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An evaluation of the Swedish trainee replacement schemes

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ABSTRACT

This paper estimates the employment effects of the Swedish trainee replacement schemes (an active labour market program that was in operation during the 1990s). The empirical analysis exploits a large and rich administrative data set, and we control for observed and unobserved selection bias by using a multiple equation model and the maximum likelihood estimation method. The estimation results point at a selection of participants having a high ex ante probability of employment. In addition, the results suggest that participation in replacement schemes increased the re-employment probability by 5 to 10 percentage points.

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1. INTRODUCTION

In the early 1990s the Swedish economy experienced a serious slump, and the unemployment figures rose drastically. This development paved the way for a massive expansion of active labour market policies (ALMPs) in order to enhance the chances of the unemployed[1] to return to regular employment. In 1994, approximately 5 percent of the labour force (more than 200,000 individuals) was engaged in different labour market programmes, whereas open unemployment approached two-digit levels.

A number of new ALMPs were launched during the 1990s. One such policy was the so-called trainee replacement schemes. By subsidising training costs for employed workers as well as the cost associated with employing a substitute, the idea was to provide an opportunity for employers to enhance the skills of their employees and, at the same time, create temporary jobs for unemployed individuals. On the surface these temporary jobs appear to have been relatively successful; a survey conducted by the National Labour Market Board suggests that individuals who participated in replacement schemes in 1996 experienced higher re-employment rates than participants in other labour market programmes (except for recruitment subsidies).[2]

The difficulty in evaluating programmes lies in the fact that we do not know how well participants would have performed had they not participated in the programme. The purpose of this paper is to study the employment effects of the temporary jobs that were created as part of the replacement schemes. Specifically, did the programme have a positive effect on individuals' re-employment probabilities? Or, were the favourable re-employment rates mainly the result of a selection of participants having a high ex ante probability of employment? The empirical analysis exploits non-experimental data from the HÄNDEL database, which is administered by the National Labour Market Board. We control for observed and unobserved selection bias by using a multiple equation model and the maximum likelihood estimation method. By allowing for heterogeneity in

1 In this paper "unemployed" means "registered at a local unemployment office". An unemployed person may be openly unemployed, or participate in some policy programme.

2 AMS (1999) p. 28. The survey asks for the employment status in late 1997 for individuals who finished a programme spell during the last quarter of 1996. The re-employment rate for those who had participated in trainee replacement schemes was 53.6 percent. For participants in labour market training, work experience schemes (ALU) and relief work, the corresponding figures were in the order of 20-35 percent.

the estimated programme effects, the paper will also analyse whether certain types of individuals stand a better chance than others to benefit from participation.[3]

Previous studies of Swedish ALMPs during the 1990s have in general found very modest, or even negative, effects of policy programmes on participants' labour market outcomes.[4] Ackum Agell (1995) found that participants in trainee replacement schemes were more likely to go from the programme to a permanent job than participants in other ALMPs (relief work, labour market training and work experience schemes). The study most comparable to the present one is AMS (1999). Using a methodology similar to the one adopted here, the study set out to compare wage and employment outcomes for various Swedish ALMPs. The results suggested that recruitment subsidies and replacement schemes were the most favourable ALMPs in terms of increased employment probabilities.

The remainder of the paper is organised as follows. Section 2 gives some empirical background. The econometric model and the data are introduced in Sections 3 and 4. Estimation results are presented in Section 5. Section 6 concludes.

2. TRAINEE REPLACEMENT SCHEMES

Trainee replacement schemes were introduced in September 1991. The idea was to create temporary jobs for unemployed individuals and, at the same time, provide an opportunity for the already employed to enhance their skills. Briefly, by subsidising training costs for employed workers as well as the cost associated with employing a substitute, the employer was expected to have an unemployed individual replace the worker who was on leave for education. Thus, in contrast to many other ALMPs,

3 Since public programmes generally affect non-participants as well (e.g. through taxes, wages and displacement effects), the effects on participants' future labour market prospects only provide partial information on total programme effects. The general equilibrium implications are however not the subject of the present study. A recent study on displacement effects of ALMPs in Sweden is Dahlberg & Forslund (1999), who find that there are substantial direct displacement effects from those ALMPs that generate subsidised labour.

4 See e.g. SOU (1993), Regnér (1997), AMS (1999) and Larsson (2000) for evaluations of relief work, labour market training, youth practice and work experience schemes. Similarly, Martin (1998) shows that most OECD countries have experienced very limited (if any) positive effects of large-scale policy programmes. For a survey of Swedish studies from the 1980s, see e.g. Zetterberg (1996).

participants in replacement schemes were expected to perform another individual's regular duties.[5]

The participants were selected from among potential candidates by the local employment office. To be qualified for a temporary replacement job, the unemployed person had to be at least 20 years of age. In addition to the formal age restriction, the unemployed individual presumably had to meet certain standards set by the employer/organiser. Consequently, that the assignment of programme participants was random, or done on a roughly first-come, first-serve basis, seems highly unlikely.

The substitute was paid according to the collective agreement at the work place where the replacement scheme took place. The employer was allowed to deduct from the payroll tax approximately SEK 450 per day[6] to cover the labour cost associated with employing the substitute. Moreover, training costs for the employee on leave for education were deductible from the payroll tax up to an amount of SEK 20,000.

The vast majority of trainee replacement schemes took place in the public sector.[7] This can probably be attributed to the fact that temporary jobs, and the use of substitutes, are more common in the public sector than in the private sector. In terms of the scale of the programme, replacement schemes never became a particularly important ALMP. Instead, the massive expansion of programme participation during the 1990s occurred in other programmes, such as the more low-budget oriented work experience schemes (ALU). Table 1 shows the number of participants (yearly averages) in selected ALMPs between 1992 and 1997. Replacement schemes were expanded until 1994 when participation approached (on average) 12,700 individuals, or slightly more than 5 percent of total programme participation. Presumably due to a cut in employer benefits (see footnote 6), the number of individuals in replacement schemes declined sharply in 1997. In December 1997, about six years after the introduction, replacement schemes as described in this section were finally cancelled.

5 Individuals in, for example, work experience schemes and relief work were not intended to perform tasks that comprised the normal activities of the organiser.

6 The programme period was limited to six months, but it could be extended to another six months' period. The tax-deductible amount was SEK 475 in 1994, but was lowered to SEK 400 in 1996 and SEK 350 in 1997.

7 AMS (1999) reports that in 1996 almost 90 percent of the replacement schemes took place in the public sector.

Table 1. Participants in labour market training (AMU), work experience schemes (ALU) and trainee replacement schemes (TRS) 1992-1997 (yearly averages, 1000's).

year	*AMU*	*ALU*	*TRS*	*total*
1992	86.3	-	8.3	162.4
1993	53.1	35.1	9.7	191.3
1994	59.5	44.5	12.7	233.3
1995	54.6	41.3	11.2	197.9
1996	45.6	52.4	9.8	201.9
1997	35.8	52.5	3.6	190.1

Source: The National Labour Market Board.

3. THE EMPIRICAL MODEL

3.1 The evaluation problem

Success criterion, programme effects and response periods

Active labour market programmes are supposed to have a positive effect on the future labour market prospects of unemployed workers. The probability of getting a job and keeping it may increase. Participation may decrease the duration of unemployment periods. The probability of getting a better-paid job may increase. In the present study we concentrate on the employment effects, primarily because the main purpose of the trainee replacement schemes was to increase employability. In our empirical analysis we use employment in a non-subsidised job as the success criterion.

The counterfactual, or benchmark state, of interest to this paper is the state of the world had replacement schemes not been in operation. Then, the effect of the programme could, broadly defined, be thought of as the difference between participants' observed outcome (e.g. the employment status some time after the programme finished) and the outcome had they not participated but continued searching for a job. Allowing the hypothetical non-participation state to run from the onset of the programme, the effect would reflect the joint influence of two separate components. Firstly, the time constraint suggests that, while participating in the programme, individuals presumably have less time for job-searching activities, i.e., a "lock-in" effect. Secondly, participation might have the hoped-for effect of improving individuals' future labour market prospects, a "human capital" effect. Although we recognise the possible existence of both effects, the present study will focus mainly on the human capital aspects of participation.

Empirical evidence suggests that search activity may diminish considerably during the programme period (see e.g. Edin & Holmlund (1991) or Ackum Agell (1996)). In particular, Ackum Agell (1996) reports that participants in replacement schemes virtually cancelled all search activities. Building on this result, the present study adopts the approximation that participants stopped searching for a job during the programme period. The human capital effect of participating may then be identified by having the hypothetical non-participation state run from the end rather than the start of the programme.

The time span between the programme end and the date at which the outcome variable is observed will be referred to as the response period. When assessing the impact of a programme, the empirical analyst frequently relies on survey data collected some time after the programme finished. By asking respondents about the state of the outcome variable(s) at a particular date, for example one year after the programme end, the subsequent evaluation has to settle with one distinct response period. By contrast, the register data used in this paper (described in Section 4 below) contain continuous updates of individuals' labour market outcomes, which makes it possible to select response periods of varying lengths. In the empirical application we let the response periods vary from 3 months up to 18 months in order to study both short and long-term effects of participating in the programme.

Non-experimental data and selection bias

The difficulty in evaluating policy programmes is that we do not observe single individuals in both states at the same time, as participants and non-participants. We thus have a serious identification problem due to "missing" data. The usual remedy is to use the outcome of non-participants (the control group) to proxy the outcome of participants (the treatment group) had they not participated.

An important feature of the Swedish institutional set-up is the fact that ALMPs take place continuously over time. In general, the choice open to unemployed job-seekers (and programme officers) is not whether to participate or not participate at all, but whether to participate *now* or to postpone the participation decision and maybe join the programme later on. It might therefore be argued that non-participants never truly represent a hypothetical benchmark state in which the programme is excluded.[8] Within this institutional context the benchmark state thus needs to be slightly redefined; what we evaluate is the effect of joining the programme compared to further postponing the participation decision by not joining the programme *at least up to the point of evaluation*.

Relying on non-experimental data, and using the outcome of non-participants to proxy the non-participation outcome of participants, the question of selection bias arises. Selection bias due to observed differences between participants and members of the control group can be accounted for using non-parametric matching estimators[9] or single equation regression methods. The presence of selection on unobservables is usually dealt with using either multi-stage regression methods or simultaneous equations estimation. Selection on unobservables may, for example, occur if factors unobserved in our data (motivation, ability etc.) influence not only the individual's decision to participate, but also the person's labour market outcome. External selection is another possibility: if local unemployment offices and/or organisers have incentives to choose the best among potential participants, then incomplete observation of these assignment criteria may induce a positive selection bias.[10] Or, the local unemployment office may favour those with the poorest chances of getting a job, which would push towards a negative selection bias.

Whether or not we have selection on unobservables is an empirical question. The estimation method used in this paper, i.e., maximum likelihood estimation of a multiple equation model, allows us to test and correct for potential unobserved selectivity bias.

8 See Carling & Larsson (2000) for a discussion.

9 See e.g. Heckman et al (1999). Briefly, matching involves pairing together participants and non-participants who have similar observable characteristics. The main advantage using this method is that estimates of average treatment effects can be obtained without a parametric specification. However, the method relies on the assumption that selection into the programme is based entirely on observable characteristics (an assumption that cannot be tested).

10 This type of behaviour is commonly referred to as "creaming" (see e.g. Anderson et al. (1993)); that is, serving individuals who are the most employable at the expense of those most in need.

3.2 The econometric model

Let y_i^* be a latent indicator of labour market success in terms of an individual's employment probability:

$$y_i^* = \gamma' z_i + d_i \alpha_i + u_i \tag{1}$$

where i indexes individuals. y_i^* is assumed to depend on a vector of independent variables z_i, such as human capital indicators and local labour market conditions, and an error term u_i. The employment probability also depends on the impact of the programme, represented by α_i. The dummy indicator d_i equals 1 if a person participated in trainee replacement schemes, and 0 otherwise.

The observable dependent variable in this study is whether or not the individual is employed by the end of the response period. This variable, denoted by y_i, is assumed to be generated as

$$\begin{aligned} y_i &= 1 \text{ if } y_i^* > 0 \\ y_i &= 0 \text{ if } y_i^* \leq 0 \end{aligned} \tag{2}$$

The observable dummy indicator d_i in (1) is assumed to be generated by the following selection equation:

$$\begin{aligned} d_i^* &= \beta' x_i + \varepsilon_i \\ d_i &= 1 \text{ if } d_i^* > 0 \\ d_i &= 0 \text{ if } d_i^* \leq 0 \end{aligned} \tag{3}$$

where d_i^* is a latent variable, x_i a vector of variables explaining entry to the programme and ε_i a random error term measuring the impact of unobserved factors on the selection process.[11]

In this study we allow for heterogeneity in the estimated programme effects. α_i in (1) is specified as

$$\alpha_i = \delta' q_i \tag{4}$$

11 Given the available data, we are unable to discriminate between self-selection and external selection.

where q_i is a vector of explanatory variables with corresponding vector of parameters δ. This design has several advantages compared to the standard approach, where programme effects usually are represented by a single constant term. Besides giving us a richer and more flexible empirical model, we may also study which background characteristics are linked with the best programme effect.

For the empirical application we use full information maximum likelihood to estimate jointly eq. (1) (the employment equation) and eq. (3) (the selection equation). This procedure allows us to control for potential selection bias and provides an estimate of the correlation ρ between the error terms in the two equations, where it is assumed that the error terms follow a bivariate standard normal distribution, $(\varepsilon_i, u_i) \sim \text{BN}(0;1;\rho)$. Estimation of a positive ρ suggests that those most likely to be selected are also the most likely to obtain jobs. A negative ρ would indicate that those most likely to be selected are the least likely to obtain jobs.

Dropping the i subscripts, and assuming we have a random sample of participants and non-participants[12], the log-likelihood function to be maximised is

$$\ln L = \sum_{\substack{d=1\\y=1}} \ln \int_{-\beta' x}^{\infty} \int_{-\gamma' z-\delta' q}^{\infty} \phi_2(\varepsilon,u;\rho)\,du\,d\varepsilon + \sum_{\substack{d=1\\y=0}} \ln \int_{-\beta' x}^{\infty} \int_{-\infty}^{-\gamma' z-\delta' q} \phi_2(\varepsilon,u;\rho)\,du\,d\varepsilon +$$

$$+ \sum_{\substack{d=0\\y=1}} \ln \int_{-\infty}^{-\beta' x} \int_{-\gamma' z}^{\infty} \phi_2(\varepsilon,u;\rho)\,du\,d\varepsilon + \sum_{\substack{d=0\\y=0}} \ln \int_{-\infty}^{-\beta' x} \int_{-\infty}^{-\gamma' z} \phi_2(\varepsilon,u;\rho)\,du\,d\varepsilon \qquad (5)$$

where $\phi_2(\cdot)$ denotes the p.d.f. of the bivariate standard normal distribution. Note that for the special case where ρ equals zero, the log-likelihood function segments into separate parts such that the parameters of the selection and employment equations may be estimated separately using univariate probit methods:

$$\ln L = \left[\sum_{d=1} \ln \int_{-\beta' x}^{\infty} \phi(\varepsilon)\,d\varepsilon + \sum_{d=0} \ln \int_{-\infty}^{-\beta' x} \phi(\varepsilon)\,d\varepsilon \right] +$$

12 As described in Section 4 below, the sampling technique used in this paper oversamples participants in replacement schemes relative to their proportion in the population of unemployed. As described in Heckman & Robb (1985), choice-based sampling can be accounted for by weighting the sample at hand back to random sample proportions. We accomplish this by attaching to each observation in eq. (5) the weight $w=d(p/p^*)+(1-d)[(1-p)/(1-p^*)]$. Here $p=N_1/(N_1+N_0)$ and $p^*=n_1/(n_1+n_0)$, where N_1 and N_0 are the number of participants and non-participants in the population, and n_1 and n_0 the number of observations in the sample from each category.

$$+\left[\sum_{\substack{d=1\\y=1}}\ln\int_{-\gamma'z-\delta'q}^{\infty}\phi(u)du+\sum_{\substack{d=1\\y=0}}\ln\int_{-\infty}^{-\gamma'z-\delta'q}\phi(u)du+\sum_{\substack{d=0\\y=1}}\ln\int_{-\gamma'z}^{\infty}\phi(u)du+\sum_{\substack{d=0\\y=0}}\ln\int_{-\infty}^{-\gamma'z}\phi(u)du\right] \quad (6)$$

where $\phi(\cdot)$ denotes the p.d.f. of the univariate standard normal distribution.

4. DATA

A vast majority (about 90 percent) of unemployed Swedish workers are registered at a local employment office. These offices register events such as changes from one job seeker category to another and participation in ALMPs. The resulting database (HÄNDEL), which is administered by the National Labour Market Board, contains individual background variables such as education and work experience, as well as individual labour market histories. Consequently, we know what ALMPs the unemployed have participated in during the unemployment spell, and we also know the reason for the end of the spell.

4.1 Sample construction

The data used in this study is a choice-based[13] sample from the HÄNDEL database. For participants in trainee replacement schemes, we collect from the database all individuals who completed a programme spell during the period September-December 1994. To reduce unobserved individual heterogeneity we then require that the observation satisfies the following selection criteria: 1) the individual was registered as being openly unemployed[14] prior to the start of the programme, 2) the programme spell lasted at least two weeks and no more than 12 months, and, 3) the individual was 20-59 years of age, both when the programme started and 18 months after it finished. This leaves us with a sample of approximately 6,000 observations. Deleting individuals with missing (or

13 Choice-based, instead of random, sampling was chosen because random sampling of, say, 5000 observations from the population of unemployed would have severely reduced the number of participants in replacement schemes.

14 Specifically, I require that the individual was unemployed and ready to take on a new job immediately (job seeker category no. 11 in the HÄNDEL database).

clearly inconsistent) values for any of the variables used in the empirical analysis, the resulting sample consists of 3499 observations.

Non-participants are selected from the stock of unemployed at the end of October 1994. From a random sample of 10,000 observations we pick individuals who satisfy the following selection criteria: 1) the individual was registered as being openly unemployed, 2) the individual was 20-59 years of age at the time of selection and 18 months forward in time, and 3) the individual did not participate in replacement schemes before or after the time of selection. Deleting individuals with missing (or clearly inconsistent) values for any of the variables used in the empirical analysis, the resulting sample of non-participants consists of 4804 observations.[15] The joint sample of participants and non-participants will be referred to as *sample 1*.

As will become evident in subsection 4.2 below, gender appears to have been an important determinant for the probability of entering trainee replacement schemes; in *sample 1* more than 70 percent of the participants are women (Table A2 in Appendix A).[16] The fact that only 44 percent of all non-participants in *sample 1* are women points at large systematic differences between participants and non-participants. Therefore, in order to further reduce individual heterogeneity that might be difficult to capture accurately in our econometric model, we have constructed an alternative sample made up of women only. Deleting all males from *sample 1*, the alternative sample consists of 2515 participants and 2114 non-participants. We will refer to this sample as *sample 2*.

One obvious consequence of the selection procedures described above will be the occurrence of substantial heterogeneity in labour market histories across individuals. Some persons may have been engaged in several different programmes in the past, whereas others are unemployed for the first time. In our empirical model we will attempt to control for the influence of ALMPs that individuals may have completed at some point in the past, but the measures are rather crude and we do not discriminate between different types of ALMPs. Therefore, to eliminate potential "spillover effects"

15 The date October 31 can be thought of as a hypothetical end (and start) date for a programme spell that never happened. Thus, the response period for non-participants starts on October 31, 1994.

16 The overrepresentation of women became even more pronounced a few years later: AMS (1999) reports a share of 82.1 percent during the last quarter of 1996.

from earlier programme activities, we should also consider restricting our samples to individuals with no previous ALMP experience. Applying this selection criterion to *sample 1* and *sample 2*, we end up with two new samples, *sample 3* and *sample 4*. Table 2 summarises the composition of our four samples, total sample sizes and the differences in selection criteria.

Table 2. Sample sizes and selection criteria.

sample	*participants*	*non-participants*	*total*
sample 1: males and females; previous participation in ALMPs possible	3499	4804	8303
sample 2: females only; previous participation in ALMPs possible	2515	2114	4629
sample 3: males and females; no previous participation in ALMPs	1131	2156	3287
sample 4: females only; no previous participation in ALMPs	824	1025	1849

4.2 Variables

The dependent variable

In the empirical analysis we use employment in a non-subsidised job as the success criterion. The dependent variable is whether or not the individual was employed at the end of the response period. The HÄNDEL database contains information on changes from one job seeker category to another, and reasons for deactivation of an unemployed (i.e., reasons for ending an unemployment spell). Individuals registered as looking for a job are sorted into one of the following search categories: openly unemployed, in an ALMP or sheltered job, part-time employed, temporarily employed or employed but looking for a new job. Reasons for deactivation include some kind of regular employment (including recalls) and withdrawal from the labour force due to retirement, education outside the employment office or other known reasons.

In this paper we classify an individual as being employed at time t if he/she 1) was registered at time t as part-time employed, temporarily employed or employed but looking for a new job, or 2) was deactivated before time t due to transition to a regular job. Table 3 summarises the outcome measures for participants and non-participants in our four samples.

Table 3. Employment rates following programme end[a]

	sample 1		*sample 2*		*sample 3*		*sample 4*	
	part.	*non-part.*	*part.*	*non-part.*	*part.*	*non-part.*	*part.*	*non-part.*
employed after								
3 months (%)	34.0	18.2	34.2	18.6	38.2	21.3	38.9	21.4
6 months (%)	42.5	27.1	43.7	27.0	46.5	31.5	47.8	30.4
12 months (%)	43.1	34.9	42.0	31.8	46.8	40.0	45.8	36.4
18 months (%)	49.9	38.2	49.7	37.4	53.2	43.7	52.8	41.7

[a] The employment rate for non-participants refers to the rate that is measured, say, 3 months after the time of selection (i.e., on October 31, 1994).

Explanatory variables

The employment probability in eq. (1) can be expected to depend on the relationship between the wage available to the unemployed in the local labour market and the person's reservation wage, as well as characteristics of the programme and other local labour market conditions. In estimation we use as control variables typical human capital indicators such as sex, age, citizenship, experience and level of education. Additional variables include unemployment insurance, the type of job applied for, previous (pre-programme) unemployment experience and the individual's past experience of ALMPs. As indicators of local labour market conditions we use e.g. location, the local unemployment rate, the exit rate to regular employment and the programme rate (ALMP participants÷unemployed) in the municipality. To allow for individual programme effects, the full set of control variables is also included in eq. (4).

Participation in programmes is based on both self-selection and external selection by the local employment office and the organiser/employer. Since the employment probability presumably is an important decision variable, it appears that all variables in the employment equation should enter the selection equation. We should also consider variables that can be expected to influence a person's probability of entering the programme but not the employment outcome after participation. A natural candidate would be a measure reflecting the limited supply of replacement schemes. We have therefore constructed such a “rationing” variable by measuring the weight of replacement schemes in the municipality’s supply of ALMPs.[17]

Table A1 in Appendix A contains a complete list and explanation of the variables used in the empirical analysis. According to the descriptive statistics presented in Table A2, replacement schemes seem to be targeted mainly at women who apply for health, nursing or social work. Those under 25 years of age are more frequent among participants than non-participants, whereas the opposite holds for those over 50. Individuals of foreign origin appear to be underrepresented among participants, as are individuals with low formal education and no specific education for the type of job applied for. A typical replacement scheme takes place after about 15 weeks of open unemployment. Total number of weeks as openly unemployed since September 1991 averages 47 for participants and 53 for non-participants. Finally, the typical participant has completed 1.3 programmes and spent 25 weeks in various ALMPs prior to the replacement scheme, whereas non-participants have spent about 20 weeks in programmes since September 1991.

5. RESULTS

Results on the estimated determinants of enrolment are presented in Section 5.1. In Section 5.2 we study individuals’ employment probabilities in the absence of trainee replacement schemes. Sections 5.3 and 5.4 contain the estimated programme effects.

5.1 The selection equation

5.1.1 Observed selection

A straightforward way to examine the presence of non-random selection into the programme is to study whether observable personal characteristics and labour market conditions have an impact on the individual’s probability of entering the programme. Parameter estimates, standard errors and marginal effects generated by the bivariate

17 Identification of the bivariate probit model requires that at least one variable is not included in both equations (employment and selection). The correlation between the “rationing” variable and the local unemployment rate (programme rate) is only about -0.20 (+0.20). In addition, several variables are time varying, like the labour market variables and the person’s age, such that they may differ in the selection and the employment equation.

probit model, with the response period set to 6 months[18], are displayed in Table 4 (*sample 1* and *sample 2*) and Table B1 in Appendix B (*sample 3* and *sample 4*).

The probability of females entering replacement schemes is about 4 percentage points higher than for males. This is perhaps what one would expect given that the vast majority of replacement schemes took place in the public sector, and that the public sector mainly attracts women. For *sample 1*, being over 50 years of age reduces the probability of entering the programme by 2.4 percentage points. However, this effect is insignificant when the sample is restricted to females or individuals with no previous ALMP experience. For the latter samples, the results suggest that those under 25 have the highest probability of entering the programme. Variables such as education level, experience and citizenship turn out statistically insignificant at conventional levels. The type of job applied for appears to be an important determinant of enrolment into replacement schemes. Those who applied for a job other than health, nursing or social work have a 6-8 percentage points lower probability of entering the programme (8-11 percentage points when the sample is restricted to females). A more widespread accustomedness to temporary jobs and the use of substitutes would seem like a plausible explanation to why replacement schemes mainly took place within the public sector, e.g. in healthcare and social work.

Previous experience of open unemployment (since September 1991) seems to matter negatively for participation. This might perhaps reflect a tendency among employment officers to give precedence to unemployed with strong labour market attachments, while directing persons with long unemployment periods to some other, more low-qualified, policy programme. However, the effect is not large: for each additional week as openly unemployed, the probability of participating in replacement schemes is reduced by about 0.1 percentage points. Previous experience of ALMPs appears to be positive for placement in the programme. One explanation could be that unemployed with past experience of programmes may themselves be more active in getting into more programmes. Finally, it should be noted that the supply of replacement schemes has a significantly positive effect; that is, an increased share of replacement

18 The main results in subsection are quite insensitive to the choice of response period (3 months, 6 months etc.). The results for other response periods are available upon request.

Table 4. The selection equation. Response period: 6 months.

	sample 1			sample 2		
variable	*estimate*	*std.error*	*marg. eff.*	*estimate*	*std.error*	*marg. eff.*
constant	-1.882***	0.243	27.47	-1.592***	0.435	31.71
female	0.288***	0.065	4.24			
age24	0.080	0.077	1.32	0.062	0.092	1.30
age29	0.079	0.077	1.31	0.065	0.089	1.39
age49	0.002	0.082	0.04	0.031	0.092	0.66
age59	-0.161*	0.096	-2.35	-0.124	0.120	-2.42
cit1	-0.172	0.188	-2.46	-0.234	0.207	-4.26
cit2	-0.181	0.127	-2.58	-0.201	0.149	-3.76
dis	0.015	0.113	0.25	-0.079	0.135	-1.59
ed1	0.077	0.073	1.21	0.141	0.091	2.84
ed2	-0.038	0.112	-0.60	0.001	0.119	0.01
exp1	-0.002	0.075	-0.04	-0.055	0.089	-1.14
exp2	-0.031	0.076	-0.49	-0.044	0.093	-0.92
edspec	0.093	0.062	1.46	0.116	0.073	2.35
job1	-0.660***	0.151	-6.85	-0.767***	0.174	-10.11
job2	-0.745***	0.087	-7.90	-0.797***	0.090	-11.36
job3	-0.820***	0.109	-7.93	-0.850***	0.116	-11.10
job4	-0.790***	0.186	-7.38	-1.064***	0.318	-11.42
job5	-0.774***	0.139	-7.38	-0.732***	0.233	-9.76
job6	-0.741***	0.088	-8.19	-0.748***	0.143	-10.12
job7	-0.456***	0.089	-5.76	-0.471***	0.096	-7.90
ui	0.113	0.105	1.72	0.101	0.117	2.01
ca	-0.055	0.158	-0.85	-0.009	0.168	-0.19
move	-0.102	0.077	-1.56	-0.116	0.095	-2.29
scat12	0.197***	0.075	3.44	0.134	0.093	2.93
ue	0.001	0.003	0.02	-0.003	0.004	-0.06
ue^2	0.000	0.000	0.00	0.000*	0.000	0.00
uet	-0.004***	0.001	-0.07	-0.005***	0.001	-0.10
nue	0.069**	0.029	1.16	0.088**	0.034	1.92
prog	-0.003	0.002	-0.05	-0.004	0.003	-0.08
nprog	0.104***	0.040	1.79	0.112**	0.045	2.49
progx	0.222***	0.080	3.52	0.292***	0.085	6.02
reg1	-0.120	0.101	-1.81	-0.157	0.123	-3.04
reg2	0.009	0.071	0.14	0.057	0.082	1.19
reg3	0.038	0.076	0.62	0.041	0.086	0.86
ler	-0.009	0.019	-0.15	-0.009	0.025	-0.18
lur	-0.012	0.020	-0.19	0.001	0.026	0.01
lpr	0.002	0.003	0.04	-0.001	0.004	-0.02
lrs	0.051***	0.008	0.85	0.060***	0.008	1.30
log-likelihood		-5978.90			-3621.63	
goodness of fit		0.087			0.094	
chi-squared		1138.06			748.34	
no. of observations		8303			4629	

Note: Bivariate probit model, * significant at the 10% level, ** at the 5% level and *** at the 1% level. The log-likelihood refers to the value obtained for the full model, including the parameters of the employment equation and the equation for programme effects. The goodness of fit measure is 1-($\ln L/\ln L_0$), where $\ln L_0$ is the log-likelihood corresponding to a specification with constant terms only (McFadden, 1974). The chi-squared statistic is -2($\ln L_0$-$\ln L$).

schemes in the municipality's mix of ALMPs increases the probability of participation. We find no significant effects of other supply side variables such as the local unemployment and programme rates.

5.1.2 Unobserved selection

The joint estimation of eq. (1) (the employment equation) and eq. (3) (the selection equation) allows us to control for potential selection bias, and provides an estimate of the correlation ρ between the error terms in the two equations. Estimation of a positive ρ suggests that those most likely to be selected are also the most likely to obtain jobs. A negative ρ would indicate that those most likely to be selected are the least likely to obtain jobs. Estimation of only the employment equation in (1) would result in biased estimates unless ρ is equal to zero.

The results are displayed in Table 5. Note that we have also estimated the more conventional specification in which programme effects are constrained to be constant across individuals, i.e.,$\alpha_i = \delta_0$. The estimated covariance between the error terms is in most cases both small and insignificant. Likelihood ratio test of the restriction ρ=0 cannot be rejected at conventional significance levels, expect for a few cases when the response period is set to 12 months. However, the null hypothesis (ρ=0) cannot be rejected for this response period when the sample is restricted to individuals with no previous ALMP experience.

Hence, if factors unobserved in our data (motivation, ability etc.) influence participation decisions, then these factors do not appear to have any significant effects on the likelihood of successful job placement, and vice versa.[19] In the following we therefore regard the correlation between the error terms in the equations for selection and employment as being equal to zero by imposing the restriction ρ=0 in estimation. As described in Section 3.2, the log-likelihood function then segments into separate parts such that the parameters of the employment equation may be estimated separately using the univariate probit model.

19 AMS (1999) reached a similar conclusion in an analysis of all the major Swedish ALMPs.

Table 5. The correlation coefficient.

response period	sample 1: $\alpha_i = \delta' q_i$	sample 1: $\alpha_i = \delta_0$	sample 2: $\alpha_i = \delta' q_i$	sample 2: $\alpha_i = \delta_0$
3 months	-0.045 (0.02)	0.158 (0.98)	0.003 (0.002)	0.159 (1.40)
6 months	0.088 (0.14)	0.170 (1.24)	0.215 (0.80)	-0.244 (2.68)
12 months	0.398** (4.20)	0.313** (4.96)	0.407* (2.84)	0.315* (3.04)
18 months	0.149 (0.48)	0.161 (1.26)	0.048 (0.04)	0.079 (0.22)
	sample 3: $\alpha_i = \delta' q_i$	**sample 3**: $\alpha_i = \delta_0$	**sample 4**: $\alpha_i = \delta' q_i$	**sample 4**: $\alpha_i = \delta_0$
3 months	0.059 (0.04)	0.134 (0.28)	0.172 (0.20)	0.100 (0.12)
6 months	-0.135 (0.08)	0.072 (0.08)	0.268 (0.42)	0.170 (0.38)
12 months	-0.143 (0.06)	0.142 (0.26)	0.394 (0.92)	0.243 (0.60)
18 months	-0.395 (0.90)	-0.034 (0.02)	-0.073 (0.02)	-0.048 (0.02)

Note: Bivariate probit model, * significant at the 10% level, ** at the 5% level and *** at the 1% level. Chi-square test statistics in parentheses. We perform a likelihood ratio test of the restriction ρ=0. The test statistic is -2(lnL^R -lnL^U), where L^R is the likelihood corresponding to the model with one linear restriction (ρ=0) and L^U the likelihood for the unrestricted model.

5.2 The employment equation

In this section we study whether observable personal characteristics and labour market conditions have an impact on the individual's employment probability. Programme effects are discussed in sections 5.3 and 5.4 below. The results for a response period of 6 months are displayed in Table 6 (*sample 1* and *sample 2*) and Table B2 in Appendix B (*sample 3* and *sample 4*).[20]

Many coefficients are significant and have signs according to economic theory. The probability of females having a job at the end of the response period is about 3 percentage points lower than for males.[21] However, this effect is insignificant when the sample is restricted to individuals with no previous ALMP experience (*sample 3*). Being over 50 years of age decreases significantly the probability of finding a job. The results also suggest that those under 25 have difficulties finding a job.

20 The results for other response periods are available upon request. Coefficient estimates and significance levels vary slightly with the length of the response period, but the main results reported in this subsection remain virtually unchanged.

21 Using data from the mid-1990s, Carling et al (1999) found a similar pattern in a study of how job-finding rates were affected by a reduction in replacement rates. In other studies using data from the early 1990s, e.g. Carling et al (1996), the escape rates to employment were estimated to be higher for women than for men.

Table 6. The employment equation. Response period: 6 months.

variable	sample 1 estimate	sample 1 std.error	sample 1 marg. eff.	sample 2 estimate	sample 2 std.error	sample 2 marg. eff.
constant	0.175	0.623	38.29	0.144	0.188	38.26
female	-0.087**	0.039	-3.09			
age24	-0.146**	0.059	-5.01	-0.048	0.069	-1.73
age29	0.060	0.048	2.14	0.053	0.060	1.92
age49	-0.008	0.048	-0.28	0.033	0.063	1.20
age59	-0.304***	0.056	-9.92	-0.251***	0.076	-8.55
cit1	0.000	0.108	0.00	0.043	0.124	1.57
cit2	-0.530***	0.080	-15.91	-0.559***	0.103	-17.18
dis	-0.552***	0.081	-16.58	-0.460***	0.108	-14.66
ed1	0.106**	0.046	3.67	0.115*	0.059	4.08
ed2	0.210***	0.068	7.62	0.304***	0.079	11.37
exp1	0.025	0.051	0.89	0.103*	0.062	3.72
exp2	0.002	0.053	0.07	0.080	0.065	2.87
edspec	0.091**	0.037	3.16	0.056	0.049	2.01
job1	-0.314***	0.080	-10.10	-0.413***	0.097	-13.24
job2	-0.205***	0.059	-6.88	-0.173***	0.059	-6.01
job3	-0.247***	0.068	-8.16	-0.394***	0.072	-12.83
job4	0.007	0.099	0.24	-0.141	0.160	-4.91
job5	0.006	0.081	0.19	-0.016	0.131	-0.58
job6	-0.178***	0.062	-6.03	-0.385***	0.092	-12.50
job7	-0.157**	0.066	-5.35	-0.208***	0.072	-7.16
ui	-0.049	0.060	-1.74	-0.093	0.069	-3.38
ca	0.112	0.079	4.04	0.110	0.100	4.05
move	-0.026	0.042	-0.89	0.054	0.063	1.97
scat12	0.030	0.051	1.05	0.145**	0.070	5.31
ue	-0.007***	0.002	-0.24	-0.009***	0.003	-0.32
ue^2	0.000***	0.000	0.00	0.000***	0.000	0.00
uet	-0.007***	0.001	-0.24	-0.007***	0.001	-0.23
nue	0.153***	0.018	5.56	0.130***	0.026	4.78
prog	0.001	0.001	0.02	0.001	0.002	0.05
nprog	-0.006	0.027	-0.22	-0.018	0.038	-0.63
progx	-0.004	0.047	-0.14	0.045	0.064	1.61
reg1	-0.045	0.096	-1.55	0.037	0.070	1.33
reg2	-0.005	0.047	-0.17	0.069	0.058	2.48
reg3	-0.088	0.064	-3.05	-0.024	0.064	-0.86
ler	-0.002	0.029	-0.05	-0.003	0.016	-0.12
lur	-0.039***	0.010	-1.36	-0.037**	0.014	-1.31
lpr	0.001	0.003	0.04	-0.003	0.003	-0.10
log-likelihood		-4659.70			-2590.04	
goodness of fit		0.072			0.078	
chi-squared		723.56			438.62	
no. of observations		8303			4629	

Note: Univariate probit model, * significant at the 10% level, ** at the 5% level and *** at the 1% level. The log-likelihood refers to the value obtained for the full model, including the parameters of the equation for programme effects. The goodness of fit measure is $1-(\ln L/\ln L_0)$, where $\ln L_0$ is the log-likelihood corresponding to a specification with constant terms only (McFadden, 1974). The chi-squared statistic is $-2(\ln L_0-\ln L)$.

Non-Nordic immigrants and the disabled are the two groups with the smallest chances of being employed at the end of the observation period. For example, among women with no previous experience of ALMPs (*sample 4*), non-Nordic immigrants have an employment probability that is almost 30 percentage points lower than for Swedish citizens. Better education is uniformly associated with higher job finding rates. Similarly, improved experience has the expected positive effects (although insignificant in a few of our samples). The type of job applied for appears to be an important determinant of the employment probability. Those who applied for health, nursing or social work (i.e. the type of jobs that frequently stood as organisers for replacement schemes) seem to have considerably better chances of finding a job than individuals in almost any other line of work.[22]

Previous episodes of open unemployment seem to have a negative influence on the probability of finding a job. A common interpretation of this negative relationship refers to the stigmatising effects of being openly unemployed. Survey evidence in e.g. Behrenz (1998) and Agell & Lundborg (1999) confirm that employers often regard individuals with extensive unemployment records as less productive. Another possibility is that search activity may decrease with the duration of open unemployment. However, there is little empirical evidence for the existence of such discouragement effects (see e.g. Ackum Agell (1996) or Harkman & Jansson (1995)). Previous participation in various ALMPs does not appear to make a significant difference. This is consistent with the view that policy programmes in general have little, or even a negative, influence on the exit rate to regular employment (see e.g. the citations in the introduction). Similarly, we find no significant effects of supply side variables such as the dummies for location and the programme rate, but the local unemployment rate is significant and has the expected negative sign.

Let us conclude this subsection by turning to the question whether replacement schemes were given to individuals with a high ex ante probability of employment.

22 Recall that the success measure used in this paper includes part-time and temporary employment. It is unclear whether the higher employment probabilities for health, nursing and social work (where part-time and temporary work is fairly common) would remain if the employment measure were restricted to full-time employment in permanent jobs.

Evaluating the estimated employment function at mean sample values[23], Table 7 reports the probability of having a job by the end of the response period *in the absence of replacement schemes*. The results suggest that participants indeed have a higher expected employment rate whether they participate or not. The difference compared to non-participants is about 3 to 5 percentage points, depending on the composition of the sample and the choice of response period.

Table 7. Predicted employment rates in the absence of replacement schemes.

	sample 1		*sample 2*		*sample 3*		*sample 4*	
	part.	*non-part.*	*part.*	*non-part.*	*part.*	*non-part.*	*part.*	*non-part.*
employed after								
3 months (%)	20.3	16.6	21.6	16.5	24.1	19.7	24.6	19.7
6 months (%)	30.7	25.3	32.4	25.1	34.5	30.2	34.6	28.5
12 months (%)	36.1	33.4	35.3	30.4	39.9	38.8	39.4	34.8
18 months (%)	40.0	36.8	41.2	36.0	43.7	42.8	44.2	40.6

One can think of several explanations to why this may have occurred. First, as noted in Section 2 above, since the substitute was expected to replace a regularly employed worker, a potential participant was presumably supposed to have a certain level of education, labour market experience etc., and other special characteristics required by the employer. Thus, the selection process would to some degree reflect employers' normal recruitment behaviour[24], with little room for employment officers to give priority to the unemployed with the poorest chances of getting a job.

Another explanation may possibly be found in the behaviour of employment officers. Recall that participants were selected from among qualified candidates by the local employment office. If programme administrators were interested in maximising re-employment rates, or for some other reason gave priority to the better off workers, then we expect to find a strong positive correlation between factors affecting selection into the programme and job placement. As we have seen, this is certainly true for a number

23 Using equations (1) and (2), the expected employment probability is calculated separately for participants and non-participants as $\mathrm{pr}(y=1|d=0)=\Phi(\gamma'\bar{z})$, where $\Phi(\cdot)$ is the c.d.f. of the univariate standard normal distribution.

24 Using survey data on the recruitment behaviour of Swedish employers, Behrenz (1998) finds that lack of education/experience and being over 45 years of age are important selection variables when the employer decides not to call a job applicant to an interview. Also, many employers seem to view open unemployment as a negative signal. Among those who are called to an interview, characteristics such as personal engagement and social competence are important for the hiring decision.

of variables. However, this explanation is not entirely convincing. For example, the disabled, non-Nordic immigrants and people with less experience were not significantly underrepresented among the participants in replacement schemes. For females and young people in their early 20s, we even find some support for a negative relationship between job placement and selection.

5.3 Programme effects

We now turn to the employment effects of replacement schemes. We interpret the estimated effect as the change in individuals' employment probabilities following participation in the programme. Evaluated at sample means (the sub-sample of participants), an estimate of the average programme effect is given by pr(y=1| d=1, $\bar{z}$, $\bar{q}$) - pr(y=1| d=0, $\bar{z}$), or,

$$\textit{programme effect} = \Phi(\gamma' \bar{z} + \delta' \bar{q}) - \Phi(\gamma' \bar{z}) \tag{7}$$

Programme effects will in the following be referred to as short-term or long-term. Short-term (long-term) refers to the results associated with a response period of 3-6 months (12-18 months).

After allowing for person specific effects, and adjusting for observed selection, the results in Table 8 suggest that participation in replacement schemes increased the short-term employment probability by on average 11 to 13 percentage points. Long-term effects appear to be smaller, somewhere in the range 6-9 percentage points. However, it should be noted that the decomposed programme effects underlying the figures in Table 8, i.e. the coefficients in the vector δ in (7), were estimated with poor precision. In fact, not a single coefficient in the regressions turned out to be significantly different from zero at the 5 percent level or better.[25]

To obtain more precise estimates of the individualised programme effects, we first narrowed down the set of explanatory variables in the equation for programme effects to a vector of personal characteristics such as sex, age, citizenship, education and

25 For this reason, and to conserve on space, estimates of the decomposed programme effects are not reported in the paper. The results are, of course, available upon request.

experience. This procedure did not change the overall results much; the constant term and the age dummy for individuals in their 50s came out significant in a few of the regressions. However, likelihood ratio tests of the joint hypothesis $\delta_0=\delta_1=\ldots=\delta_k=0$ were usually rejected at conventional significance levels.

Table 8: Average programme effects (percentage points); $\alpha_i = \delta' q_i$.

response period	*sample 1*	*sample 2*	*sample 3*	*sample 4*
3 months	12.60	11.61	12.68	13.05
6 months	11.02	10.91	11.41	13.00
12 months	6.35	6.05	5.89	5.44
18 months	9.62	8.38	9.43	8.46

The model was therefore re-estimated under the assumption of identical programme effects across individuals (i.e., the parameter vector δ in (7) was restricted to consist of a constant term δ_0). Coefficient estimates, the estimated programme effects and confidence intervals are displayed in Table 9. The coefficients are in most cases significantly different from zero at the 5 percent level or better. The estimated programme effects are very much in line with the results reported in Table 8 above; that is, participation in replacement schemes appears to have increased the short-term employment probability by 11 to 13 percentage points, whereas long-term effects seem to be slightly (insignificantly) smaller, about 6-9 percentage points.[26]

To sum up, the results presented in this subsection appear to be somewhat at odds with the view that policy programmes in general have little, if any, influence on the exit rate to regular employment. One likely explanation is that trainee replacement schemes, to a larger extent than many other ALMPs (where participants mainly performed low-qualified tasks), may have provided individuals with useful work experience and an opportunity to make valuable contacts. One such contact was, of course, the employer/organiser of the replacement scheme. If the substitute's stay with the employer

26 Using a similar specification and a response period of about 12 months, AMS (1999) reports a considerably larger programme effect (a coefficient estimate of 0.566) for participants in replacement schemes. The precise reason for this discrepancy is unclear, but may well reflect differences in sample periods (their study covers individuals who finished the programme during the last quarter of 1996), selection criteria and the construction of variables. Another difference is that AMS (1999) used survey data to measure the dependent variable. Moreover, our inference is that AMS (1999) did not reweigh their samples in order to adjust for choice-based sampling.

proved successful, then he/she supposedly had a good chance of getting a regular job once the employer needed to fill a vacancy. This is also confirmed by the survey evidence in AMS (1999): 12 months after leaving the programme in late 1996, more than 60 percent of those who held a regular job had found employment with the organiser of the replacement scheme.[27] The corresponding figure for work experience schemes was less than 20 percent, and for relief work about 30 percent.

Table 9: Programme effects: $\alpha_i = \delta_0$.

response period	*sample 1*	*sample 2*	*sample 3*	*sample 4*
coefficient:				
3 months	0.397*** (29.92)	0.357*** (20.64)	0.383*** (11.62)	0.380*** (9.84)
6 months	0.301*** (18.16)	0.294*** (14.72)	0.303*** (7.52)	0.334*** (7.86)
12 months	0.170** (5.72)	0.163** (4.48)	0.158 (1.98)	0.146 (1.46)
18 months	0.244*** (12.00)	0.212*** (7.86)	0.236** (4.42)	0.210* (3.02)
programme effect (percentage points):				
3 months	12.86***	11.77***	13.31***	13.38***
6 months	11.23***	11.10***	11.68***	12.94***
12 months	6.50**	6.20**	6.20	5.70
18 months	9.64***	8.38***	9.38**	8.34*
confidence interval (5 percent level):				
3 months	7.9 , 18.1	6.4 , 17.5	5.4 , 21.8	4.8 , 22.6
6 months	5.9 , 16.7	5.4 , 17.0	3.2 , 20.3	3.8 , 22.2
12 months	1.2 , 12.0	0.5 , 12.1	-2.4 , 15.0	-3.5 , 15.2
18 months	3.9 , 15.4	2.4 , 14.4	0.6 , 18.0	-1.1 , 17.6

Note: Univariate probit model, * significant at the 10% level, ** at the 5% level and *** at the 1% level. Chi-square test statistics in parentheses. We perform a likelihood ratio test of the restriction δ_0=0. The test statistic is -2(lnL^R -lnL^U), where L^R is the likelihood corresponding to the model with one linear restriction (δ_0=0) and L^U the likelihood for the unrestricted model. Confidence intervals are calculated using (7) and the estimated standard error for δ_0.

5.4 Redefining the response period

As discussed in Section 3.1 above, we have so far interpreted the programme effects in terms of human capital accumulation. Another aspect of participation is the cost of having less time for job-searching activities. In this section we expand the concept of programme effects by taking "lock-in" effects into account. The response period is now

27 A large fraction of the hirings presumably took place instantly at the end of the programme period. According to the register data used in this paper, slightly more than 20 percent of the programme spells ended in some kind of employment. We have, however, no way of telling whether these individuals were employed by the organiser or elsewhere.

redefined as the time span between the programme *start* and the moment the outcome is measured. Consequently, the estimated programme effects may now be interpreted as the joint effect of human capital accumulation and reduced (zero) search activity.[28]

In sum, the results generated by the bivariate probit model offered no strong evidence for the existence of unobserved selection bias (see Table B3 in Appendix B). Disregarding selection on unobservables by imposing the restriction ρ=0, the individual specific programme effects were again estimated with poor precision. The model was therefore re-estimated under the assumption of identical programme effects across individuals. Coefficient estimates, the estimated programme effects and confidence intervals are displayed in Table 10.

Table 10: Programme effects: $\alpha_i = \delta_0$.

response period	*sample 1*	*sample 2*	*sample 3*	*sample 4*
coefficient:				
3 months	-0.230*** (7.78)	-0.260*** (8.50)	-0.241* (3.70)	-0.184 (1.86)
6 months	-0.034 (0.22)	-0.034 (0.18)	-0.059 (0.28)	-0.037 (0.10)
12 months	0.149** (4.42)	0.180** (5.56)	0.133 (1.40)	0.173 (2.06)
18 months	0.105 (2.20)	0.045 (0.34)	0.141 (1.56)	0.120 (1.00)
programme effect (percentage points):				
3 months	-5.83***	-6.72***	-6.74*	-5.19
6 months	-1.18	-1.21	-2.14	-1.33
12 months	5.70**	6.89**	5.22	6.77
18 months	4.11	1.76	5.60	4.77
confidence interval (5 percent level):				
3 months	-9.2 , -1.8	-10.4 , -2.3	-12.3 , 0.3	-11.4 , 2.8
6 months	-5.9 , 4.0	-6.4 , 4.4	-9.7 , 6.2	-9.5 , 7.8
12 months	0.3 , 11.2	1.2 , 12.8	-3.3 , 14.0	-2.4 , 16.1
18 months	-1.3 , 9.7	-4.0 , 7.7	-3.1 , 14.4	-4.5 , 14.1

Note: Univariate probit model, * significant at the 10% level, ** at the 5% level and *** at the 1% level. Chi-square test statistics in parentheses. We perform a likelihood ratio test of the restriction δ_0=0. The test statistic is -2(lnL^R -lnL^U), where L^R is the likelihood corresponding to the model with one linear restriction (δ_0=0) and L^U the likelihood for the unrestricted model. Confidence intervals are calculated using (7) and the estimated standard error for δ_0.

First, it should be noted that (with a slight variation across samples) almost 50 percent of the programme spells lasted 3 months or longer, 25 percent lasted 4 months or longer, and that only a small fraction had a duration of 6 months or longer. This

28 Alternatively, suppose that participants' search activities were unaffected during the programme period. The approach used in this subsection would then be appropriate for capturing the human capital effect. However, as noted in Section 3.1, there seems to be a strong case against this assumption.

should account for the negative programme effect associated with a response period of 3 months; that is, in the very short-run the “lock-in” effect outweighs the human capital effect of participating. Six months after entering the programme the estimated effect appears to be insignificantly different from zero, which suggests that human capital effects now make up for the cancelling of job-search activities during participation. Extending the response period beyond 6 months, it appears that the human capital effect outweighs the lock-in effect. Evaluating the employment effects 12 months after entering the programme, thus taking both human capital effects and the time spent in the programme into account, participation in replacement schemes seems to have increased the employment probability by 5 to 7 percentage points.

6. CONCLUSION

The objective of this paper has been to estimate the employment effects of the temporary jobs that were created as part of the trainee replacement schemes. Trainee replacement schemes, which were in operation from 1991 to 1997, seem to have been targeted mainly at women who applied for public sector work such as health, nursing or social work. Previous experience of open unemployment appears to have mattered negatively for participation. This might perhaps reflect a tendency among employment officers to give precedence to unemployed with strong labour market attachments, while directing persons with long unemployment periods to some other, more low-qualified, policy programme.

Studying whether observable personal characteristics and labour market conditions have an impact on the individual’s employment probability, many coefficients turn out statistically significant with signs according to economic theory. The results suggest that participants in replacement schemes had a higher ex ante probability of employment. A plausible explanation lies in the fact that the substitute was expected to replace a regularly employed worker, which presumably meant that a potential participant needed a certain level of education and labour market experience.

We were unable to obtain precise estimates of the individualised programme effects. Estimating the model under the assumption of identical programme effects across individuals, the results suggest that participation in trainee replacement schemes increased the (long-term) employment probability by 5 to 10 percentage points.[29] Several earlier studies have found little, if any (or even a negative), influence of various policy programmes on the exit rate to regular employment. It seems likely that replacement schemes, to a larger extent than many other ALMPs (classroom vocational training or work experience schemes where participants mainly perform low-qualified tasks), may have provided individuals with useful work experience and an opportunity to make valuable contacts. Further, spending time at the working site presumably improved the chances of getting a regular job once the employer needed to fill a vacancy. This is confirmed by survey evidence, which suggest that many substitutes in replacement schemes subsequently were hired on a regular basis by the organiser.

29 The effect concerns the impact of joining the programme compared to not joining the programme *at least up to the point of evaluation (*which of course does not rule out participation later on; see Section 3.1 above).

REFERENCES

Ackum Agell, S. (1995), "Swedish Labor Market Programs: Efficiency and Timing", *Swedish Economic Policy Review,* 2(1), no. 1, 65-98.

Ackum Agell, S. (1996), "Arbetslösas sökaktivitet", FIEF Reprint Series 106, reprinted from *Aktiv arbetsmarknadspolitik,* SOU 1996:34.

Agell, J. & P. Lundborg (1999), "Survey Evidence on Wage Rigidity and Unemployment: Sweden in the 1990s", Working Paper 1999:2*,* IFAU, Uppsala.

AMS (1999), "Åtgärdsundersökningen 1998 - åtgärdernas effekt på deltagarnas sysselsättning och löner", Ura 1999:1, Arbetsmarknadsstyrelsen, Solna.

Anderson, K., R.V. Burkhauser & J.E. Raymond (1993), "The Effect of Creaming on Placement Rates Under the Job Training Partnership Act", *Industrial and Labor Relations Review*, 46(4), 613-624.

Behrenz, L. (1998), *Essays on the Employment Service and Employers' Recruitment Behaviour*. Ph.D. Thesis, Department of Economics, Lund University, Economic Studies 79.

Carling, K., P-A. Edin, A. Harkman & B. Holmlund (1996), "Unemployment Duration, Unemployment Benefits and Labour Market Programs in Sweden", *Journal of Public Economics*, 59, 313-334.

Carling, K., B. Holmlund & A. Vejsiu (1999), "Do Benefit Cuts Boost Job Findings? Swedish Evidence From the 1990s", Working Paper 1999:8*,* IFAU, Uppsala.

Carling, K. & L. Larsson (2000), "Att utvärdera arbetsmarknadsprogram i Sverige: Rätt svar är viktigt, men vilken var nu frågan? ", Research Report 2000:6*,* IFAU, Uppsala.

Dahlberg, M. & A. Forslund (1999), "Direct Displacement Effects of Labour Market Programmes: The Case of Sweden", Working Paper 1999:7*,* IFAU, Uppsala.

Edin, P-A. & B. Holmlund (1991), "Unemployment, Vacancies and Labour Market Programmes: Swedish Evidence", in Padoa-Schioppa, F. (ed.), *Mismatch and Labour Mobility*, Cambridge University Press, Cambridge.

Harkman, A. & F. Jansson (1995), "Sökaktivitet, återanställning och chansen att få jobb", Ura 1995:4, AMS, Stockholm.

Heckman, J. & R. Robb (1985), "Alternative Methods for Evaluating the Impact of Interventions", in J. Heckman & B. Singer (eds.), *Longitudinal Analysis of Labor Market Data*, Cambridge University Press, Cambridge.

Heckman, J., R.J. LaLonde & J.A. Smith (1999), "The Economics and Econometrics of Active Labor Market Programmes", in O. Aschenfelter & D. Card, eds., *Handbook of Labor Economics,* Volume III.

Larsson, L. (2000), "Evaluation of Swedish Youth Labour Market Programmes", Working Paper 2000:1, IFAU, Uppsala.

Martin, J. P. (1998), "What Works Among Active Labour Market Policies: Evidence From OECD Countries", Labour Market and Social Policy - Occasional Papers 35, OECD, Paris.

McFadden, D. (1974), "The Measurement of Urban Travel Demand", *Journal of Public Economics,* 3, 303-328.

Regnér, H. (1997), *Training at the Job and Training for a New Job: Two Swedish Studies*. Ph.D. Thesis, Swedish Institute for Social Research, 29.

SOU 1993:43, *Politik mot arbetslöshet.* Betänkande av EFA, Allmänna förlaget, Stockholm.

Zetterberg, J. (1996), "Effekter av arbetsmarknadspolitik - en översikt av svensk empirisk forskning", FIEF Reprint Series 105, reprinted from *Aktiv arbetsmarknadspolitik,* SOU 1996:34.

APPENDIX A

Table A1. List of variables.

variable	*explanation*
female	=1 if female, otherwise 0
age24	=1 if aged 20 to 24, otherwise 0
age29	=1 if aged 25 to 29, otherwise 0
age39	aged 30 to 39 (reference category)
age49	=1 if aged 40 to 49, otherwise 0
age59	=1 if aged 50 to 59, otherwise 0
cit0	Swedish citizen (reference category)
cit1	=1 if foreign citizen: Nordic, otherwise 0
cit2	=1 if foreign citizen: non-Nordic, otherwise 0
dis	=1 if disabled, otherwise 0
ed0	compulsory level of education (reference category)
ed1	=1 if high school level of education, otherwise 0
ed2	=1 if university level of education, otherwise 0
exp0	no experience from the type of job applied for (reference category)
exp1	=1 if some experience, otherwise 0
exp2	=1 if good experience, otherwise 0
edspec	has specific education for the type of job applied for, otherwise 0
job0	applying for health and nursing work, social work; the NYK occupational classification, NYK1 (reference category)
job1	=1 if applying for professional, technical or related work (NYK0)
job2	=1 if applying for administrative, managerial or clerical work (NYK2)
job3	=1 if applying for commercial work (NYK3)
job4	=1 if applying for agricultural, forestry or fishing work (NYK4)
job5	=1 if applying for transport or communications work (NYK6)
job6	=1 if applying for work in manufacturing or related work (NYK5, 7, 8)
job7	=1 if applying for service work (NYK9)
ui	=1 if receiving unemployment insurance benefits, otherwise 0
ca	=1 if receiving cash assistance, otherwise 0
nb	neither unemployment insurance benefits nor cash assistance (reference category)
move	=1 if willing to accept a job that involves moving/commuting, otherwise 0
scat12	=1 if ever registered in search category 12 (special assistance needed), otherwise 0
ue	number of weeks openly unemployed before the programme start (before being selected to the control group)
uet	number of weeks openly unemployed since September 1, 1991
nue	number of unemployment spells ending with regular employment
prog	number of weeks in different ALMPs since September 1, 1991
nprog	number of ALMP spells since September 1, 1991
progx	=1 if participating in an ALMP during the last 12 months, otherwise 0
reg0	living in a region other than a big city or forest region (reference category)
reg1	=1 if living in the Stockholm region, otherwise 0
reg2	=1 if living in any other big city region, otherwise 0
reg3	=1 if living in forest region, otherwise 0
ler[a]	exit rate to regular employment (exiting ÷ unemployed) in the municipality
lur[a]	unemployment rate (unemployed ÷ population aged 16-64) in the municipality
lpr[a]	programme rate (ALMP participants ÷ unemployed) in the municipality
lrs[a]	participants in replacement schemes ÷ ALMP participants in the municipality

[a] Multiplied by 100

Table A2. Sample means[a]

	sample 1[b]		sample 2[c]		sample 3[d]		sample 4[e]	
variable	*part.*	*non-part.*	*part.*	*non-part.*	*part.*	*non-part.*	*part.*	*non-part.*
female	0.719	0.440	1.000	1.000	0.729	0.475	1.000	1.000
age24	0.275	0.198	0.286	0.203	0.242	0.165	0.238	0.155
age29	0.209	0.192	0.206	0.200	0.247	0.205	0.251	0.225
age39	0.257	0.266	0.254	0.274	0.238	0.269	0.249	0.304
age49	0.181	0.200	0.179	0.183	0.191	0.200	0.184	0.176
age59	0.078	0.144	0.075	0.140	0.082	0.161	0.078	0.140
cit0	0.943	0.919	0.940	0.906	0.961	0.934	0.965	0.921
cit1	0.016	0.022	0.018	0.031	0.017	0.018	0.018	0.026
cit2	0.041	0.059	0.042	0.063	0.022	0.048	0.017	0.053
dis	0.064	0.062	0.052	0.061	0.043	0.032	0.033	0.027
ed0	0.162	0.259	0.144	0.258	0.150	0.270	0.134	0.267
ed1	0.693	0.604	0.698	0.578	0.639	0.549	0.640	0.530
ed2	0.145	0.137	0.158	0.164	0.211	0.181	0.226	0.203
exp0	0.175	0.170	0.174	0.169	0.163	0.149	0.161	0.134
exp1	0.392	0.295	0.407	0.340	0.321	0.244	0.324	0.280
exp2	0.433	0.535	0.419	0.491	0.516	0.607	0.515	0.586
edspec	0.684	0.609	0.704	0.575	0.705	0.606	0.729	0.576
job0	0.528	0.163	0.654	0.270	0.563	0.180	0.672	0.312
job1	0.031	0.058	0.020	0.058	0.034	0.063	0.022	0.056
job2	0.097	0.153	0.106	0.237	0.091	0.171	0.100	0.248
job3	0.056	0.124	0.056	0.156	0.056	0.133	0.055	0.152
job4	0.015	0.035	0.005	0.018	0.014	0.032	0.005	0.018
job5	0.023	0.061	0.011	0.027	0.028	0.069	0.016	0.026
job6	0.130	0.292	0.034	0.078	0.106	0.231	0.027	0.054
job7	0.120	0.114	0.114	0.156	0.108	0.121	0.103	0.165
ui	0.880	0.823	0.874	0.813	0.836	0.765	0.842	0.787
ca	0.052	0.080	0.053	0.071	0.057	0.100	0.055	0.074
nb	0.068	0.097	0.073	0.116	0.107	0.135	0.103	0.139
move	0.134	0.169	0.110	0.126	0.148	0.166	0.115	0.118
scat12	0.179	0.137	0.155	0.133	0.087	0.037	0.069	0.039
ue	14.57	17.20	12.881	16.276	16.92	17.82	14.47	16.54
uet	46.97	53.16	42.670	47.091	33.15	33.66	29.70	30.45
nue	0.751	0.589	0.774	0.539	0.653	0.570	0.640	0.483
prog	24.86	19.87	24.145	18.030	0.000	0.000	0.000	0.000
nprog	1.332	1.032	1.289	0.920	0.000	0.000	0.000	0.000
progx	0.543	0.446	0.533	0.400	0.000	0.000	0.000	0.000
reg0	0.094	0.177	0.094	0.207	0.130	0.238	0.125	0.253
reg1	0.277	0.286	0.294	0.285	0.280	0.295	0.292	0.309
reg2	0.296	0.262	0.279	0.234	0.292	0.218	0.292	0.209
reg3	0.333	0.275	0.333	0.274	0.298	0.249	0.291	0.229
ler	8.47	8.15	8.425	8.135	8.32	8.00	8.38	7.98
lur	8.28	8.35	8.295	8.225	8.26	8.21	8.24	8.15
lpr	48.75	45.36	48.699	44.919	47.09	43.27	47.76	43.17
lrs	7.74	6.18	7.861	6.144	7.41	6.04	7.54	5.93

[a] calculated at the onset of individuals' programme spells (October 31 1994 for non-participants),
[b] males and females; previous participation in ALMPs possible,
[c] females; previous participation in ALMPs possible,
[d] males and females; no previous participation in ALMPs,
[e] females; no previous participation in ALMPs.

APPENDIX B

Table B1. The selection equation. Response period: 6 months.

	sample 3			sample 4		
variable	*estimate*	*std.error*	*marg. eff.*	*estimate*	*std.error*	*marg. eff.*
constant	-2.204***	0.632	27.61	-1.913***	0.699	31.90
female	0.294***	0.107	4.35			
age24	0.305**	0.137	5.47	0.311**	0.154	7.13
age29	0.137	0.123	2.32	0.129	0.136	2.81
age49	0.130	0.130	2.23	0.173	0.147	3.86
age59	-0.111	0.168	-1.68	-0.027	0.191	-0.57
cit1	-0.194	0.321	-2.76	-0.348	0.335	-6.00
cit2	-0.242	0.248	-3.34	-0.442	0.312	-7.20
dis	0.151	0.214	2.67	0.104	0.276	2.32
ed1	0.150	0.127	2.36	0.192	0.149	3.93
ed2	0.024	0.162	0.39	0.027	0.184	0.56
exp1	-0.014	0.139	-0.23	-0.132	0.153	-2.72
exp2	-0.075	0.136	-1.22	-0.161	0.151	-3.40
edspec	0.142	0.101	2.20	0.167	0.117	3.37
job1	-0.695***	0.217	-7.14	-0.733***	0.271	-10.02
job2	-0.849***	0.139	-8.52	-0.896***	0.142	-12.20
job3	-0.879***	0.165	-8.28	-0.905***	0.182	-11.62
job4	-0.771**	0.303	-7.37	-0.870*	0.479	-10.73
job5	-0.821***	0.235	-7.73	-0.568*	0.331	-8.55
job6	-0.771***	0.153	-8.25	-0.723***	0.262	-9.99
job7	-0.513***	0.145	-6.30	-0.564***	0.160	-9.08
ui	0.080	0.138	1.25	0.053	0.159	1.09
ca	-0.152	0.203	-2.24	-0.051	0.242	-1.04
move	-0.079	0.124	-1.24	-0.178	0.151	-3.46
scat12	0.467***	0.172	9.62	0.289	0.211	6.96
ue	0.007	0.005	0.11	0.004	0.006	0.08
ue^2	0.000	0.000	0.00	0.000	0.000	0.00
uet	-0.001	0.002	-0.01	-0.001	0.003	-0.02
nue	0.019	0.055	0.31	0.022	0.061	0.48
reg1	-0.076	0.167	-1.18	-0.046	0.183	-0.95
reg2	-0.011	0.125	-0.17	0.018	0.131	0.38
reg3	0.073	0.123	1.20	0.078	0.140	1.68
ler	-0.007	0.038	-0.11	-0.014	0.042	-0.30
lur	-0.014	0.039	-0.22	-0.006	0.041	-0.12
lpr	0.007	0.006	0.11	0.007	0.006	0.15
lrs	0.046***	0.014	0.77	0.065***	0.014	1.43
log-likelihood		-2519.78			-1499.09	
goodness of fit		0.080			0.098	
chi-squared		436.94			324.12	
no. of observations		3287			1849	

Note: Bivariate probit model, * significant at the 10% level, ** at the 5% level and *** at the 1% level. The log-likelihood refers to the value obtained for the full model, including the parameters of the employment equation and the equation for programme effects. The goodness of fit measure is 1-($\ln L/\ln L_0$), where $\ln L_0$ is the log-likelihood corresponding to a specification with constant terms only (McFadden, 1974). The chi-squared statistic is -2($\ln L_0$-$\ln L$).

Table B2. The employment equation. Response period: 6 months.

	sample 3			***sample 4***		
variable	*estimate*	*std.error*	*marg. eff.*	*estimate*	*std.error*	*marg. eff.*
constant	0.043	0.240	38.11	0.053	0.414	38.10
female	-0.068	0.055	-2.50			
age24	-0.231***	0.083	-8.26	-0.066	0.117	-2.42
age29	0.035	0.069	1.31	0.046	0.092	1.71
age49	0.019	0.070	0.68	0.080	0.098	2.99
age59	-0.177**	0.080	-6.31	-0.135**	0.067	-4.85
cit1	-0.275	0.182	-9.51	-0.098	0.204	-3.55
cit2	-0.792***	0.146	-23.11	-1.141***	0.214	-28.85
dis	-0.383***	0.149	-12.91	-0.501**	0.235	-16.28
ed1	0.158**	0.065	5.76	0.098	0.092	3.61
ed2	0.286***	0.086	10.82	0.382***	0.118	14.52
exp1	0.035	0.078	1.28	0.252**	0.114	9.41
exp2	0.062	0.076	2.28	0.308***	0.112	11.30
edspec	0.095*	0.055	3.49	0.107	0.081	3.91
job1	-0.409***	0.111	-13.65	-0.627***	0.157	-19.43
job2	-0.289***	0.079	-10.05	-0.280***	0.092	-9.78
job3	-0.278***	0.087	-9.66	-0.312***	0.111	-10.76
job4	0.133	0.149	5.03	-0.068	0.261	-2.46
job5	-0.052	0.108	-1.88	-0.020	0.205	-0.74
job6	-0.174**	0.084	-6.21	-0.205	0.157	-7.22
job7	-0.230**	0.093	-8.11	-0.164	0.113	-5.87
ui	-0.074	0.072	-2.75	0.030	0.104	1.12
ca	0.167*	0.097	6.31	0.307**	0.148	11.81
move	0.061	0.065	2.26	0.080	0.101	3.00
scat12	0.103	0.127	3.84	0.243	0.170	9.25
ue	-0.010***	0.003	-0.38	-0.017***	0.004	-0.64
ue^2	0.000***	0.000	0.00	0.000***	0.000	0.01
uet	-0.004***	0.001	-0.16	-0.002	0.002	-0.07
nue	0.155***	0.032	5.88	0.109**	0.046	4.09
reg1	0.000	0.078	0.01	0.159	0.113	6.00
reg2	0.005	0.067	0.20	0.175*	0.094	6.53
reg3	-0.095	0.076	-3.47	0.065	0.110	2.41
ler	-0.014	0.020	-0.52	-0.027	0.031	-0.97
lur	-0.028*	0.016	-1.03	-0.048*	0.026	-1.77
lpr	0.002	0.004	0.07	-0.005	0.005	-0.17
log-likelihood		-1996.53			-1087.85	
goodness of fit		0.062			0.082	
chi-squared		264.2			193.90	
no. of observations		3287			1849	

Note: Univariate probit model, * significant at the 10% level, ** at the 5% level and *** at the 1% level. The log-likelihood refers to the value obtained for the full model, including the parameters of the equation for programme effects. The goodness of fit measure is 1-($\ln L/\ln L_0$), where $\ln L_0$ is the log-likelihood corresponding to a specification with constant terms only (McFadden, 1974). The chi-squared statistic is -2($\ln L_0$-$\ln L$).

Table B3. The correlation coefficient; the response period includes time spent in the programme.

	sample 1		sample 2	
response period	$\alpha_i = \delta' q_i$	$\alpha_i = \delta_0$	$\alpha_i = \delta' q_i$	$\alpha_i = \delta_0$
3 months	-0.036 (0.02)	0.152 (0.76)	-0.043 (0.02)	0.129 (0.40)
6 months	0.026 (0.01)	0.146 (0.96)	0.130 (0.26)	0.231 (1.80)
12 months	0.415** (4.56)	0.261* (3.26)	0.461* (3.73)	0.299 (2.62)
18 months	0.116 (0.28)	0.203 (1.92)	0.047 (0.04)	0.139 (0.64)
	sample 3		***sample 4***	
	$\alpha_i = \delta' q_i$	$\alpha_i = \delta_0$	$\alpha_i = \delta' q_i$	$\alpha_i = \delta_0$
3 months	0.066 (0.02)	0.148 (0.30)	0.151 (0.12)	0.181 (0.32)
6 months	-0.267 (0.32)	0.036 (0.02)	0.278 (0.44)	0.142 (0.22)
12 months	-0.183 (0.08)	-0.033 (0.02)	0.432 (1.16)	0.155 (0.26)
18 months	-0.441 (1.12)	-0.061 (0.06)	-0.109 (0.08)	-0.052 (1.06)

Note: Bivariate probit model, * significant at the 10% level, ** at the 5% level and *** at the 1% level. Chi-square test statistics in parentheses. We perform a likelihood ratio test of the restriction ρ=0. The test statistic is -2(lnL^R - lnL^U), where L^R is the likelihood corresponding to the model with one linear restriction (ρ=0) and L^U the likelihood for the unrestricted model.