-0.053	2.866 (*)	-0.672 (*)	0.061
	0.063	0.300	0.178	0.280
Primary (4 years)	0.090 (***)	1.431 (*)	-0.472 (*)	-0.552 (*)
	0.052	0.131	0.158	0.208
Compulsory Secondary (9 years)	0.155 (*)	1.455 (*)	-0.399 (*)	-1.261 (*)
	0.048	0.106	0.148	0.192
Secondary (12 years)	0.119 (**)	1.090 (*)	-0.466 (*)	-1.120 (*)
	0.048	0.098	0.148	0.191
Superior (15 or more years)	(a)	(a)	(a)	(a)
Previous occupational group				
- None	-0.551	-0.283	-17.188	0.381
	0.464	1.122	.	0.957
- Management	0.021	1.022 (*)	1.224 (*)	1.877 (*)
	0.088	0.377	0.346	0.599
- Scientific specialist	0.450 (*)	1.709 (*)	0.858 (*)	0.531 (**)
	0.062	0.193	0.190	0.242
- Technical worker	0.229 (*)	0.988 (*)	0.687 (*)	0.630 (*)
	0.043	0.186	0.130	0.161
- Administrative worker	0.163 (*)	0.640 (*)	0.321 (*)	0.449 (*)
	0.035	0.128	0.086	0.111
- Seller	0.017	0.325 (*)	0.387 (*)	0.202 (**)
	0.034	0.112	0.078	0.098
- Farmer	0.073	-0.004	0.356 (*)	0.534 (*)
	0.052	0.169	0.111	0.168
- Manufacturer's worker	0.113 (*)	0.384 (*)	0.593 (*)	0.365 (*)
	0.031	0.125	0.084	0.112
- Machine's operator	0.042	0.872 (*)	0.538 (*)	0.500 (*)
	0.035	0.183	0.100	0.137
- No-qualified worker	(a)	(a)	(a)	(a)
First employment (yes)	0.892 (**)	0.423	17.567 (*)	0.382
	0.464	1.119	0.131	0.949
Re-application at IEFP (yes)	-0.230 (*)	-0.545 (*)	-0.388 (*)	-0.456 (*)
	0.020	0.067	0.051	0.066
Reasons for unemployment register				
- End of formal education	(a)	(a)	(a)	(a)
- Dismissal	0.300 (*)	0.779 (*)	-0.476 (*)	0.550 (*)
	0.067	0.143	0.151	0.168
- End of temporary occupation	0.328 (*)	0.884 (*)	-0.567 (*)	0.479 (*)
	0.067	0.139	0.149	0.164
- Re-application	0.252 (*)	-0.540 (*)	-0.896 (*)	-0.537 (*)
	0.081	0.146	0.172	0.189
- Other	-0.113 (**)	-0.305 (**)	-1.001 (*)	-0.273 (***)
	0.064	0.130	0.144	0.162
Constant	-4.158 (*)	-2.855 (*)	0.435 (***)	0.508
	0.107	0.245	0.240	0.321

Notes: (a) denotes the reference variable. *, **, and *** denote statistical significance at 0.01, 0.05, and 0.1. Standard errors are in parentheses.

Table 2c): The Determinants of Participation on TE, PEP and BT comparing with the remaining ones

	TE (comparing with)			PEP (comparing with)		BT (comparing with)
VARIABLES	NP	PEP	BT	NP	BT	NP
Sex	-0.558 (*)	-0.103	-0.300 (*)	-0.643 (*)	-0.163 (***)	-0.590 (*)
	0.063	0.100	0.107	0.050	0.088	0.065
Age	-0.039 (*)	-0.037 (*)	-0.014 (**)	-0.009 (*)	0.031 (*)	-0.029 (*)
	0.004	0.005	0.006	0.002	0.004	0.003
Persons at charge (yes)	0.212 (*)	-0.129	-0.060	0.314 (*)	-0.010	0.307 (*)
	0.067	0.088	0.100	0.044	0.077	0.059
Geographic location	(a)	(a)	(a)	(a)	(a)	(a)
Norte	-0.935 (*)	-0.221	-0.419 (***)	-0.483 (*)	-0.092	-0.273
	0.116	0.185	0.229	0.110	0.217	0.180
Centro	-0.186	-0.485 (**)	-0.664 (*)	0.378 (*)	-0.106	0.536 (*)
	0.118	0.191	0.235	0.112	0.221	0.183
Lisboa e Vale do Tejo	-1.300 (*)	-0.400 (**)	-1.304 (*)	-0.528 (*)	-0.922 (*)	0.433 (**)
	0.119	0.187	0.226	0.109	0.212	0.174
Alentejo	-0.598 (*)	-1.423 (*)	-1.814 (*)	0.924 (*)	-0.341	1.331 (*)
	0.141	0.212	0.250	0.114	0.223	0.183
Algarve	(a)	(a)	(a)	(a)	(a)	(a)
Educational level						
None	-2.876 (*)	-3.805 (*)	-2.985 (*)	0.754 (*)	0.745 (**)	0.103
	0.284	0.335	0.402	0.152	0.312	0.255
Primary (4 years)	-1.472 (*)	-2.030 (*)	-2.072 (*)	0.604 (*)	-0.107	0.682 (*)
	0.105	0.196	0.239	0.136	0.251	0.188
Compulsory Secondary (9 years)	-1.491 (*)	-1.887 (*)	-2.717 (*)	0.555 (*)	-0.836 (*)	1.370 (*)
	0.081	0.176	0.217	0.129	0.238	0.174
Secondary (12 years)	-1.075 (*)	-1.685 (*)	-2.270 (*)	0.563 (*)	-0.629 (*)	1.166 (*)
	0.074	0.171	0.212	0.128	0.239	0.173
Superior (15 or more years)	(a)	(a)	(a)	(a)	(a)	(a)
Previous occupational group						
- None	0.016	-0.220	2.004	-0.023	18.361	-1.570 (**)
	0.741	2.122	1.350	1.013	.	0.712
- Management	-1.148 (*)	0.128	0.746	-0.962 (*)	0.637	-1.611 (*)
	0.349	0.571	0.805	0.325	0.683	0.585
- Scientific specialist	-1.253 (*)	-1.137 (*)	-1.207 (*)	-0.283 (***)	-0.288	-0.220
	0.169	0.267	0.330	0.166	0.306	0.219
- Technical worker	-0.818 (*)	-0.169	-0.038	-0.455 (*)	0.032	-0.461 (*)
	0.168	0.223	0.244	0.117	0.192	0.146
- Administrative worker	-0.470 (*)	-0.349 (**)	-0.146	-0.111	0.168	-0.293 (*)
	0.114	0.148	0.161	0.074	0.126	0.096
- Seller	-0.296 (*)	0.001	-0.116	-0.339 (*)	-0.147	-0.178 (**)
	0.099	0.124	0.134	0.064	0.109	0.081
- Farmer	0.143	0.252	0.361 (**)	-0.225 (*)	-0.030	-0.260 (**)
	0.146	0.179	0.210	0.084	0.166	0.132
- Manufacturer's worker	-0.186	0.153	0.036	-0.392 (*)	-0.153	-0.128
	0.116	0.143	0.158	0.074	0.129	0.099
- Machine's operator	-0.813 (*)	-0.312	-0.425 (***)	-0.425 (*)	-0.060	-0.303 (**)
	0.173	0.206	0.224	0.088	0.158	0.121
- No-qualified worker	(a)	(a)	(a)	(a)	(a)	(a)
First employment (yes)	0.171	0.422	-1.516	-0.118	-18.057 (*)	1.105
	0.738	2.121	1.343	1.012	0.175	0.709
Re-application at IEFP (yes)	0.231 (*)	0.008	0.052	0.149 (*)	0.054	0.184 (*)
	0.055	0.083	0.090	0.044	0.076	0.058
Reasons for unemployment register						
- End of formal education	(a)	(a)	(a)	(a)	(a)	(a)
Dismissal	-0.502 (*)	-1.337 (*)	-0.488 (*)	0.610 (*)	0.977 (*)	-0.309 (**)
	0.118	0.182	0.190	0.126	0.185	0.140
End of temporary occupation	-0.612 (*)	-1.454 (*)	-0.628 (*)	0.628 (*)	0.932 (*)	-0.269 (**)
	0.114	0.176	0.184	0.124	0.179	0.136
Re-application	0.774 (*)	-0.575 (*)	-0.311	1.010 (*)	0.422 (**)	0.530 (*)
	0.110	0.190	0.201	0.139	0.203	0.152
Other	0.157	-0.764 (*)	-0.230	0.793 (*)	0.700 (*)	0.092
	0.101	0.166	0.176	0.120	0.176	0.134
Constant	-0.781 (*)	4.036 (*)	3.960 (*)	-4.532 (*)	-0.405	-4.609 (*)
	0.198	0.325	0.385	0.207	0.378	0.288

Notes: (a) denotes the reference variable. *, **, and *** denote statistical significance at 0.01, 0.05, and 0.1. Standard errors are in parentheses.

Table3: Tests for the Binomial *Logit* Models

		DP (comparing with)					JC (comparing with)				TE (comparing with)			PEP (comparing with)		BT (comparing with)
		NP	JC	TE	PEP	BT	NP	TE	PEP	BT	NP	PEP	BT	NP	BT	PEP
Observations N		152962	18995	7100	7964	6898	161129	15267	16131	15065	149234	4236	3170	150098	4034	149032
TG	N	5414	5414	5414	5414	5414	13581	13581	13581	13581	1686	1686	1686	2550	2550	1484
	%	3.53	28.5	76.25	67.98	78.49	8.43	88.96	84.19	90.15	1.13	39.8	53.19	1.70	63.21	1.0
CG	N	147548	13581	1686	2550	1484	147548	1686	2550	1484	147548	2550	1484	147548	1484	147548
	%	96.46	71.5	23.75	32.02	21.51	91.57	11.04	15.81	9.85	98.87	60.2	46.81	98.3	36.79	99.0
Pseudo R^2 (%)		12.39	30.82	18.15	16.17	13.4	4.09	29.08	16.87	23.65	14.17	25.42	21.16	5.49	9.5	7.04
$LR\chi^2(26)$		5800.53	6996.3	1412.82	1615.23	962.57	3812.3	3085.14	2375.29	2293.2	2617.47	1447.43	927.19	1418.12	504.02	1170.63
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log-Likelihood		-20506.03	-7853.915	-3185.384	-4185.920	-3110.372	-44678.76	-3761.52	-5853.111	-3701.14	-7926.308	-2123.719	-1727.243	-12210.90	-2401.60	-7731.650
CPR_{TG} (%)		67.53	75.66	72.63	69.04	66.01	64.44	78.28	73.85	76.57	65.3	65.54	63.76	63.84	62.78	70.15

Notes: Subscripts TG and CG denote treatment and control groups, respectively. CPR is the Correction Prediction Rate for Participants

Table 4: Matching Quality

Comparison Group		Treatment Group											
		NP		DP		JC		TE		PEP		BT	
		Before	After	Before	After	Before	After	Before	After	Before	After	Before	After
NP	MSAB			18.91	1.64	10.02	1.14	30.29	1.27	13.95	1.64	17.03	2.79
	Pseudo-R2			12.5	0.2	4.1	0.1	14.0	0.2	5.5	0.2	7.1	0.5
	Log-Like			5866.21	30.06	3817.92	52.84	2580.09	8.95	1432.46	15.79	1182.54	18.52
	P>chi			(0.000)	(0.265)	(0.000)	(0.001)	(0.000)	(0.999)	(0.000)	(0.921)	(0.000)	(0.856)
DP	MSAB	18.91	5.34			25.44	4.63	23.75	2.48	18.41	2.97	13.41	2.78
	Pseudo-R2	12.5	1.3			31.0	1.5	29.1	0.5	16.9	0.7	23.8	0.7
	Log-Like	5866.21	5174.68			7036.10	549.71	3091.85	25.32	2384.7	48.11	2303.35	27.22
	P>chi	(0.000)	(0.000)			(0.000)	(0.000)	(0.000)	(0.501)	(0.000)	(0.004)	(0.000)	(0.398)
JC	MSAB	10.02	1.34	25.44	3.06			36.44	2.71	18.93	3.33	26.04	3.38
	Pseudo-R2	4,1	0.1	31.0	0.6			18.2	0.7	16.1	0.6	13.3	0.8
	Log-Like	3817.92	460.32	7036.10	90.06			1419.8	31.8	1611.15	42.82	957.78	31.28
	P>chi	(0.000)	(0.000)	(0.000)	(0.000)			(0.000)	(0.200)	(0.000)	(0.000)	(0.000)	(0.218)
TE	MSAB	30.29	6.24	23.75	5.02	36.44	8.43			30.63	4.41	27.23	2.22
	Pseudo-R2	14.0	2.6	18.2	1.4	29.1	4.4			25.5	1.4	21.1	0.3
	Log-Like	2580.09	10511.49	1419.8	208.14	3091.85	1619.22			1449.89	92.19	926.4	12.83
	P>chi	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			(0.000)	(0.000)	(0.000)	(0.985)
PEP	MSAB	13.95	2.42	18.41	3.81	18.93	3.78	30.63	4.67			13.24	3.74
	Pseudo-R2	5,51	0.4	16.1	0.9	16.9	0.8	25.5	1.4			9.5	0.8
	Log-Like	1432.46	1715.4	1611.15	134.35	2384.7	301.17	1449.89	64.17			505.01	31.53
	P>chi	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			(0.000)	(0.172)
BT	MSAB	17.03	6.94	13.41	3.75	26.04	8.55	27.23	6.01	13.24	4.73		
	Pseudo-R2	7.1	1.8	13.3	1.0	23.8	2.3	21.1	2.2	9.5	1.4		
	Log-Like	1182.54	7282.18	957.78	152.92	2303.35	774.77	926.4	101.25	505.01	102.08		
	P>chi	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		

Table 5: Average unemployment register of matched individuals, before and after treatment

Period −1 to −5: $\Delta^{\acute{A}TT}_{Mt'}$; Period 1 to 5: $\Delta^{\acute{A}TT}_{Mt}$

Period - 1 ($\Delta^{\acute{A}TT}_{Mt'}$)

Comparison Group \ Treatment Group	NP	DP	JC	TE	PEP	BT
NP		6.2%	-1.1%	5.9%	7.6%	17.5%
DP	-7.6%		0.7%	0.7%	-1.4%	5.7%
JC	-9.6%	-10.9%		-6.2%	-2.8%	9.9%
TE	-11.2%	-5.9%	-8.4%		-4.6%	7.2%
PEP	-7.5%	-1.6%	0.8%	2.2%		9.3%
BT	-15.1%	-10.9%	-6.4%	-9.0%	-12.2%	

Period - 2 ($\Delta^{\acute{A}TT}_{Mt'}$)

Comparison Group \ Treatment Group	NP	DP	JC	TE	PEP	BT
NP		-1.5%	-7.5%	0.2%	-1.1%	12.8%
DP	-2.1%		2.5%	1.3%	-4.4%	8.9%
JC	-2.6%	2.7%		7.7%	-3.5%	13.7%
TE	-16.5%	-9.1%	-13.1%		-15.1%	4.1%
PEP	-0.8%	0.4%	6.8%	-0.1%		11.0%
BT	-11.6%	-8.7%	-7.7%	-3.9%	-13.9%	

Period - 3 ($\Delta^{\acute{A}TT}_{Mt'}$)

Comparison Group \ Treatment Group	NP	DP	JC	TE	PEP	BT
NP		-5.1%	-39.4%	-4.2%	-12.3%	-2.3%
DP	3.2%		-21.3%	-0.2%	-6.6%	0.3%
JC	25.1%	14.6%		14.1%	13.1%	20.4%
TE	3.5%	-2.4%	-33.3%		-6.7%	-0.1%
PEP	11.6%	4.2%	-10.2%	1.4%		3.9%
BT	2.1%	-2.9%	-25.9%	1.0%	-10.2%	

Period - 4 ($\Delta^{\acute{A}TT}_{Mt'}$)

Comparison Group \ Treatment Group	NP	DP	JC	TE	PEP	BT
NP		-5.7%	-26.3%	-6.7%	-11.7%	-5.1%
DP	2.2%		-14.3%	-2.0%	-3.3%	-1.1%
JC	17.0%	8.3%		6.2%	5.8%	9.9%
TE	6.0%	-0.3%	-14.2%		-3.0%	-1.5%
PEP	7.9%	2.3%	-5.2%	-3.0%		-1.2%
BT	5.6%	-0.1%	-13.5%	1.2%	-3.8%	

Period - 5 ($\Delta^{\acute{A}TT}_{Mt'}$)

Comparison Group \ Treatment Group	NP	DP	JC	TE	PEP	BT
NP		-1.2%	-12.4%	-4.1%	-3.5%	-3.6%
DP	-1.7%		-7.8%	-2.0%	0.0%	0.7%
JC	6.2%	2.4%		1.7%	3.8%	3.3%
TE	1.1%	-2.5%	-5.3%		-0.8%	2.1%
PEP	1.0%	-1.3%	-3.1%	-4.2%		-3.2%
BT	0.5%	-2.7%	-6.7%	-1.3%	-3.3%	

Period 1 ($\Delta^{\acute{A}TT}_{Mt}$)

Comparison Group \ Treatment Group	NP	DP	JC	TE	PEP	BT
NP		-24.0%	14.2%	-39.1%	21.5%	-28.2%
DP	28.4%		48.9%	-18.6%	51.0%	-3.7%
JC	-15.2%	-39.5%		-51.6%	4.3%	-43.8%
TE	44.9%	13.5%	67.4%		69.4%	13.8%
PEP	-22.3%	-49.8%	-5.6%	-65.8%		-52.7%
BT	26.6%	2.1%	43.1%	-14.5%	54.9%	

Period 2 ($\Delta^{\acute{A}TT}_{Mt}$)

Comparison Group \ Treatment Group	NP	DP	JC	TE	PEP	BT
NP		-12.7%	15.1%	-7.0%	18.5%	2.4%
DP	17.2%		36.2%	0.8%	35.2%	14.0%
JC	-13.3%	-20.3%		-16.5%	4.2%	-12.2%
TE	11.7%	-4.6%	33.3%		29.5%	5.7%
PEP	-20.0%	-29.2%	-3.7%	-27.3%		-19.0%
BT	5.9%	-11.1%	24.5%	-7.5%	21.2%	

Period 3 ($\Delta^{\acute{A}TT}_{Mt}$)

Comparison Group \ Treatment Group	NP	DP	JC	TE	PEP	BT
NP		-6.4%	10.5%	-2.3%	12.9%	1.5%
DP	12.8%		24.5%	0.8%	23.8%	5.2%
JC	-6.8%	-10.7%		-6.2%	3.8%	-4.1%
TE	3.7%	-4.5%	22.1%		14.8%	0.2%
PEP	-12.5%	-16.4%	-3.1%	-12.3%		-13.4%
BT	7.1%	-7.6%	14.9%	-5.4%	16.0%	

Period 4 ($\Delta^{\acute{A}TT}_{Mt}$)

Comparison Group \ Treatment Group	NP	DP	JC	TE	PEP	BT
NP		-4.6%	17.1%	1.7%	13.1%	7.0%
DP	9.1%		25.4%	4.2%	21.5%	9.0%
JC	-11.5%	-8.6%		-4.1%	3.4%	-2.6%
TE	0.1%	-5.3%	23.8%		12.1%	2.8%
PEP	-17.0%	-16.5%	2.0%	-12.9%		-10.5%
BT	0.8%	-8.0%	15.0%	-2.6%	9.0%	

Period 5 ($\Delta^{\acute{A}TT}_{Mt}$)

Comparison Group \ Treatment Group	NP	DP	JC	TE	PEP	BT
NP		-6.6%	-8.4%	-8.0%	-2.5%	-6.6%
DP	13.8%		5.6%	2.3%	9.8%	3.1%
JC	8.1%	-2.9%		-0.6%	5.0%	0.3%
TE	10.4%	0.4%	7.0%		6.5%	0.9%
PEP	1.4%	-7.3%	-5.2%	-7.1%		-3.2%
BT	8.7%	-1.7%	0.5%	-3.9%	6.0%	

Table 6: Results of the CDiD estimator - Average Treatment on the treated in terms of register unemployment

$\Delta^{\acute{A}TT}_{Mt} - \Delta^{\acute{A}TT}_{Mt'}$ (t'=t)

Period	Comparison Group	Treatment Group					
		NP	DP	JC	TE	PEP	BT
1	NP		-30.2%	15.4%	-45.0%	13.9%	-45.7%
	DP	36.0%		48.1%	-19.3%	52.4%	-9.4%
	JC	-5.6%	-28.5%		-45.4%	7.1%	-53.8%
	TE	56.1%	19.3%	75.8%		74.0%	6.6%
	PEP	-14.8%	-48.1%	-6.4%	-68.0%		-62.0%
	BT	41.8%	13.0%	49.6%	-5.5%	67.2%	
2	NP		-11.2%	22.6%	-7.2%	19.6%	-10.4%
	DP	19.2%		33.7%	-0.5%	39.5%	5.1%
	JC	-10.7%	-23.0%		-24.1%	7.6%	-25.8%
	TE	28.3%	4.5%	46.4%		44.5%	1.7%
	PEP	-19.2%	-29.6%	-10.5%	-27.2%		-30.0%
	BT	17.6%	-2.3%	32.2%	-3.7%	35.1%	
3	NP		-1.3%	49.9%	1.9%	25.2%	3.8%
	DP	9.5%		45.9%	1.1%	30.4%	4.9%
	JC	-32.0%	-25.3%		-20.3%	-9.3%	-24.5%
	TE	0.2%	-2.2%	55.5%		21.6%	0.3%
	PEP	-24.1%	-20.6%	7.1%	-13.7%		-17.2%
	BT	5.0%	-4.8%	40.8%	-6.4%	26.1%	
4	NP		1.1%	43.4%	8.4%	24.8%	12.1%
	DP	7.0%		39.7%	6.2%	24.8%	10.0%
	JC	-28.5%	-16.9%		-10.3%	-2.4%	-12.5%
	TE	-5.9%	-5.0%	38.0%		15.0%	4.3%
	PEP	-24.9%	-18.8%	7.1%	-9.9%		-9.3%
	BT	-4.8%	-7.9%	28.4%	-3.8%	12.8%	
5	NP		-5.4%	3.9%	-3.9%	0.9%	-3.0%
	DP	15.5%		13.5%	4.3%	9.8%	2.4%
	JC	1.9%	-5.3%		-2.3%	1.2%	-3.0%
	TE	9.3	2.8%	12.3%		7.3%	-1.2%
	PEP	0.5	-6.1%	-2.1%	-2.9%		0.1%
	BT	8.3	1.0%	7.2%	-2.5%	9.3%	

$\Delta^{\acute{A}TT}_{Mt} - \Delta^{\acute{A}TT}_{Mt'}$ (t'=-1)

Period	Comparison Group	Treatment Group					
		NP	DP	JC	TE	PEP	BT
1	NP		-30.2%	15.4%	-45.0%	13.9%	-45.7%
	DP	36.0%		48.1%	-19.3%	52.4%	-9.4%
	JC	-5.6%	-28.5%		-45.4%	7.1%	-53.8%
	TE	56.1%	19.3%	75.8%		74.0%	6.6%
	PEP	-14.8%	-48.1%	-6.4%	-68.0%		-62.0%
	BT	41.8%	13.0%	49.6%	-5.5%	67.2%	
2	NP		-18.9%	16.3%	-12.9%	10.9%	-15.1%
	DP	24.7%		35.5%	0.2%	36.6%	8.3%
	JC	-3.6%	-9.4%		-10.2%	6.9%	-22.1%
	TE	22.9%	1.3%	41.7%		34.0%	-1.5%
	PEP	-12.5%	-27.6%	-4.5%	-29.5%		-28.3%
	BT	21.1%	-0.2%	31.0%	1.4%	33.4%	
3	NP		-12.7%	11.6%	-8.2%	5.2%	-16.0%
	DP	20.3%		23.8%	0.2%	25.2%	-0.5%
	JC	2.8%	0.3%		0.0%	6.6%	-14.0%
	TE	14.9%	1.3%	30.5%		19.4%	-7.0%
	PEP	-5.0%	-14.8%	-3.9%	-14.6%		-22.7%
	BT	22.3%	3.3%	21.3%	3.6%	28.2%	
4	NP		-10.8%	18.2%	-4.2%	5.4%	-10.5%
	DP	16.7%		24.7%	3.5%	22.9%	3.3%
	JC	-1.8%	2.3%		2.1%	6.2%	-12.6%
	TE	11.3%	0.6%	32.2%		16.6%	-4.5%
	PEP	-9.5%	-14.9%	1.2%	-15.1%		-19.8%
	BT	15.9%	2.8%	21.4%	6.4%	21.3%	
5	NP		-12.9%	-7.3%	-13.9%	-10.2%	-24.1%
	DP	21.3%		4.9%	1.6%	11.2%	-2.6%
	JC	17.7%	8.0%		5.6%	7.8%	-9.6%
	TE	21.6%	6.2%	15.4%		11.0%	-6.3%
	PEP	8.9%	-5.7%	-5.9%	-9.3%		-12.5%
	BT	23.9%	9.2%	6.9%	5.1%	18.3%	