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Evaluation of the Effects of Two Classes of Active Labour Market Policies for Welfare Recipients: a Danish Study Case

Alberto Fossaluzza

Dipartimento di Scienze Statistiche, Università di Padova

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Unità locali del progetto:

Dip. di Economia "S. Cognetti De Martiis", Univ. di Torino	(coord. B. Contini)
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Dipartimento di Scienze Statistiche
via C. Battisti 241-243, 35121 Padova
www.valutazione2003.stat.unipd.it

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Contents

1 Introduction[0]

Helping the unemployed to become competitive in the labour market is preferable to providing them with income support only: this is the basic rationale for Active Labour Market Policies (ALMPs), contrary to passive labour market policies which try to alleviate unemployment problems by guaranteed cash benefits.

Action to combat unemployment is a central element of the Danish labour market policy. Indeed, since their birth in 1978, ALMPs in Denmark have changed a lot, concerning the instruments adopted and the efficiency of its programmes. The results of these reforms in the implementation of ALMPs are undoubtedly encouraging[1].

The aim of this paper is to evaluate ALMPs. In Denmark, an unemployed person will in a fairly short time end up in an ALMP. Thus, it is difficult, if not impossible, to find unemployed people who have never participated in a programme. As a consequence, I will focus on the relative efficiency of different programmes, *i.e.* comparing people who participated in two different programmes (see *e.g.* Carling and Richardson (2001) and Sianesi (2002)). Such an evaluation exercise, however, is by no means useless: comparing the impacts of two programmes can help the policy maker in allocating resources efficiently.

Among ALMPs, private sector programmes (PRPs) have always been pointed to as the most successful programmes to help the unemployed to go back to work. But they have never been compared to public sector programmes (PRPs)[2]. Just looking at the raw data[3] may be misleading since

[0]This working paper is part of my master's degree final thesis. I am grateful to Prof. Ugo Trivellato who gave the possibility to reach Denmark to work on this project and to Prof. Peter Jensen for helping me during the period I spent at the University of Aarhus.

ADDRESS FOR CORRESPONDENCE: fossaluzza@stat.unipd.it

[1]See The Danish Ministry of Employment.

[2]Graversen and Jensen (2004) compare PRPs to all the other ALMPs

[3]The dataset used is a register-based dataset constructed by The Danish National Institute of Social Research in collaboration with Statistics Denmark. See Section 3 for

there might be some deeper reasons why PRPs are so successful. To answer these questions, I use an empirical model originally formulated by Aakvik et al. (2000).

In Denmark, there are two different administrative systems referring to two groups of unemployed people: the first group comprises unemployed people who are insured against unemployment and who qualify for unemployment benefits, while the second group comprises unemployed people who either are not insured against unemployment or do not meet the conditions for qualifying for unemployment benefits, but are entitled to social assistance. I will concentrate my attention on welfare benefit claimants (non-insured workers), since evaluations for unemployment benefits claimants have been numerous and detailed, while there has been much less interest in the unemployed on social assistance[4].

For both groups, the decision to assign unemployed workers to any specific available active labour market policy is done by caseworkers, at local level (a discussion on caseworkers added value can be found in Lechner and Smith (2003)). In this way, people are selected into different programmes on the base of observable characteristics. However, in some cases selection might be based on unobservable characteristics as well: caseworkers may not gain all the necessary information from the interview so that some relevant characteristics could remain hidden. Obviously, these hidden characteristics (individual, but also regional), if not accounted for, may lead to possible bias in the results. To avoid this, in the empirical model I will take both observable and unobservable characteristics into consideration.

A third special trait of the model used here is the possibility to control for possible heterogeneity in the way participants respond to programmes. Because of "the fundamental problem of policy evaluation" (Holland, 1986),

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details.

[4]The administration of the social system is the responsibility of the Ministry of Social Affairs and it is decentralized and run by the municipalities (in contrast with the labour market system, which is quite centralized). The instruments which local authorities may use under the Act on an active social policy may comprise guidance and introduction programmes, job training, participation in voluntary and unpaid activities, adult vocational training or continued training, job rotation, special tailor-made training activities.

to calculate the impact of a specific programme one usually refers to an average impact, which is assessed using population averages. However, in some cases (depending on the model specification) it is possible to calculate other parameters of interest. The model used in this paper allows the treatment effect to vary among observationally identical individuals so that it is possible to calculate the distribution of the treatment effect.

I will only look at the employment effect of the programmes, since it is the main purpose of ALMPs. Examples of previous papers evaluating employment effects are Andrén and Andrén (2002), who examine employment effects of Swedish training programmes, and Gerfin and Lechner (2002), who evaluate the effects of ALMPs on individual employment probability in Switzerland.There might be other effects, *e.g.* occupational choice and subsequent earnings, but these are beyond the aim of this study. I will also consider three different time horizons for the employment outcome, namely 6, 12 and 24 months after the end of the programme, to check whether there is a trend over time on the employment effect of the programmes.

2 The econometric model

To estimate the employment effect of private sector programmes relative to public sector programmes I use the latent variable model of Aakvik et al. (2000). This model uses simple latent variable structures to take into account the observed characteristics affecting the selection rule into PRP and the potential employment equation for both PRP and PUP participants, and a one-factor model for the unobserved characteristics, under the assumption of correct specification.

The fundamental issue of the evaluation problem is that it is not possible to have people in two different employment states (*unemployed*, *employed*). So for each person i one assumes two potential outcomes (Y_{0i},Y_{1i}) corresponding to the potential employment outcomes if the person participated in a public sector programme or in a private sector programme. Let D_i be a dummy variable that equals 1 if the individual i participated in a private sector programme and 0 if the individual participated in a public sector programme, respectively. Putting together these few elements it is possible to write the observed employment state as

$$Y_i = D_i Y_{1i} + (1 - D_i) Y_{0i} \,. \tag{1}$$

For the participation equation the model assumes a latent variable structure:

$$\begin{aligned} D_i^* &= Z_i \beta_D - U_{Di} \\ D_i &= 1 \quad \text{if} \quad D_i^* \geq 0 \\ D_i &= 0 \quad \text{if} \quad D_i^* < 0 \,, \end{aligned} \tag{2}$$

where Z_i is a vector of observed variables and U_{Di} is an unobserved random variable.

The potential employment state has a latent index structure, with a linear specification in the parameters and additive separation between the observed and unobserved components:

$$\begin{aligned} Y_{ji}^* &= X_i \beta_j - U_{ji} \\ Y_{ji} &= 1 \quad \text{if} \quad Y_{ji}^* \geq 0 \\ Y_{ji} &= 0 \quad \text{if} \quad Y_{ji}^* < 0 \end{aligned} \tag{3}$$

with $j = 0, 1$ meaning PUPs- and PRPs-takers, respectively, and where X_i is a vector of observed variables and (U_{1i}, U_{0i}) are unobserved random variables.

Henceforth, the following assumptions are taken throughout the rest of the paper:

1. (Y_{1i}, Y_{0i}) are defined $\forall\, i$;

2. there is no interaction among agents;

3. $Z\beta_D$ is a nondegenerate random variable conditional on $X = x$;

4. $(U_D{,}U_1)$ and $(U_D{,}U_0)$ are absolutely continuous with respect to Lebesgue measure on $\Re^2$;

5. (U_D, U_1) and (U_D, U_0) are independent of (Z, X);

6. Y_1 and Y_0 have finite first moments;

7. $0 < \Pr[\, D = 1 \,|\, X \,] < 1$.

In particular, assumption (3) implies the existence of an instrumental variable[5] (it is basically an exclusion restriction on the two employment equations).

2.1 Individual treatment effects

Before writing all the parameters of interest, I need to explain one of the main features of this model, *i.e.* the possibility for the treatment effect to vary among individuals (that is, why I can estimate also distributional parameters).

First, let define the individual differential treatment effect $\triangle_i$ in the following way:

$$\triangle_i = Y_{1i} - Y_{0i} = \mathbf{1}(X_i\beta_1 \geq U_{1i}) - \mathbf{1}(X_i\beta_0 \geq U_{0i}) \,,$$

so that $\triangle_i$ measures for all individuals the difference between the employment state in case of participation in a PRP and the state in case of participation in a PUP. It is straightforward to see that $\triangle_i$ can attain three values: -1, 0, 1. But even if the effect of the unobserved variables U_{1i} and U_{0i} was the same in the two potential states ($U_{1i} = U_{0i}$), $\triangle_i$ could only attain two different values for individuals with a given value of X. However, in this framework I allow individuals to differ from each other either on observed and/or unobserved characteristics, so that all the three values of $\triangle_i$ may be experienced.

For ease of exposition and to simplify the notation, throughout the rest of the paper I suppress the i subscript without lost of generality.

[5] See *e.g.* Heckman (1990) for details.

2.2 Mean treatment parameters

Let $\triangle$ denote the treatment effect for a given individual, where $\triangle = Y_1 - Y_0$. This difference cannot be formed for anyone since Y_1 or Y_0 is missing. The statistical approach to this problem is to replace the missing data on people using group means. Here I examine three different mean parameters:

- the average differential treatment effect (ATE), which answers the question of how much a randomly chosen individual would gain from participating in a PRP instead of a PUP,

- the average differential treatment effect on the treated (ATT), which measures how much gained a person who participated in a PRP from participating in it,

- and the marginal differential treatment effect[6] (MTE), which identifies the effect of participating in a PRP on those individuals who are indifferent between participation in a PRP or PUP for a given value of $U_D = u$. For small values of u, $\triangle^{MTE}(x, u)$ is the average effect of those who have characteristics that make them most likely to participate on a private sector programme, while for large values of u, $\triangle^{MTE}(x, u)$ is the average effect of those who are least likely to participate in a private sector programme because of their characteristics.

In this special case, with the outcome variable being dichotomous, the mean parameters above take the following form:

[6]For further connections between $\triangle^{ATE}$ and $\triangle^{ATT}$ with $\triangle^{MTE}$ see Heckman, Vytlacil (2000).

$$
\begin{aligned}
\triangle^{ATE}(x) &= F_{U_1}(x\beta_1) - F_{U_0}(x\beta_0) \\
\\
\triangle^{ATT}(x, z, D = 1) &= F_{U_D}(z\beta_D)^{-1}[F_{U_D,U_1}(z\beta_D, x\beta_1) - \ldots \\
&\quad \ldots - F_{U_D,U_0}(z\beta_D, x\beta_0)] \\
\\
\triangle^{MTE}(x, u) &= F_{U_1\,|\,U_D}(x\beta_1\,|\,u) - F_{U_0\,|\,U_D}(x\beta_0\,|\,u)
\end{aligned}
$$

where $F_{U_j|U_D}(t_j|t_D) = \Pr[U_j \leq t_j|U_D = t_D]$ for $j = 0, 1$.

2.3 Distributional treatment parameters

I now consider differential treatment parameters for the distribution of differential treatment effects.

In this special case, $\triangle$ can take three values:

1. $\triangle = 1$ if the individual would have a successful outcome if treated (*i.e.*, be employed if (s)he participates in a PRP) and an unsuccessful outcome otherwise ($Y_0 = 0, Y_1 = 1$);

2. $\triangle = 0$ if the individual would have a successful outcome in either state ($Y_0 = 1, Y_1 = 1$), or the individual would have an unsuccessful outcome in either state ($Y_0 = 0, Y_1 = 0$);

3. $\triangle = -1$ if the individual would have a successful outcome if not treated (*i.e.*, be employed if participation in a PUP) and an unsuccessful outcome if treated ($Y_0 = 1, Y_1 = 0$).

Consider, for example, $\triangle = 1$:

$$E[\triangle = 1|X = x] = F_{U_1}(x\beta_1) - F_{U_0,U_1}(x\beta_0, x\beta_1)$$

$$E[\triangle = 1 \,|\, X = x, Z = z, D = 1] =$$
$$= F_{U_D}(z\beta_D)^{-1}\Big[F_{U_D,U_1}(z\beta_D, x\beta_1) - F_{U_D,U_0,U_1}(z\beta_D, x\beta_0, x\beta_1)\Big]$$

$$E[\triangle = 1|X = x, U_D = u] = F_{U_1|U_D}(x\beta_1|u) - F_{U_0,U_1|D}(x\beta_0, x\beta_1|u)$$

Identification of the distributional treatment parameters is anyway more difficult than identification of the mean treatment effect: it requires knowledge of the full trivariate distribution F_{U_D,U_0,U_1}. Since Y_0 and Y_1 are never jointly observed, this trivariate distribution is not identified nonparametrically even when treatment is exogenous. However, the distribution of treatment effect can be identified if additional assumptions are made. I now discuss the assumption of a normal factor structure.

2.4 Factor structure model

In this empirical analysis I specify a discrete-choice, latent-index framework where the unobservables are generated by a normal factor structure (this special trait of the model was first introduced by Heckman in 1981).

It is assumed that the error terms in (2) - (3) are governed by the following factor structure:

$$\begin{aligned} U_{Di} &= -\alpha_D\theta + \epsilon_{Di} \\ U_{1i} &= -\alpha_1\theta + \epsilon_{1i} \\ U_{0i} &= -\alpha_0\theta + \epsilon_{0i}\,, \end{aligned} \tag{4}$$

where I need to set $\alpha_D = 1$ to reach identification of the model. I assume i.i.d. observations; besides the following normality assumption is taken:

$$\theta, \epsilon_D, \epsilon_1, \epsilon_0 \sim N(0, I)$$

where I is the identity matrix, which implies that

$$(U_D, U_1, U_0) \sim N(0, \sum),$$

with:

$$\sum = \begin{bmatrix} \sigma_D^2 & \sigma_{D1} & \sigma_{D0} \\ & \sigma_1^2 & \sigma_{10} \\ & & \sigma_0^2 \end{bmatrix} = \begin{bmatrix} 1+\alpha_D^2 & \alpha_D\alpha_1 & \alpha_D\alpha_0 \\ & 1+\alpha_1^2 & \alpha_1\alpha_0 \\ & & 1+\alpha_0^2 \end{bmatrix}$$

Thus, identification of α_0 and α_1 immediately imply identification of $\mathrm{Cov}(U_0, U_1) = \alpha_1\alpha_0$. Given joint normality, this implies that the joint distribution U_D, U_1, U_0 is known: no exclusion restrictions are required and assumption (3) could be relaxed.

I decide to run two specifications of this model: one with selection *only on observable* characteristics and one with selection *also on unobservables*. The former is obtained setting α_1 and α_0 to 0, while in the latter the two factor loadings are set free. The exclusion restriction can be relaxed, but I keep it to improve the empirical identification of the model.

2.5 Estimating the Mixture Model

Conditioning on θ, and restoring the i subscript, the likelihood function for the factor model has the form:

$$\prod_{i=1}^{N} \Pr[D_i, Y_i | X_i, Z_i, \theta_i]$$

where

$$\Pr[D_i, Y_i | X_i, Z_i, \theta_i] = \Pr[D_i | Z_i, \theta_i] \Pr[Y_i | D_i, X_i, \theta_i],$$

and

$$\begin{aligned} \Pr[D_i = 1 | Z_i, \theta_i] &= \Phi(Z_i\beta_D + \theta_i) \\ \Pr[Y_i = 1 | D_i = 1, X_i, \theta_i] &= \Phi(X_i\beta_1 + \alpha_1\theta_i) \\ \Pr[Y_i = 1 | D_i = 0, X_i, \theta_i] &= \Phi(X_i\beta_0 + \alpha_0\theta_i). \end{aligned}$$

Since θ is unobserved I need to integrate over its domain to account for its existence, assuming that $\theta \perp (X, Z)$.

The likelihood function integrating out θ has the form:

$$L = \prod_{i=1}^{N} \int \Pr[D_i, Y_i | X_i, Z_i, \theta_i] \phi(\theta) d\theta \, .$$

Identification of the parameters of the model, $(\beta_D, \beta_1, \beta_0)$ and (α_1, α_0), is assured by the joint normality assumption for $\epsilon_D, \epsilon_1, \epsilon_0$ and θ. Parameters are estimated by maximum likelihood, where I use a Gaussian quadrature to approximate the integrated likelihood.

2.6 Heckman-Singer procedure

Another approach to the problem of missing conditioning variable is to assume different values of the missing θ value and to perform a sensitivity analysis. Heckman and Singer (1984) propose a procedure that abstracts from the assumption of a specific parametric representation of the distribution of the fixed effect. This specification allows the unknown distribution to be represented non-parametrically by a step function. In this manner the probability density function is approximated by a discrete distribution with a finite number of points of support, and estimates are made for the location and density of each point. The exact number of points of support is determined by beginning with one support (*i.e.* no heterogeneity) and working upward until the likelihood fails to improve significantly. In this model I use three points. Let v_1, v_2 and v_3 be the three points of support (with $v_1 < v_2 < v_3$) and p_1, p_2 and p_3 the associated probabilities (with $p_1 + p_2 + p_3 = 1$). Since it is possible to derive p_3 as a difference of probabilities, the only additional parameters to calculate (if compared to the model with the normally distributed common factor) are p_1 and p_2.

Although the distribution of the fixed effect is not likely to be well characterized by the step function, Heckman and Singer (1984) have shown that the coefficients of the explanatory variables can be estimated with great precision.

Following the notes above, it is now possible to rewrite the likelihood function as

$$L = \prod_{i=1}^{N} \sum_{j=1}^{3} \Pr[D_i, Y_i | X_i, Z_i, v_{ij}] \cdot p_j \, .$$

and the correspondent expressions for the characterizing probabilities can be derived by straightforward modification of the ones written in the previous subsection.

3 The data

The data used in this dissertation are taken from the dataset *The register for Analyses relating to the Social Responsibility of Enterprises*. It contains a 10% random sample representative of the Danish population in the 17-66 age group. The dataset is updated every year and at present it is possible to follow the individuals in the sample for the period 1984-2000.

I did not use the entire sample to run my analyses since there were a number of conditions to be met first[7] (see Table 1): the final sample is made up of 2,651 observations, 1,391 of which are private sector programmes participants and 1,260 are public sector programmes participants.

3.1 Variables

The regressors used in the three equations of the model are the same, except from an additional instrument added in the selection equation, and are divided into two main groups: individual and municipality characteristics[8]. The former include marital state, year when the programme started, presence of children, age, level of education, years of work experience, fraction of time spent by the individual in different employment states during the 12 months before and during the period 12-36 months preceding the programme; in the latter I include the number of residents in the municipality in which the individual lives and a measure of the regional unemployment rate relative to the

[7]The final sample I use was manipulated by Brian Krogh Graversen and Peter Jensen in their previous studies, so all the restrictions mentioned below were made by them.

[8]See Appendix A for all the descriptive statistics.

Restrictions	**Obs.**
Individuals who ended an ALMP during 1994-1998	20,105
Restricted to ALMP starting in 1993 or later	20,060
Restricted to ALMP with length between 2 weeks and 5 years	18,454
Individuals with missing basic information excluded	18,339
Restricted to men	9,193
Immigrants and refugees excluded	7,841
Restricted to age 18-59 when starting ALMP	7,181
Restricted to individuals with information for all years include 1 year before and after the programme period	6,987
Individuals in public sector employment programmes with missing data excluded	6,822
Individuals from municipalities with less than 10 ALMP participants excluded	6,613
To keep private and public sector programmes participants	2,651

Table 1: Dataset's restrictions.

countrywide unemployment rate (it can be used to account for differences in local labour markets).

As anticipated in Section 2, I introduce an additional instrument in the selection equation, *i.e.* the yearly proportion of PRP programmes used in each municipality relative to the countrywide proportion of this type of programme[9]:

$$W_{it} \equiv \frac{N_{it}^{PRP}/N_{it}^{ALMP}}{N_{t}^{PRP}/N_{t}^{ALMP}} \ .$$

To be a valid instrument the local treatment intensity should have a direct effect on the selection process but no direct influence on the employment outcome after the programme: the only effect on the employment outcome should be via participation to the programme itself.

However, there would be a problem of endogeneity, if I included in the model the variable as defined above. If individual i participates in a programme during year t, this fact will have an impact on W_{it}. To solve this endogeneity problem I decided to use $W_{i(t+2)}$ instead of W_{it}. In this way if individual i starts a programme during year t, this does not have any impact on

[9]see Frlich and Lechner (2004)

$W_{i(t+2)}$ since this variable refers to two years later (on average, a programme lasts 6 months). Of course, to be a good instrument W should have some degree of correlation over time. It is reasonable to assume that municipalities with a high proportion of PRP programmes in one year should have a high proportion of the same programmes in the surrounding years. I did not lag W since there would have been a problem of missing data.

4 Results

4.1 Coefficient estimates

The estimated parameters of the selection equation show clearly that participants in the two programmes are significantly different with respect to observable characteristics[10]. People married or cohabitating, with more than 2 years of work experience, living in municipalities where PRPs are more important and those who spent a large fraction of time in employment during the two years period starting three years before the programme, have a higher probability of being assigned into private sector programmes, while individuals with a higher education degree and living in regions where the unemployment rate is higher have more probability to be assigned to public sector programmes.

Besides, the estimates of the programme starting year dummies show a decreasing trend in the probability of being assigned into a private sector programme, since they diminish from 1993 to 1998.

Looking at the employment equations, I now decide to focus basically on the model which allows for selection on the unobservables. Some characteristics have an impact on both the PRP and PUP employment outcomes and, apart from a few cases, all of these significant variables maintain their influence with time. Younger people, people with higher educational degrees, people with more work experience and people who spent less time in unemployment have a significantly higher probability of being employed after the

[10] I do not report all the estimates for ease of brevity.

end of the programme. This is consistent with the results obtained by Graversen and Jensen (2004) in a recent study where they use the same model to investigate the impact of private sector programmes relative to all other types of ALMP. From the estimates, it is seen that the older the person the lower the probability of being employed and the more work experience the higher the probability of being employed. Furthermore, living in big cities, in regions with little unemployment rate and having children are characteristics positively influencing the probability of finding a job after the end of the programme.

Considering the three different time horizons, there seems to be some difference with time, in the sense that for each time, apart from some characteristics influencing constantly, there are different variables having an influence on the probability to get a job. But the 12 month version has a further difference with the other two time horizons, specially in the public sector employment equation: only four estimates are statistically different from zero, and just at a 10% level.

Comparing the selection-on-unobservables version of the model with the version without selection allowance[11], the coefficient estimates are very similar: this is in accordance with the fact that the loadings of the common factor in the model with selection are not significantly different from zero. However, it does increase the estimated standard errors in the public programme employment outcome: this is the main reason why several variables fail to be significant when controlling for selection on unobservables.

4.2 Mean treatment effects

Looking at the raw data , PRP participants have a 20.35 percentage points higher employment rate than PUP participants, when their employment state is compared 6 months after the end of the programme. This advantage falls to 15.9 and 14.36 percentage points, respectively, 12 and 24 months after the end of the programme.

[11] I do not report in this paper any estimate for the model without selection on unobservable characteristics since it is the least satisfactory one.

When controlling for the observable characteristics, the negative trend does not change, even though values are smaller. After 6 months, a randomly selected PRP participant has 17.1 percentage points higher employment rate than a PUP participants and this difference is significantly different from zero; the difference decreases to 12.7 and 11.5 respectively 12 and 24 months after, although always strongly significant.

If I further control for selection on unobservables, then this difference is much smaller for the 6 and 12 months, while it basically does not change for the 24 months. But, more important, the differential effect fail to be significant. So the first evidence is the importance of controlling also for unobservable characteristics: the average treatment effect is smaller and the trend is inverted if compared with the model without selection on unobservables.

The results for the treated (ATT) are even more surprising. In the version where I control also for unobservable characteristics the mean treatment effect on the treated is negative for the 6 and 12 month versions and positive (but really close to zero) for the 24 month version, though not statistically significant. The smaller estimates suggest that those treated are not those (on average) expected to gain more from the programme, but those expected to gain less (specially 12 months after the end of the programme) and, moreover, they are penalized. This result is similar to the results obtained by Graversen and Jensen (2004) and other studies based on the same model[12].

The results above highlights the importance of controlling also for the unobservable characteristics. Now, in the model with allowance for selection on unobservables, the calculations of the mean marginal treatment effect (MTE) for different values of $Z\beta = u$ allow a better understanding of the role of the unobservables. This index reports the treatment effect for those people on the border between being assigned into a private or a public sector programme; so, setting different values of u it is possible to investigate how the treatment varies for people more or less likely to be selected into a private sector programme, the smaller the value of u the more likely the participation

[12]See *e.g.* Andrén and Andrén (2002) or Aakvik et al. (2003).

in a PRP programme. I calculate the $\triangle^{MTE}$ parameters for three values of u ($u = -2$, $u = 0$, $u = 2$). The estimation results (even though not significant) reveal an increasing trend of the $\triangle^{MTE}$ in U_D: individuals most likely to be selected into private sector programmes (low u-values) are penalized from participating, while individuals with characteristics which make them least likely to be selected benefit the most from participating. This difference persists with time and becomes bigger after 12 months. Hence, the mean MTE agrees with what is suggested by the ATE and ATT mean effects since they also reported that a randomly selected individual would be better off than an actual participant in PRPs.

4.3 Distributional treatment effect

As described in Section 2, the model used in this study allows the impact to vary among individuals, hence accounting for possible heterogeneity in the population.

Appendixes B, C and D report the distributional impacts obtained using the specification which allows selection on the unobservables after 6, 12 and 24 months, respectively. For the first two time horizons, almost the same fraction of randomly selected individuals (ATE) will benefit and will be hurt from participating in PRP programmes ($\mathrm{P}^{ATE}_{Y_1,Y_0}(1,0)$ and $\mathrm{P}^{ATE}_{Y_1,Y_0}(0,1)$, respectively), while around half of the population will not be affected by the type of programme since they will be employed or not regardless of which type of programme they participate in ($\mathrm{P}^{ATE}_{Y_1,Y_0}(1,1) + \mathrm{P}^{ATE}_{Y_1,Y_0}(0,0)$). On the contrary, 24 months after the end of the programme, participants benefiting will be almost twice as many as those being hurt by it. Differently from the $\triangle^{ATE}$, all these probabilities are significantly different from zero.

Looking at the treatment effect on the treated (ATT), the story does not change so much. The majority of the population will be unaffected by the type of the programme, while the others will be equally divided into those who benefit and those hurt by participating in PRPs. As before, there is one time horizon different from the others, but in this case is the 12 months:

those being hurt are twice as many as those who benefit from PRPs. In any case, only the estimates for those not affected are significant at a 1% level.

As for the mean treatment effects, the last parameters I consider are those for the marginal treatment effect: it is possible to see who benefits the most from participating just comparing the parameters for different values of $U_D = u$. The distributional treatment effects for individuals with a value of unobservable characteristics that make them most likely to participate in PRPs (low u-values) give the same information of the ATT parameters. As the u-values increase, *i.e.* for individuals less and less likely to take private sector programmes, the probability of benefitting from participating increases, the probability of getting hurt by the programme decreases while the fraction of people unaffected by the programme remains substantially constant. Differences among the population seem to be bigger for the 12 months employment state: for individuals most likely to get a PRP, almost half of them will be hurt by the participation, at the same time less than 10% will benefit. On the contrary, for individuals least likely to participate, more than half will benefit from it and only 7.6% will be hurt. As well as for ATE and ATT distributional parameters, the majority of people have no advantage from participating in a private sector programme instead of a public sector programme.

Thanks to the model specification, it has been shown that there is a considerable amount of heterogeneity in the impact of the programmes. A less sophisticated index for this heterogeneity could be the empirical standard deviation of the mean treatment effects:

	$\triangle^{ATE}$	$\sigma_{\triangle}^{ATE}$	$\triangle^{ATT}$	$\sigma_{\triangle}^{ATT}$
6 months	.021	.104	-.049	.11
12 months	.057	.097	-.149	.091
24 months	.119	.097	.017	.106

Regardless of the time horizon, the empirical standard deviation of the mean treatment effect and the mean treatment effect on the treated are quite big; they show that the impact of participating in a private sector programme can vary considerably, for both a randomly selected individual and a treated person.

4.4 Selection on observables and unobservables

To gain further knowledge on which extent observable and unobservable characteristics for selection and employment outcome are connected, I calculated some correlations. Given the normalizations introduced in Section 2, for the 6 months employment state the correlations between unobservables are:

$$\begin{aligned}
\text{Corr}_{6\ months}(U_0, U_1) &= 0.078 \\
\text{Corr}_{6\ months}(U_D, U_0) &= 0.382 \\
\text{Corr}_{6\ months}(U_D, U_1) &= 0.102
\end{aligned}$$

From the first correlation, unobservable characteristics determining employment in PRP takers are not correlated with unobservable characteristics determining employment in PUP takers. From the latter two correlations, individuals with high values of U_D (thus those least likely to participate in a private sector programme) are likely to have unobserved characteristics negatively influencing their employment state after the programme, regardless of which programme they participate in, but less likely to be unemployed if they are PRP participants (given the values of X and Z). For the 12 months version, things are slightly different:

$$\begin{aligned}
\text{Corr}_{12\ months}(U_0, U_1) &= -0.261 \\
\text{Corr}_{12\ months}(U_D, U_0) &= 0.461 \\
\text{Corr}_{12\ months}(U_D, U_1) &= -0.283
\end{aligned}$$

The correlation between U_0 and U_1 is negative. Secondly, correlations between unobservables promoting selection into PRPs and each employment outcome have opposite signs: this shows a perverse selection on unobservables, since people assigned to a certain type of programme are those benefiting the least from that type of programme.

The same conclusions can be derived from the correlation on the 24 months specification:

$$\begin{aligned}
\text{Corr}_{24\ months}(U_0, U_1) &= -0.074 \\
\text{Corr}_{24\ months}(U_D, U_0) &= 0.177 \\
\text{Corr}_{24\ months}(U_D, U_1) &= -0.21
\end{aligned}$$

Here, even though values are smaller than before, estimates show the same distorted selection rule.

After having considered how unobservable characteristics affect the selection and employment outcomes, it may be useful to know if observables have the same impact. Unlike before, indices are all positively correlated to each other:

$$\begin{aligned}
\text{Corr}_{6\ months}(X\beta_0, X\beta_1) &= 0.829 \\
\text{Corr}_{6\ months}(Z\beta_D, X\beta_0) &= 0.413 \\
\text{Corr}_{6\ months}(Z\beta_D, X\beta_1) &= 0.433
\end{aligned}$$

$$\begin{aligned}
\text{Corr}_{12\ months}(X\beta_0, X\beta_1) &= 0.797 \\
\text{Corr}_{12\ months}(Z\beta_D, X\beta_0) &= 0.501 \\
\text{Corr}_{12\ months}(Z\beta_D, X\beta_1) &= 0.265
\end{aligned}$$

$$\begin{aligned}
\text{Corr}_{24\ months}(X\beta_0, X\beta_1) &= 0.778 \\
\text{Corr}_{24\ months}(Z\beta_D, X\beta_0) &= 0.315 \\
\text{Corr}_{24\ months}(Z\beta_D, X\beta_1) &= 0.259
\end{aligned}$$

Thus, unlike what arises in the analysis of unobservables, a higher index for participation is associated with higher employment outcomes in both the private and public sector programmes. Note that correlation between $X\beta_0$ and $X\beta_1$ is strong, but they are not perfectly correlated, meaning that employment after one type of programme does not imply certain employment even after the second type of programme. Besides, correlation between $Z\beta_D$ and $X\beta_0$ is higher than correlation between $Z\beta_D$ and $X\beta_1$ (except for the 6 month version, which is equal) : this can be seen again as a proof of the "wrong" selection process.

Thus, correlations, probabilities and impacts based only on observable characteristics are too optimistic, while those based on unobservables are reporting worse and sometimes negative effects from participating in private sector programmes. In particular, individuals most likely to enter a PRP are those most likely to be employed anyway and least likely to benefit from participating. This is true for both observed and unobserved characteristics:

$$\begin{aligned}
\text{Corr}_{6\ months}(U_D, U_1 - U_0) &= -0.234 \\
\text{Corr}_{6\ months}(Z\beta_D, X(\beta_1 - \beta_0)) &= -0.182 \\
\\
\text{Corr}_{12\ months}(U_D, U_1 - U_0) &= -0.478 \\
\text{Corr}_{12\ months}(Z\beta_D, X(\beta_1 - \beta_0)) &= -0.524 \\
\\
\text{Corr}_{24\ months}(U_D, U_1 - U_0) &= -0.264 \\
\text{Corr}_{24\ months}(Z\beta_D, X(\beta_1 - \beta_0)) &= -0.125
\end{aligned}$$

So I found that characteristics associated with better labour market outcomes are negatively correlated with training effects, *i.e.* individuals with characteristics which make them more likely to get a job after programme participation are those with worse treatment effects. To improve the overall effectiveness of these programmes a change in the allocation process made by caseworkers is required: selecting for each type of programme those individuals more likely to gain from participating in such a programme.

4.5 Sensitivity analyses

In the model presented in this study I introduce an additional instrumental variable in the equation that accounts for selection into programmes. Given the normal factor structure used to model the unobservables, it was not required to add this variable; as explained in Section 2, I decided to append the instrument to improve the identification of the model. I have also estimated the model without the additional instrument to show the difference in the estimates (results are not reported in this paper). Results are basically the same; however, in the version without the additional instrument there is an increase in the estimates' standard errors. This confirms that the instrument improves the identification of the model.

A second crucial issue is the common factor's normality. To test whether this hypothesis influences my results, I estimate the model with another assumption for the common factor, namely that it follows a discrete distribution with a fixed number of points of support (this is the so called Heckman-Singer procedure). I use three points of support since the improvement in the likelihood failed to be significant any more. Coefficient estimates are very similar to the ones obtained from the model with the assumption of a normal distributed factor, but mean and distributional parameter estimates are slightly different: they are qualitatively similar but vary considerably in size (again, results are not reported here).

5 Conclusions

Some words of caution are in order, about these conclusions. First, I focused my attention on the employment effects only of the programmes. This is because the main purpose of these programmes is to facilitate unemployed workers return to work. Even though there might be some additional possibly interesting effects (*e.g.*, occupational choice, subsequent earnings, etc.), which are beyond the scope of this study.

Second, all the results presented here are employment effects of private sector programmes relative to public sector programmes. In some senses, this type of differential treatment effect analysis should be done as a second stage analyses, in order to choose the most effective programme for any given category of individuals, after a first stage analyses has ascertained finding out if a programme has a positive treatment effect if compared with no participation.

Third, it should be kept in mind that the results depend on the assumptions made, specification and distributional assumptions. The simple one factor assumption could be relaxed, and a more flexible structure may lead to different results. The normality assumption for the common factor allows simple manipulation and calculation of the probabilities induced by the model, but it is clearly restrictive.

The raw data suggest a large employment effect of private sector programmes and a smaller success for public sector programmes. Besides, the probability of being employed for PRPs participants (slightly) decreases with time, while it (slightly) increases for PUPs participants.

Results from the model based analyses can be summarized in three points. If I take into account the selection on observable characteristics only, the results do not change that much: PRP programmes still have a higher employment effect, but smaller in size, and the negative trend persists. When considering also the selection on unobservables, the story is completely different: mean parameters fail to be statistically significant (values are negative or close to zero) and the trend becomes positive, as if PRPs were more helpful in bringing people back to work as time passes. While a randomly selected individual would gain (on average) from participating in a PRP instead of a PUP programme in each of the time horizons, an actual PRP participant will benefit from it (on average) only 2 years after the end of the programme.

A second main result is the variability of the treatment effect. Thanks to the model structure, it is possible to see to what extent the relative impact of the PRPs varies among individuals: the empirical variance of the mean treatment effects is fairly big, $\triangle^{ATE}$ and $\triangle^{ATT}$ are much different from each other, the former being larger than the latter, and the distributional parameters show that the majority of the participants are not affected by the programme they are exposed to (if they were employed/unemployed after a PRP they would be employed/unemployed after a PUP as well, respectively), while some individuals are hurt and others benefit from participation.

A third result is about the characteristics that make people more or less likely to benefit from a programme. The MTE distributional parameters clarify the perverse selection process, according to which individuals most likely to participate in a PRP programme are those who are likely to benefit less from it, or even to be penalized from it (this conclusion is in accordance with ATE and ATT parameters).

These results summarized above suggest that there is room for improvement in the allocation process made by caseworkers: if individuals benefiting the most from a private sector programme were allocated to it, there would be an overall improvement in the treatment effect. This conclusion is based on the model where selection on the unobservables is allowed; so, if the allocation to different types of programmes was based not only on observable characteristics but on unobservables as well, there would be better results. Obviously, caseworkers need to know this and, for example, they might try to gain it directly from individuals during an interview or by basing their decisions on previous evaluations.

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A Appendix: descriptive statistics

	PRPs	**PUPs**
Number of observations	1391 (52.47%)	1260 (47.53%)
Outcome variables		
Proportion of employed:		
6 months after end of programme	54.64%	34.29%
12 months after end of programme	53.2%	37.3%
24 months after end of programme	51.19%	36.83%
Individual characteristics		
Marital state:		
Single	76.42%	84.13%
Married	6.9%	4.21%
Cohabitating	16.68%	11.67%
Year when programme started:		
1993	20.06%	5.95%
1994	38.17%	31.35%
1995	20.56%	23.1%
1996	10.14%	18.73%
1997	7.12%	12.22%
1998	3.95%	8.65%
Has children	13.37%	8.41%
Age:		
17-24	55.79%	60%
25-29	14.16%	10.56%
30-39	17.47%	16.35%
40-49	9.56%	10.32%
50-66	3.02%	2.78%
Completed education:		
Primary or lower secondary school	57.87%	58.65%
Upper secondary school	20.92%	24.92%
Vocational education	19.12%	12.78%
Further or higher education	2.08%	3.65%

	PRPs	PUPs
Work experience:		
0-2 years	51.19%	64.44%
2-5 years	20.7%	13.73%
5-10 years	15.74%	11.67%
10+ years	12.37%	10.16%
Time spent in different states during the 12 months preceding programme period:		
Employment	37%	36.1%
Unemployment	47.49%	45.61%
Ordinary education	15.51%	18.29%
Time spent in different states during a 2 years period starting 3 years and ending 1 year before the programme period:		
Employment	30.74%	22.38%
Unemployment	31.98%	33.17%
Ordinary education	9.25%	11.28%
No available information:	28.03%	33.17%
Municipalities		
Residents in municipality, 1996:		
<20,000	27.39%	26.82%
20,000-40,000	18.26%	18.17%
40,000-100,000	29.98%	24.52%
>100,000	24.37%	30.48%
Regional unemployment rate relative to countrywide rate	101.28%	103.87%
Proportion of programme participants in PRPs relative to countrywide importance of PRPs	122.17%	107.88%

B Appendix: impact distributions, 6 months after the end of the programme

$P^{ATE}_{Y_1,Y_0}(1,0)$	$P^{ATE}_{Y_1,Y_0}(0,1)$	$P^{ATE}_{Y_1,Y_0}(1,1)$	$P^{ATE}_{Y_1,Y_0}(0,0)$	$\triangle^{ATE}$
.226	.205	.271	.298	.021
(.126)	(.055)	(.08)	(.112)	(.172)
**	***	***		

$P^{ATT}_{Y_1,Y_0}(1,0)$	$P^{ATT}_{Y_1,Y_0}(0,1)$	$P^{ATT}_{Y_1,Y_0}(1,1)$	$P^{ATT}_{Y_1,Y_0}(0,0)$	$\triangle^{ATT}$
.191	.24	.355	.214	-.049
(.145)	(.112)	(.145)	(.112)	(.25)
	**	**	*	

$P^{MTE}_{Y_1,Y_0}(1,0)$	$P^{MTE}_{Y_1,Y_0}(0,1)$	$P^{MTE}_{Y_1,Y_0}(1,1)$	$P^{MTE}_{Y_1,Y_0}(0,0)$	$\triangle^{MTE}$
.149	.275	.404	.171	-.126
(.19)	(.178)	(.208)	(.155)	(.358)
		*		

a. Values for $U_D = -2$.

$P^{MTE}_{Y_1,Y_0}(1,0)$	$P^{MTE}_{Y_1,Y_0}(0,1)$	$P^{MTE}_{Y_1,Y_0}(1,1)$	$P^{MTE}_{Y_1,Y_0}(0,0)$	$\triangle^{MTE}$
.232	.209	.268	.291	.023
(.114)	(.066)	(.088)	(.099)	(.178)
***	***	***		

b. Values for $U_D = 0$.

$P^{MTE}_{Y_1,Y_0}(1,0)$	$P^{MTE}_{Y_1,Y_0}(0,1)$	$P^{MTE}_{Y_1,Y_0}(1,1)$	$P^{MTE}_{Y_1,Y_0}(0,0)$	$\triangle^{MTE}$
.297	.13	.149	.424	.166
(.249)	(.09)	(.079)	(.252)	(.329)
		*	*	

c. Values for $U_D = 2$.

C Appendix: impact distributions, 12 months after the end of the programme

$P^{ATE}_{Y_1,Y_0}(1,0)$	$P^{ATE}_{Y_1,Y_0}(0,1)$	$P^{ATE}_{Y_1,Y_0}(1,1)$	$P^{ATE}_{Y_1,Y_0}(0,0)$	$\triangle^{ATE}$
.293	.236	.299	.173	.057
(.101)	(.07)	(.044)	(.117)	(.149)
**	***	***		

$P^{ATT}_{Y_1,Y_0}(1,0)$	$P^{ATT}_{Y_1,Y_0}(0,1)$	$P^{ATT}_{Y_1,Y_0}(1,1)$	$P^{ATT}_{Y_1,Y_0}(0,0)$	$\triangle^{ATT}$
.177	.326	.355	.143	-.149
(.103)	(.119)	(.103)	(.119)	(.212)
**	***	***		

$P^{MTE}_{Y_1,Y_0}(1,0)$	$P^{MTE}_{Y_1,Y_0}(0,1)$	$P^{MTE}_{Y_1,Y_0}(1,1)$	$P^{MTE}_{Y_1,Y_0}(0,0)$	$\triangle^{MTE}$
.098	.441	.341	.12	-.344
(.103)	(.199)	(.147)	(.165)	(.291)
	**	**		

a. Values for $U_D = -2$.

$P^{MTE}_{Y_1,Y_0}(1,0)$	$P^{MTE}_{Y_1,Y_0}(0,1)$	$P^{MTE}_{Y_1,Y_0}(1,1)$	$P^{MTE}_{Y_1,Y_0}(0,0)$	$\triangle^{MTE}$
.273	.217	.326	.185	.056
(.104)	(.073)	(.082)	(.102)	(.176)
***	***	***		

b. Values for $U_D = 0$.

$P^{MTE}_{Y_1,Y_0}(1,0)$	$P^{MTE}_{Y_1,Y_0}(0,1)$	$P^{MTE}_{Y_1,Y_0}(1,1)$	$P^{MTE}_{Y_1,Y_0}(0,0)$	$\triangle^{MTE}$
.536	.076	.205	.183	.46
(.24)	(.056)	(.101)	(.221)	(.295)
***		**		

c. Values for $U_D = 2$.

D Appendix: impact distributions, 24 months after the end of the programme

$P^{ATE}_{Y_1,Y_0}(1,0)$	$P^{ATE}_{Y_1,Y_0}(0,1)$	$P^{ATE}_{Y_1,Y_0}(1,1)$	$P^{ATE}_{Y_1,Y_0}(0,0)$	$\triangle^{ATE}$
.307	.187	.245	.261	.119
(.099)	(.095)	(.064)	(.122)	(.183)
****	**	***	**	

$P^{ATT}_{Y_1,Y_0}(1,0)$	$P^{ATT}_{Y_1,Y_0}(0,1)$	$P^{ATT}_{Y_1,Y_0}(1,1)$	$P^{ATT}_{Y_1,Y_0}(0,0)$	$\triangle^{ATT}$
.248	.231	.262	.26	.017
(.127)	(.159)	(.127)	(.159)	(.284)
**		**		

$P^{MTE}_{Y_1,Y_0}(1,0)$	$P^{MTE}_{Y_1,Y_0}(0,1)$	$P^{MTE}_{Y_1,Y_0}(1,1)$	$P^{MTE}_{Y_1,Y_0}(0,0)$	$\triangle^{MTE}$
.196	.285	.244	.276	-.089
(.168)	(.248)	(.175)	(.242)	(.415)

a. Values for $U_D = -2$.

$P^{MTE}_{Y_1,Y_0}(1,0)$	$P^{MTE}_{Y_1,Y_0}(0,1)$	$P^{MTE}_{Y_1,Y_0}(1,1)$	$P^{MTE}_{Y_1,Y_0}(0,0)$	$\triangle^{MTE}$
.303	.182	.252	.263	.122
(.103)	(.085)	(.082)	(.106)	(.185)
****	**	***	**	

b. Values for $U_D = 0$.

$P^{MTE}_{Y_1,Y_0}(1,0)$	$P^{MTE}_{Y_1,Y_0}(0,1)$	$P^{MTE}_{Y_1,Y_0}(1,1)$	$P^{MTE}_{Y_1,Y_0}(0,0)$	$\triangle^{MTE}$
.429	.105	.237	.229	.324
(.223)	(.091)	(.117)	(.221)	(.314)
**		**		

c. Values for $U_D = 2$.

Evaluation Of The Effects Of Two Classes Of Active Labour Market Policies For Welfare Recipients: A Danish Study Case

Summary

This paper is about impact evaluation of Active Labour Market Policies in Denmark. Since every unemployed will eventually end up in an activation programme it is preferable to analyse the differential impact between two given programmes: I concentrate on private sector programmes versus public sector programmes. The model used here to calculate the impact was first formulated by Aakvik et al. (2000) and it allows the impact to vary between observations: it consists of three equations for the observable individual and regional characteristics and a one normal factor structure for the unobservables. Main findings are the somehow perverse selection rule between the two types of programmes made by caseworkers, the high impact variability between different observations and the impact consistency between different time horizons.

Keywords: *Active Labour Market Policies, Differential Treatment Effect, Discrete Outcomes, Impact Heterogeneity, Local Treatment Intensity, Normal Factor Model, Selection On Unobservables.*

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