Causal Effects of Alternative Participation Patterns: a labour policy application

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Resumo
A política pública de emprego portuguesa oferece, ao conjunto de desempregados registados, não só a possibilidade de participar sucessivamente em diferentes programas do mercado de trabalho como, também, a possibilidade de adiar essa participação. Face à coexistência de padrões de participação alternativos, este trabalho utiliza uma metodologia dinâmica de *matching* para calcular e comparar o resultado gerado por cada uma das decisões de participação. Os resultados obtidos pela decisão de participar consecutivamente, em compração com a alternativa de adiar a participação, sugerem um maior grau de eficácia da política pública de intervenção no mercado de trabalho.

Palavras-chave: avaliação de políticas sociais, propensity score matching, políticas de trabalho

Abstract
The Portuguese public labour market policy offers, to the registered unemployed individuals, not only the possibility of successive participation in different labour programmes but also the possibility to postpone that participation. Dynamic matching techniques allow to understand the causal effects of the above alternative participation patterns, as this paper shows. The compute results of a consecutive participation decision compared with the alternative postponed participation suggest a higher degree of effectiveness of the public labour public policy.

Key words: evaluation of social programmes, propensity score matching, labour policy

Thematic Area: Quantitative Methods for Economics and Business

1. **INTRODUCTION**

A complete evaluation of public labour market measures should be, as much as possible, based on the empirical evaluation of the effects caused to the exposed population. The stimulus given to the public intervention in the European labour market followed, closely, by the increasing budget constrains turned crucial the need to develop more rigorous techniques of social programmes evaluation. Above all, techniques that could represent a major approximation to the diverse policy practices that, nowadays, compose the *menu* of labour market policies.

Heckman, Lalonde and Smith published, in 1999, a seminal paper discussing the genesis of programmes evaluation literature. Their discussion could be considered, by the light of the more recent developments, as relatively dated concerning the econometric methodology and the nature of the available data. Still, from the pioneer analysis of these authors had resulted two crucial conclusions - the inexistence of a single, and uncontested, programme evaluation method and the importance of using better data - that have cleared the way for the development and maturity of the actual econometric evaluation methodologies of social programmes. The present paper, aware of the Heckman and his co-authors lessons, follows what Kluve (2006) designates by *third generation* of labour policies microeconometric evaluation studies, characterized by the adoption - as the elected estimation technique - of a non-parametric matching estimation technique and tries to go even further by overcoming the limits of the static traditional evaluation models.

The reality of the public intervention in the European labour markets does not obey to close criteria of description. Several institutional frameworks, a vast range of distinct programmes and diverse target-populations demand specific adaptations of the econometric estimation techniques and of the available (non-experimental) data. For instance, outside the limits of theoretical models, it is an oversimplification to only assume that the actual choices have influence on future potential results. Expectations about future results also affect participation choices. In the particular case of the Portuguese institutional framework for the public intervention on the labour market it is possible to find dynamic selection problems related with endogenous elements not properly identify by static evaluation models. Indeed, an unemployed Portuguese individual can choose from a vast range of active labour market programmes. These programmes are available over time which allows the individual to choose the time of participation and/or the sequence of programme participation.

The latest theoretical evaluation literature developments do present more realistic models and identification assumptions, with a particular emphasis on dynamic models that can mimic the context of participation on a social programme more accurately. In particular, a dynamic approach provides a more realistic perspective of the public intervention on the labour market. It assumes that the individual faces not only a single participation decision but a sequence of participation choices over time since it is allowed the participation in different sequences of labour programmes. By developing new scientific evaluation tools the dynamic approach to programme evaluation is in principle better suited to explain the real impact of the labour market policies.

It is possible to report several developments concerning the introduction of dynamic elements in the traditional evaluation econometric models. To start, there are the contributions of Robins (1986, 1989, 1997), Gill and Robins (2001) and Abbring and Berg (2003). In the particular case of nonparametric models, where the causal effect is estimated by the "artificial" construction of a comparison group through a matching methodology, Lechner and Miquel (2001) extended Robins' application to epidemiology and biostatistics to the analysis of participation on active labour market policies (Robin, 1986). The suggested extension of the Robins causal model presents explicitly the causal effects of dynamic sequences making use of potential results and allowing the introduction of intermediate results which determine subsequent sequences. Empirical applications of the sequential matching methodology suggested by Lechner and Miquel (2001) are scarce. One such an application is Lechner and Miquel (2001), or Lechner (2004, 2006), who present exploratory results obtained from the empirical applications of a propensity score matching estimator to the active public intervention on the German and Swiss labour markets, respectively. Other than these two studies, we are not aware of any other application of the estimator.

The application presented in this research study adjusts an administrative dataset, containing plenty individual information concerning the active public intervention on the Portuguese labour market, to the needs of microeconometric estimation. The performed adjustments show it is possible to make a quantitative analysis on the impact of an unemployed individual participation on a sequence of active measures offered by the unemployment offices. The present empirical study analysis the power of the dynamic nonparametric model as a fundamental tool of a labour market policy evaluation and allows, even if in an exploratory way, to withdraw important conclusions relating to the participation choices of unemployed individuals engaged in the Portuguese labour market public intervention.

Specifically, the study aims to evaluate if, an unemployed individual registered in time period t, who had decided to participate in a labour market programme, would have been better of continuing to participate in another available active programme, in the sequence of the first participation and consequent results, rather than to postpone his/her participation to the next period. In analysis are the potential answers for two essential questions for the register unemployed individual: (i) to participate in a labour programme, proposed by the public employment service, collecting a remuneration and keeping the link with the labour market; or, (ii) to postpone the decision to participate in a labour market programme which does not correspond to the achievement of a regular job until he/she finds that job or has the possibility to participate in another programme.

The paper is organized as follows. Section 2 presents the microeconometric framework for a sequential treatment evaluation process. Section 3, describes the Portuguese institutional context for the public labour market intervention, the empirical application strategy and the estimation results. Section 4 concludes.

2. SEQUENTIAL PROPENSITY SCORE MATCHING MODEL

In this paper a model which uses the simplest structure developed by Lechner and Miquel (2001) will be assumed. Even if the structure could be easily adapted to a bigger number of periods and to a more vast range of treatments three periods (years) and two potential treatments will be considered, to our interest. An initial moment in which each individual is in the same treatment state and posterior moments for which each individual could be in a different state of treatment will be considered. Specifically, one initial moment where all the individuals are in an unemployment state and two subsequent periods where those same individuals are engaged in a particular labour market programme will be considered. The different T sequential time periods, after the initial period, will be present as t e $t^{'}$ and, consequently, $t,t^{'} \in \{0,1,2\}$.

As referred above, in this particular research work, the model that is being develop will be applied directly since the scope of the investigation is the evaluation of a sequential participation in active labour market programmes over only two periods. Period 1 and period 2 which is assumed as a direct time sequence of period 1. Also as referred, in period 0 the individual is registered as unemployed and, by definition, does not participate in any programme. The previous assumption implies to assume that before period 1 each individual holds the same labour history concerning the participation in a labour market programme and therefore the causal effects are not conditioned by that labour history.

The complete treatment sequence an individual is subject to over three time periods is defined by a vector of Bernoulli random variables as $\underline{D_2} = (\underline{D_0}, D_1, D_2)$. $\underline{D_0}$ represents the history of participation up to time 0 and it will always take the value $\underline{d_0}$. This value is part of the conditioning set, since everything that will be estimated will be conditioned on it, but will not appear explicitly further in the notation, this is, $\underline{D_2} = (D_1, D_2)$. A particular implementation of D_t will be represented by two possible values, $d_t \in \{0,1\}$, denoting that in each particular time period only one programme will be available and so the individual will have only two possible choices – participate, or not, in the available treatment. To clarify the mathematical notation, the history of variables up to period t will be represented by a bar under the variable. For example, $\underline{d_2} = (d_1, d_2)$, where the small letters represent specific values of a random variable represented by a capital letter. The model defined by Lechner and Miquel (2001) admits the heterogeneity of treatments over time and so the potential outcomes are defined in terms of potential treatment states sequences. The difference among different treatment sequences will be represented by an index letter. $\underline{d_t^j}$, for example, identifies the sequence of treatment j until the period t.

In period 1 an individual can be observed in one of two mutually exclusive states, participation (1) or non-participation (0). In period 2 this same individual can be observed in one of four mutually exclusive sequences of states: $(1,1)$, $(1,0)$, $(0,0)$ or $(0,1)$. Therefore the potential outcomes on the second period will be subordinated to the treatment state in period 2 and on what had happened in period 1. Consequently 2 states defined by treatment status in period 1 and 4 states defined by treatment status in both period, 1 and 2, will be considered.

For each unemployed individual several potential outcomes are defined - one outcome for each treatment state sequence. They are called potential outcomes because, of course, all but one of these treatment effects with different time lengths (1 or 2 periods), are unobservable. For each individual it is only possible to follow one treatment sequence. The potential outcomes are measured at the end of each period, whereas the treatment status is measured at the beginning of those periods, and are indexed by the treatment sequences, $Y_t^{\underline{d_1}}(t \geq 1)$ or $Y_t^{\underline{d_2}}(t \geq 2)$. The observable outcome is denoted by Y_t.

To conclude the model's presentation, the attributes X_t, which are observable characteristics that could influence the participation selection process and/or the potential outcomes, must be considered. It is possible that a participation sequence, and consequently the outcomes of previous periods, may affect the values of these variables. The k-dimensional vector of characteristics X_t may contain functions of Y_t and it is observable at the same time, this is, at the end of the time period[1].

In the dynamic model, as in the static one, the potential outcomes are used to define several average causal effects. For a specific time period t, a sequence of treatments defined up to period 1 or 2, (t, t') is compared to an alternative treatment sequence of the same or a different time length for a population defined by one of those sequences or even a third sequence. The possible average causal effects are defined by the following equation:

$$\theta_t^{\underline{d}_t^k, \underline{d}_{t'}^l}\left(\underline{d}_{\tilde{t}}^{\,j}\right) = E\left(Y_t^{\underline{d}_t^k} \middle| \underline{D}_{\tilde{t}} = \underline{d}_{\tilde{t}}^{\,j}\right) - E\left(Y_t^{\underline{d}_{t'}^l} \middle| \underline{D}_{\tilde{t}} = \underline{d}_{\tilde{t}}^{\,j}\right),$$
$$\tilde{t} \geq 0; \quad 1 \leq t, t' \leq 2 \text{ com } \tilde{t} \leq t', t; \quad k \neq l \text{ com } k, l \in (1,2); \quad \mathrm{j} \in (0,1,2) \tag{1}$$

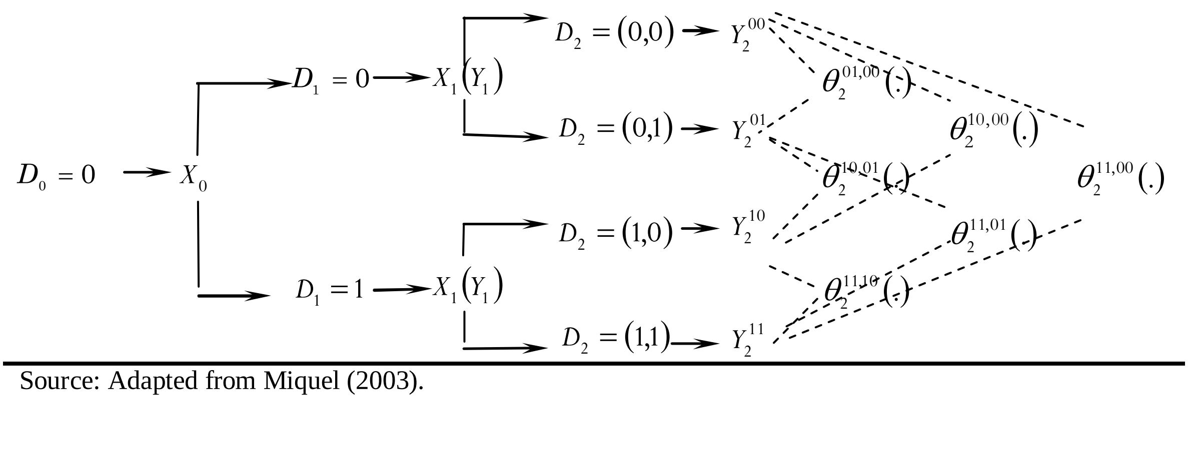
The first sequence, $\underline{d}_t^k$, defines the treated population; the second sequence, $\underline{d}_{t'}^l$, defines the nontreated population and the last sequence, $\underline{d}_{\tilde{t}}^{\,j}$, defines the population for which the causal effect will be computed. Whithin this framework, the observed result can the presented as follows:

$$\begin{aligned} Y_t &= D_1 Y_t^1 + (1 - D_1) Y_t^0 \\ &= D_1 D_2 Y_t^{11} + D_1 (1 - D_2) Y_t^{10} + (1 - D_1) D_2 Y_t^{01} + (1 - D_1)(1 - D_2) Y_t^{00} \end{aligned}, \quad t = 0,1,2 \tag{2}$$

Table 1 helps to illustrate the dynamic model for sequential treatments as well as the entire mathematical notation presented in this section.

Table 1: Dynamic Model Notation and Time Line

Time Periods						
$t = 0$		$t = 1$		$t = 2$		
Treatment Sequence	Attributes	Treatment Sequence	Attributes (Results)	Treatment Sequence	Results	Average Causal Effects



Source: Adapted from Miquel (2003).

[1] To simplify the presentation of the problem, we will assume that the variables denoted by X are not affected by the treatment states. Consequently we will explicitly add the observed outcomes in the conditioning set when the case of endogeneity (this is, when the attributes are influenced by the treatment status) is investigated. If some other variables (as the outcomes) are also influenced by the participation status all we have to do is to handle these endogenous variables in the say way as the outcomes in the conditioning set.

3. EMPIRICAL APPLICATION TO THE REGISTER UNEMPLOYEMENT

3.1. TREATMENT SEQUENCES AND INTEREST CAUSAL EFFECTS

The main concern of this research is the estimation of the participation causal effect, in successive time periods, for those individuals who are registered as unemployed in the statistical information system of the Portuguese public employment service.

As it was already discussed the adoption of a sequential dynamic model allows to deal with the endogeneity problem induced by successive labour market participations. In the particular case of the *Programas ocupacionais (POCs)* – the Public Employment Programmes – it is explicitly declared that they are programmes aiming to occupy unemployed individuals receiving an unemployment subsidy or in a situation of economical need as long as an opportunity of participation in another programme or an effective job vacancy does not appear. In this manner, in period 1, an unemployed individual participates, or not, in a *Programa Ocupacional* and the result he/she could achieve depends on the decision he/she made and of the potential result of that decision. In the second period, the same individual can participate again, or not, in one of the available active programmes offered by the unemployment office. Consequently, the participation decision, in period 2, depends not only on the observable characteristics, X_0, but also depends on the decision of participation in the first period and of the subsequent result, Y_1, giving rise to a problem of dynamic selection.

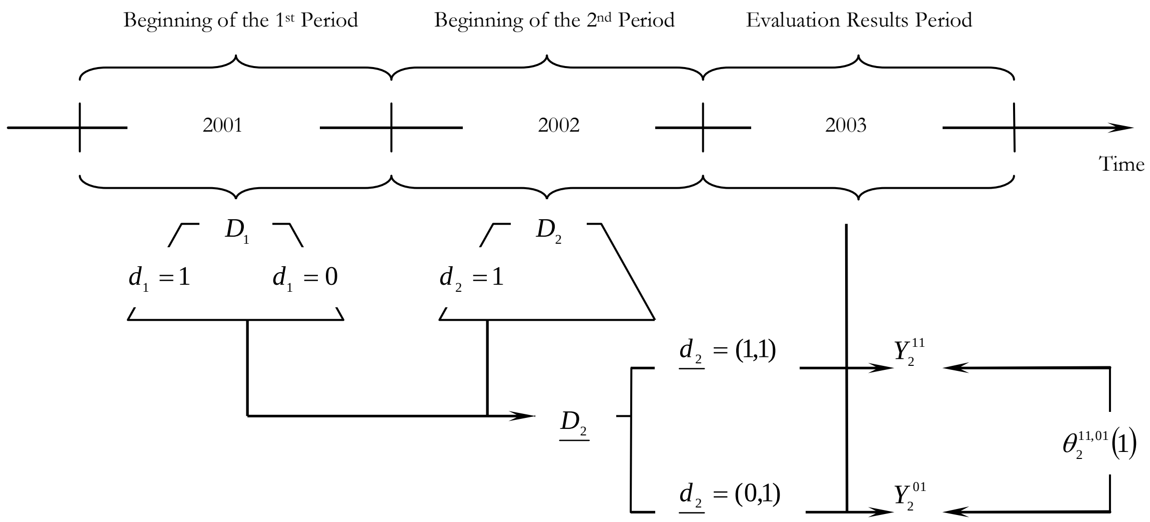
Each considered period corresponds to a year since this is the maximum extension for the participation in a POC[2]. After a year of participation the individual should, compulsorily, abandon the programme and change to another state of participation. Meanwhile if the unemployment register has not been abandoned the second state of participation could correspond to a state of participation in another active programme or to a state of non-participation in any of the interventions offered by the employment public service. The maintenance of the unemployment register and the consequent possibility of participation in another of the available active programmes for the unemployed depend, obviously, on the result obtained after the first participation. So the final impact evaluation of a sequence of participation states contains selection issues which demand a specific econometric management.

As the result of the former discussion, all the states of participation that had began over the year 2001 and were concluded over a spell of 12 months correspond to period 1: (i) participation in a POC or (ii) absence of participation in any of the active programmes available for the unemployed individual. All the states of participation that had began during the year 2002 correspond to period 2: (i) undistinguished participation in any of the available active programmes or (ii) absence of participation. Figure 1 allows to illustrate the sequences in analysis as well as the causal effects which are the object of the present evaluation process[3].

[2] It is also the maximum extension for the generality of the available active programmes offered by the public employment service.

[3] The dynamic approach is not particularly useful to some potential comparisons since their results are similar to the ones that are possible to reach with the static approach. Namely, the mentioned comparisons refer to treatment occuring only in one period and to comparisons among treatment sequences defined in two periods where the first period is equal for both sequences and for the target group. For instance, $\theta_2^{11,10}(1)$.

Figure 1: Empirical Evaluation – Time Sequences and Interest Causal Effects



With:

* $d_1 = 1$: Participation in *Programa Ocupacional* in 2001 (target population);
* $d_1 = 0$: Non-Participation in *Programa Ocupacional* in 2001 (participation decision postponed)
* $d_2 = 1$: Participation in 2002;
* $\underline{d}_2 = (1,1)$: Participation in *Programa Ocupacional* in 2001 and participation in 2002;
* $\underline{d}_2 = (0,1)$: Non-participation in *Programa Ocupacional* in 2001 and participation in a labour programme in 2002;
* $\theta_2^{11,01}(1)$: Causal effect of a consecutive participation compared to participation only in the second period, for the target population.

The sequence of intervention states is the result of the consecutive participation on the two selected time periods. That is, it is possible to define four distinct sequences: (i) if the unemployed individual registered in 2001 decides to participate in a POC in a first period, $(d_1 = 1)$, he/she must decide if in the next period he/she will participate again, or not, in another active programmes, which results in two different sequences, $\underline{d}_2 = (1,1)$ or $\underline{d}_2 = (1,0)$, respectively; (ii) if the individual decides to postpone the participation decision in the first period, $(d_1 = 0)$, in the second period he/she must decide if he/she will continue to postpone the participation or if he/she will decide to participate in one of the available active programmes, this is, $\underline{d}_2 = (0,0)$ or $\underline{d}_2 = (0,1)$, respectively.

This particular study aims to evaluate if, an unemployed individual registered in time period t (2001), who had decided to participate in a POC in a first period, would have been better of continuing to participate in another available active programme, in the sequence of the first participation and consequent results, rather than to postpone his/her participation to the second period. In analysis are the potential answers for two essential questions for the register unemployed individual: (i) to participate in the active programme proposed by the public employment service collecting a remuneration and keeping the link with the labour market; or, (ii) to postpone the decision to participate in a *Programa Ocupacional* which does not correspond to the achievement of a regular job until he/she finds that job or has the possibility to participate in another active programme. The interest results are measured by the maintenance of the register in the information system of the employment public service during the year 2003, the year where the conclusion of the second participation period is observed. The perception of a larger maintenance of the unemployment register allows the conclusion of a minor effectiveness of the analysed sequences.

3.2. OBSERVABLE CHARACTERISTICS AND INTERMEDIARY RESULTS

Table 2 presents the distribution (in percentage) of the set of observable characteristics, previous to the participation sequences, as well as the intermediary and final results for each one of the selected participation sequences. The results are measured through the unemployment register in the statistical information system of the employment offices. The individual characteristics are observed in the beginning of the first treatment period and identify the individuals relating to their age, gender, formal education level, geographical location, labour market status (namely if the individual looks for a first job or if the individual has some labour market experience) and dependents.

Table 2: Pre-Treatment Characteristics and Results

Variables	**Treatment Sequences**			
	$d_1 = 1$	$d_1 = 0$	$\underline{d_2} = (1,1)$	$\underline{d_2} = (0,1)$
Number of Observations	3445	163855	895	15872
Pre-Treatment Characteristics (Values in %)				
Gender (Men)	21.45	38.90	17.21	28.26
Age (Years Average)	36.98	37.32	36.94	35.14
Educational level				
-None	9.26	6.42	9.72	6.51
- Primary (4 years)	37.13	33.83	39.89	31.0
- Compulsory Secondary (9 years)	35.21	34.99	33.63	37.97
- Secondary (12 years)	14.22	16.07	12.29	16.53
- Superior (>12 years)	4.18	8.69	4.47	7.98
Geographical Location				
- Norte	28.65	39.11	24.02	29.25
- Centro	20.32	12.07	18.55	17.6
- LVT	27.23	39.49	26.70	34.66
- Alentejo	19.45	5.99	25.36	12.44
- Algarve	4.35	3.33	5.36	6.05
Unemployment Category				
- First Employment	9.46	10.90	10.83	12.5
- New Employment	90.54	89.1	89.16	87.5
Dependents (Yes)	60.98	48.18	63.8	51.67
Intermediate Results (Values in %)				
Unemployment 6 months after the beginning of a POC	77.41	32.44	81.56	47.22
Unemployment 12 months after the beginning of a POC	62.41	31.21	74.86	59.07
Final Results (Values in %)				
Unemployment 30 months after the beginning of a POC	26.21	5.56	38.88	25.38

After the participation in a *Programa Ocupacional,* in the first period, the participation result can be measured through the maintenance (or not) of the unemployment register. Having the annual time spell been chosen as the participation period, the identification of the unemployment register 12 months after the beginning of the first participation period is a natural solution. However, since there are no abandonment registers it is believed important to observe the unemployment registers some time before the end of the first analysed period and introduce them in the estimation process. In this specific case of this empirical application we chose go back 6 months, that is, half of the participation period initially predicted. The average value of unemployment registers two and a half years after the beginning of the first participation period was included in the descriptive table as an illustration and potential reference value for results discussion

When comparing the variable values among the different treatment sequences the high number of individuals who postpone the decision of participation to the second participation period should be stressed. The second aspect that should be stressed refers to the conclusion that women participate more in the programmes. Comparing the formal education level it is possible to observe that the unemployed individuals with more years of formal education are the ones who delay the first participation decision more frequently.

The variables appearing in the tables previously presented (with the exception of the values for the unemployment registers final results) represent the set of variables that was used to estimate the probabilities of participation, or propensity score, in each one of the treatment sequences relating to the target population – those who had participated in a POC during the year 2001. Finally, it must be reported that for the average values of the final result, even in a merely descriptive way, wide differences in the accounting of unemployment registers among the several treatment sequences are observed.

3.3. SEQUENTIAL PROPENSITY SCORE MATCHING ESTIMATION

The application of the estimator proposed by Lechner and Miquel (2001) follows the protocol suggested by Lechner (2004, 2006). The adoption of a propensity score matching estimator instead of just a matching estimator is due to the estimation simplicity offered by the first method. Conditioning the participation and the consequent result in a unique scalar value instead of conditioning in a wide set of variables simplifies the estimation process without losing the estimators properties (Rosenbaum e Rubin, 1983 e Lechner, 2004).

The probabilities of participation conditioned on the set of observable characteristics in the beginning of the first participation period (to sequences defined for only one period) and on the participation intermediary results (to sequences defined for the two periods) are presented in Table 3. The probabilities presented were estimated regarding the needs of each one of the matching sequences through binary probit models which should be (sequentially) subjected to specification tests. The parametric model is particularly simple and do not include a full set of variables since it could generate common support problems and therefore become counterproductive. In other words a complete set of variables could generate probabilities of participation so diverse that it would not be possible to find a set of values for which the individuals, in all the treatment sequences, had the same probability of participation. Since the matching process results from the selection of individuals with the same (or with a very similar) probability of participation the inexistence of a common support would not allow such individual selection.

The Mahalanobis distance metric technique with replacement of observations was applied to perform the selection of individuals in the matching process. The matching with replacement becomes more important with more diverse number of observations for each one of the defined sequences, as happens is this particular study.

Table 3: Probit Estimation

Variables	Treatment Sequences considering the participation in a POC in period 1 ($d_1 = 1$)		
	$d_1 = 0$	$\underline{d_2} = (1,1)$	$\underline{d_2} = (0,1)$
Pre-Treatment Characteristics (Values in %)			
Gender (Men)	0.293 (*) (0.0169)	-0.19 (**) (0.061)	-0.183 (*) (0.01)
Age	-0.067 (*) (0.005)	0.024 (0.018)	0.012 (*) (0.003)
Age2	0.001 (*) (0.000)	-0.000 (***) (0.000)	-0.000 (*) (0.000)
Educational level			
-None	-0.477 (*) (0.043)	(a)	0.156 (*) (0.026)
- Primary (4 years)	-0.352 (*) (0.037)	0.041 (0.086)	0.081 (*) (0.02)
- Compulsory Secondary (9 years)	-0.303 (*) (0.035)	-0.07 (0.091)	0.081 (*) (0.018)
- Secondary (12 years)	-0.275 (*) (0.037)	-0.156 (0.108)	0.061 (**) (0.02)
- Superior (>12 years)	(a)	0.048 (0.145)	(a)
Geographical Location			
- Norte	0.633 (*) (0.023)	-0.429 (*) (0.069)	-0.609 (*) (0.023)
- Centro	0.277 (*) (0.026)	-0.305 (*) (0.074)	-0.172 (*) (0.024)
- LVT	0.621 (*) (0.024)	-0.268 (*) (0.069)	-0.464 (*) (0.022)
- Alentejo	(a)	(a)	(a)
- Algarve	0.392 (*) (0.040)	-0.008 (0.121)	0.07 (**) (0.026)
Unemployment Category: First Employment	-0.026 (0.027)	0.182 (**) (0.085)	0.05 (**) (0.016)
Dependents (yes)	-0.068 (*) (0.017)	0.061 (0.054)	0.086 (*) (0.011)
Intermediate Results (Values in %)			
- Unemployment 6 months after the beginning of a POC	-----	-0.114 (0.071)	0.104 (*) (0.012)
- Unemployment 12 months after the beginning of a POC	-----	0.561 (*) (0.062)	0.816 (*) (0.012)
Constant	2.913 (*) (0.104)	-0.955 (**) (0.329)	-1.10 (*) (0.064)
Number of Observations	167300	3445	163855
$LR\chi^2(13) / LR\chi^2(15)$	1906.59 (*)	165.27 (*)	11816.28 (*)
Pseudo - R^2	0.0568	0.0419	0.1133
Log likelihood	- 15832.456	- 1890.8152	- 46221.031

Notes: (a) Reference Variable; (*) Statistical significance at 1%; (**) Statistical significant at 5%; (***) Statistical significant at 10%. Standard errors in parentheses.

The results of the model contain all the selection equations that are important to estimate the treatment causal effects defined in section 2. These results will not be discussed extensively however is important to refer the individual statistical significance of the generality of the estimated coefficients. It is also important to refer to the joint statistical significance of the coefficients included in the models. These statistical results point out to a good approximation to the definition of the unemployed individuals real probabilities of participation both in terms of individual characteristics and in terms of labour market characteristics.

The dynamic estimation results of the interest causal effects are presented in Table 4. In this table it is also possible to identify which sequences are being compared, the target population and the observations which were eliminated in each one of the propensity score matching sequences to generate a common support for the probability of participation.

When, for those who had participated in a POC, it is compared the consecutive participation in two active programmes – a *Programa Ocupacional* followed by another active programme not necessarily a POC – with a sequence characterized by a postponed participation the process of sequential propensity score matching is defined by a set of sequential steps which could be described as follows.

To obtain the counterfactual result for the participant population in a POC during the year 2001 it is necessary to select the participants in the sequence of non-participation who are the closest in terms of observable characteristics or, as happens in this specific case, in terms of the distribution of probability of participation conditioned in the set of observable characteristics. The counterfactual result corresponds to the result of the situation where that same population would have participated in a sequence characterized by the absence of some type of participation in the first period. As the target population, $d_1 = 1$, only participated once it is necessary, firstly, to select the most similar non-participant individuals, $d_1 = 0$, in terms of the participation probability in the first period of the sequence. Such selection process demands that the individuals in both groups share the same distribution of the participation probability which will be called $p_i^{d_1^0}$. In the propensity score matching methodology this first group of selected matched individuals would have constituted the comparison group if the selection process had been merely static and if it had happened in a single period[4].

Empirically, and for the estimation related to the entire population, the three steps explained above enable us to find within the group of non-participants in the first participation period the 3445 observations with the probability of participation most similar to the 3445 observations of the target population. The 3445 comparison observations do not mean the same number of distinct individuals since it was allowed the repeated use of observations whenever they were the ones which better fit in the propensity score matching process. Each time an observation was used more than once its weight increased by one for each application. In this particular case no observation of the target population was abandoned to construct the common support for the probability of participation.

However to estimate the result of the complete sequence it is necessary to select, from the group of comparison found in period 1, the group of individuals who have participated also in period 2. The result for the complete sequence arises from the result of the second comparison group which selection process corresponds to the following step.

[4] In order to guarantee the possibility of selection of the first comparison group, all the target population observations not comprised between the minimum and maximum limits of the participation probability of those individuals who form the potential comparison group were withdraw.

The step that follows consists in finding to the group of comparison individuals, achieved for the first period, those who, in the second period, will participate and have the same distribution of participation probability both for period 1, $\left(p_i^{d_1^0}\right)$, and period 2, $\left(p_i^{\underline{d}_2^0, d_1^1}\right)$, than the individuals in the target group. This second comparison group will be the suitable comparison group. When the second comparison group was obtained two observations in the entire target population were lost. This was demanded by the need to observe the same probability of participation in both groups. The causal effect is estimated only for 3443 individuals.

With respect to the estimated values for the causal effects it is observed (Table 4) that, for the participants in a POC, exists one smaller probability to maintain the unemployment register if the programme participation is followed by the participation in other programme than if those same individuals had chose postpone participate in the labour programme offered by the public employment service. At the end of a sequence period it is estimated that for individuals who had participated in a *Programa Ocupacional*, in the initial period, the decision to participate again leads to a 4.3% lower probability of keep the unemployment register than the decision to wait and postpone the participation for a second period.

Table 4: Dynamic Causal Effects.

Sequences	**Target Population**	**Sample Size**		**Observations lost due to the construction of a common support**			$E\left(Y_t^{\underline{d}_2^1} \middle| D_1 = d_1\right)$ (1)	$E\left(Y_t^{\underline{d}_2^0} \middle| D_1 = d_1\right)$ (2)	$\theta_t^{\underline{d}_2^1, \underline{d}_2^0}(d_1)$ (Values in %) (3)=(1)-(2)
$\underline{d}_2^1$ $\underline{d}_2^0$	d_1	$N_{\underline{d}_2^1}$ $N_{\underline{d}_2^0}$	N_{d_1}	t=1	t=2	% of the Target Population			
$\underline{d}_2^1 = (1,1)$ $\underline{d}_2^0 = (0,1)$	$d_1 = 1$	895 15872	3445	--- 0	2 0	0,058 0	0,283	0,326	**- 4,3**

4. CONCLUSION

The empirical application of a dynamic propensity score methodology demonstrates to be an effective tool for the estimation of dynamic causal effects where is tested the effectiveness of a sequence of participation decisions comparing to a distinct sequence of decisions. This dynamic propensity score methodology allows to introduce in the traditional static models intermediary participation results. These present a better characterization of the dynamic participation selection in the programmes offered by the public intervention in the Portuguese labour market.

The empirical application of a sequential propensity score matching methodology to evaluate the decision of a consecutive participation comparing to the option of postpone the participation decision one time period presents results favourable in terms of the effectiveness of consecutive public intervention in the labour market.

Still such results are short-run results obtained immediately after the second participation period. This time horizon limitation could, for example, hide locking-in effects- the programme participation withdraws to the unemployed individual time and availability to look for an effective job effects.

REFERENCES

Abbring, J.H. (2003), “Dynamic Econometric Program Evaluation”, IZA discussion paper, 804.

Abbring, J.H., van den Berg, G.J. (2003), “The nonparametric identification of treatment effects in duration models”, Econometrica, 71 (5), pp. 1491–1517.

Gill, R.D., Robins, J.M. (2001), “Causal inference for complex longitudinal data: the continuous case”, The Annals of Statistics, 29 (6), pp. 1785–1811.

Lechner, M. and Miquel, R. (2002), “Identification of effects of dynamic treatments by sequential conditional independence assumptions”, Discussion Paper, University of St. Gallen.

Lechner, M. (2004), “Sequential Matching Dynamic Causal Models”. IZA discussion paper, 1042.

Lechner, M. (2006), Matching Estimating of Dynamic Treatment Models: Some Practical Issues, Discussion Paper, University of St. Gallen.

Miquel, R. (2003), “Identification of Effects of Dynamic Treatments with a Difference-in Differences Approach”, Discussion Paper, University of St. Gallen.

Robins J. M. (1989), "The Analysis of Randomized and Nonrandomized AIDS Treatment Trials Using a New Approach to Causal Inference in Longitudinal Studies", in Sechrest, L., H. Freeman, A. Mulley (eds.), *Health Service Research Methodology: A Focus on Aids*, pp. 113-159, Washington, D.C., Public Health Service, National Center for Health Services Research.

Robins J. M. (1997), "Causal Inference from Complex Longitudinal Data. Latent Variable Modeling and Applications to Causality", in M. Berkane, (ed.), *Lecture Notes in Statistics* (120), New York: Springer, pp. 69-117.

Rosenbaum, P. R., e Rubin, D. B. (1983), “The Central Role of the Propensity Score in Observational Studies for Causal Effects”, Biometrika, 70(1), pp. 41-55.

Rubin, D.B., (1974), Estimating Causal Effects of Treatments in Randomized and Nonrandomized Studies, Journal of Educational Psychology, 66, pp. 688-701.