

Propensity Score Matching and Different Treatment Variable Definitions: an Evaluation of Employment Services in Italy

Propensity Score Matching e Diverse Definizioni di Variabili di Trattamento: una Valutazione dei Servizi per l'Impiego in Italia

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Riassunto: Obiettivo di questo lavoro è valutare l'efficacia dei servizi per l'impiego pubblici e privati utilizzando i dati dell'indagine continua sulle forze di lavoro dell'Istat, e la tecnica del *propensity score matching*. Rispetto ai lavori precedenti sull'argomento questo contributo si distingue su tre punti: 1) la definizione di "trattato" è più ampia rispetto alla semplice iscrizione al centro per l'impiego, ad esempio considerando l'aver avuto contatti con un'agenzia negli ultimi 6 mesi; 2) le variabili di trattamento vengono rilevate sia in *stock* -gli iscritti in un dato periodo nel tempo- sia in flussi -le nuove iscrizioni tra due istanti di tempo; 3) coerentemente alla teoria sul *propensity score matching* le variabili di controllo vengono osservate prima del trattamento. I risultati mostrano che queste differenze giocano un ruolo cruciale nell'esercizio di valutazione.

Keywords: Employment Services, Propensity score matching.

1. Introduction and definition of treatment variables

According to the European employment strategy, Italian employment services have been reformed in 1997, 2000 and 2003, following two main principles: increasing the efficiency of public employment services (PES), for instance re-defining their tasks and the technological requirements; introducing private employment services in Italy (PRES). The aim of this paper is to evaluate the impact of these reforms on the efficacy of public and private Italian employment services, using the propensity score matching technique.

We use the labour force survey (LFS) data, collected by the new continuous survey conducted by Istat (2004 and the first two quarters of 2005). It is worth noting that in 2004 the Italian LFS has been completely renewed (facing up to Eurostat regulations), entailing a relevant increase in data quality, basically because of the use of computer assisted interviews and the new professional interviewers network. Moreover, in the new survey the section dedicated to PES has been improved and enlarged, and new questions concerning PRES have been introduced (see Istat, 2006).

Households selected in the LFS sample have to be interviewed four times during a 15 months period, according to a rotation scheme; merging data collected in different quarters we may observe transitions in the labour market.

In this way we can evaluate whether the unemployment to employment transition probability of “treated” unemployed is significantly greater than the one for non-treated. In previous papers -see for instance Barbieri *et al.*, 2002, 2003-, the “treated” are usually defined as unemployed enrolled to PES. In this paper we extend this definition for several reasons. First of all, because it is possible to benefit from PES services without being enrolled. Second, because the enrolment to PES in Italy is not always associated to an active job search: for instance, an individual can use this enrolment status to receive unemployment subsidies or to attend some training courses. Third, the enrolment is not closely related to the period in which the interview takes place: an unemployed can be enrolled to a PES and at the same time having no contacts with PES to look for a job. For these reasons, we carry out separate analysis using the following treatment variables: a) enrolment to PES; b) having had contacts in the last six months with PES; c) having had contacts in the last six months with PRES.

Moreover, in previous papers regarding this topic (see for instance: Barbieri *et al.*, 2002, 2003), treatment variables have been always considered as “stock variables”, meaning that the treatment refers to a status in a given instant in time (no matter if those individuals were treated or not previously). In our work we are interested in analyzing these variables also as “flow variables”, detecting as “treated” those who benefit from the treatment in a specific interval of time and were non-treated before. Results obtained using “flow” and “stock” treatment variables will be compared.

LFS data collected at three reference periods, $t1$, $t2$ and $t3$, have been merged ($t2-t1 = 3$ months; $t3-t2 = 9$ months); in the “flow” setting, “treated” are those who are non-treated at $t1$ and treated at $t2$; in the “stock” setting “treated” are defined only with respect to the treatment status at $t2$; transition probabilities from $t2$ to $t3$ for “treated” unemployed persons (compared with the non-treated one) will be evaluated. We claim that the differences between stock and flows treatment variables is relevant to carry out a proper employment services evaluation, because the flow variables are more capable to capture effective job search activities, just before the time period in which the interview takes place.

The LFS also provides a rich set of control variables, a necessary requirement in order to carry out a proper propensity score matching analysis, based on selection on observables. We use information on the following categories: personal information (age, gender, education, search intensity, previous job experience, adaptability in the job search, duration of the search activity); household information (number of family members, household typology); macroeconomic variables estimated at the provincial-NUT3 level (unemployment rate, employment variation (%) in the related quarter, unemployment vs. employment transition probabilities as a measure of the labour market dynamics, agriculture share on employment, efficiency of PES at the provincial level).

Another important remark concerns the fact that in previous papers (Barbieri *et al.*, 2002, 2003) control variables and treatment variables are observed in the same period of time (at $t2$). This entails a serious methodological problem and biased results, because propensity score matching theory argues that at first individuals have to be observed in a pre-treatment status, then the treatment takes place and finally the outcome is observed. This means that when treated and non-treated are compared it is important to use pre-treatment variables, comparing individuals that were the same before the treatment took place. In our paper we deal with this problem because we observe the control variables at $t1$, the treatment variables at $t2$ and the outcome at $t3$.

2. Propensity score matching technique and main results

OLS cannot usually be used to estimate the impact of a treatment mostly because selection into treatment is not random, but can be affected by individual characteristics (self selection issues). To deal with this problem we use propensity score matching, whose basic assumption is the selection on observables (unconfoundedness). More specifically, the selection into treatment is completely determined by observed variables, and when conditioning on these variables the assignment into treatment may be assumed as random. Using this assumption it is possible to compute the propensity score, i.e. the probability to participate to the treatment conditioning to the pre-treatment control variables. Finally, comparing treated with non-treated -with the same propensity score- it is possible to estimate the average treatment effect on the treated (ATT). Since it is often unfeasible to have individuals with exactly the same propensity score, several algorithms are usually used to match treated and not treated. In this paper we use three different methods, in order to test the robustness of results: the nearest neighbour, radius and kernel.¹

Table 1 reports our main results. As already stressed, we enlarge the standard definition of treated, i.e. enrolment to PES, in two ways: a) we introduced a new treatment variable –having had contacts in the last 6 months; b) we claim that important differences can apply when considering the treatment variables either in stock or in flow specification. We argue that these differences in definitions might lead to very different policy evaluation. Table 1 shows that these intuitions are strongly confirmed by data. First of all, as for PES evaluation it is worth noting that the standard variable –the stock of enrolment to PES- is not significant, as in previous papers. Second, when considering the flows counterpart of this variable – new enrolment in PES – the coefficient becomes clearly significant and positive, no matter the method used to compute the ATT (nearest, radius, kernel). Third, the new variable we introduced –‘having had contact with PES’- is actually significant and positive, both in stock and in flow specification. On the one hand, it means that this variable better capture the efficacy of the PES services, with respect to the enrolment status. On the other hand, for this variables the differences between stocks and flows specification is –as expected- not as relevant as for the enrolment status, mainly because ‘having had contact in the last six months’ is already a closer measure of the timing of PES services, i.e. at least a job-search activity has been carried out in the last six months. The flow specification –‘having had contact in the last 6 months (but not before)’- only reinforces this effect.

As far as PRES are concerned, it is not possible to identify an enrolment status, like for the PES. This means that the only treatment variable available is ‘having had contacts in the last 6 months’, in stock and in flows. Similarly to the PES case, there are not relevant differences between the two specifications, and coefficients for PRES are positive when –rarely- significant.

The comparison of the results between PES and PRES strongly depends on the treatment variable used. Considering the enrolment status for PES and contacts in the last 6 months for PRES leads to a slight preference for the PRES. Results are clearly reversed when we consider for PES either the flows of enrolment status or the variable ‘having had contacts in the last 6 months’: PES become more efficient in providing job

¹ For further details see for instance Rosenbaum and Rubin, 1983, and Ichino and Becker, 2002, for an explanation of the software we use.

opportunities. Nevertheless, further research is required in order to compare public and private employment services.

Table 1: *ATT of PES and PRES on employment probabilities for unemployed*

PES	Num. treated	OLS		ATT - Propensity score matching						BPNS
				Nearest		Radius		Kernel*		
Stock variables		coeff	t	coeff	t	coeff	t	coeff	t	
Enrolments to PES	1140	0.015	0.580	0.009	0.152	0.012	0.275	0.011	0.306	0
Contacts last 6 months	421	0.066	0.149	0.065	1.902	0.067	2.680	0.068	3.213	0
Flow variables										
New enrolments to PES	103	0.123	3.090	0.117	1.747	0.169	3.439	0.152	4.169	0
New cont.last 6 months	257	0.110	4.170	0.080	1.951	0.111	3.603	0.111	3.670	0
PRES										
Stock variables										
Contacts last 6 months	153	-0.003	-0.090	-0.046	-0.790	0.081	2.105	0.006	0.179	0
Flow variables										
New cont.last 6 months	93	-0.029	-0.690	-0.022	-0.310	0.042	0.888	0.010	0.190	0

BPNS stands for balancing properties not satisfied. * is for bootstrapped standard errors

3. Conclusion

In this paper we carry out an evaluation of public and private employment services, using propensity score matching. With respect to previous papers, we enlarge the treatment definition because we claim that the standard one –enrolment to PES– is not a proper measure of the search activity. Hence, we introduce two new treatment variables: a) the new/recent enrolments; b) having had contacts in the last 6 months. While for the standard treatment definition the PES evaluation is always negative, i.e. PES do not seem to increase the probability to find a job, using the two new variables PES evaluation (ATT) is clearly positive, entailing a significant higher probability to find a job, from 5 to 16%.

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