Labour Market Programmes and Labour Market Outcomes: A study of the Swedish Active Labour Market Interventions

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Abstract

This paper assesses the impact of Swedish welfare-to-work programs on labour market performance including wages, labour market status, unemployment duration and future welfare-to-work participation. We develop a structural dynamic model of labour supply which includes detailed institutional features of these policies and allows for selection on observables and unobservables. We estimate the model from a rich administrative panel data set and show that training programs- which accounts for a large proportion of programs- have little effect on future outcomes, whereas job experience programs have a beneficial effect.

1 Introduction

Active labour market programmes have become increasingly important in a number of OECD countries as a way of combatting unemployment and helping workers reallocate to new sectors, following economic shocks. Such programmes have indeed become the centrepiece for UK employment policy, through the "New Deal" introduced in 1998 and have been a well established institution in Sweden, where there has been a strong link with benefit eligibility. In one form or another they have also been an important presence in the US, with programmes such as the JTPA or other smaller scale training programmes. However, the success of such programmes is controversial, with a large number of evaluations putting in doubt their overall effectiveness. Nevertheless, the programmes considered are highly heterogeneous, comprising anything from job-search assistance, to training and subsidised work.

There is an extensive body of evidence from micro-econometric studies on the effects of various types of programs on participants' subsequent labour market outcomes. Evidence from different OECD countries shows that subsidised employment has a greater impact than public training (for which negative effects have at times been estimated). Recent work comparing the effectiveness of the four options of the New Deal for Young People in the UK similarly finds that the employment option performs best compared to full-time education and training, the voluntary sector and the environmental task force (Bonjour et al., 2001; Dorsett, 2004). The finding that the 'work first' approach of the employment programme dominates the human capital approach of the training measure is also in line with the meta-analysis of US welfare-to-work programs by Greenberg et al. (2004). Using similar data as in this paper and based on a non-parametri matching approach, Sianesi (2001a,b and 2004) finds that those programmes providing subsidised workplace experience and on-the-job training at an employer are not only cheaper, but considerably more effective for participants' subsequent labour market success when compared to classroom training courses.

The focus of traditional empirical approaches to evaluation (reviewed extensively in Heckman et al., 1999) is mostly on statistical robustness; seeking to identify causal effects without functional-form restrictions, they typically rely on conditional independence assumptions or the availability of instrumental variables or direct randomisation. Considering mainly reduced-form models and lacking economic structure, the conventional treatment effect literature is essentially static. However, labour market choices are intrinsically dynamic as current decisions affect future outcomes and expected future outcomes affect current decisions. To understand how programmes operate on employment, and unemployment durations and earnings and to be in a position to study policy reforms we require to model the underlying dynamics.

To achieve this we need to model selection into the (different) programmes and into subsequent employment (cf. Ham and Lalonde, 1996) as economic decisions. Moreover, we need to account for the incentive structure generated by the institutional framework. For example, labour market institutions such as the Swedish one (or those of many European countries) add to the dynamic nature of the problem in two ways: first, by having a large set of different programmes from which to choose from and second, by linking programme participation to the renewal of eligibility unemployment benefits.

To deal with these issues, we develop a dynamic structural model to assess the impact of a complex welfare-to-work system taking into account how it affects working and future programme participation incentives. We model labour supply decisions, programme participation decisions and earnings, taking into. account the institutional features, in particular the eligibility to unemployment insurance and its renewal through program participation or work. We allow for selection on unobserved heterogeneity and model explicitly the dynamic selection of forward and optimizing individuals.

We estimate the differential impact of each type of programme or of sequences of programmes, the short- and long-term effects, and the effects on final and on intermediate outcomes. We estimate the mean and the full distribution of treatment effects. In the presence of selection into the programmes based on (unobserved) returns, the average effects uncovered by reduced-form methods may mask important heterogeneity in impacts by types of individuals.

Thus the aim of this paper is to provide a unified framework for evaluating programmes, recognising their dynamic effects and intertemporal incentives and considering the longer term impacts on individual careers, including employment and unemployment durations, welfare dependency and wages. In doing so we specify a model that is capable of simulating the effects of reforms to the existing system. Thus our approach differs from the recent spate of evaluations in that we seek to specify and estimate a dynamic economic model of programme participation, employment and wages. This model is capable both of offering an evaluation of existing programmes and of simulating alternative policies.

Our context, which is the Swedish labour market programmes have been considered before[1] but never in such a systematic way as we propose here. The chosen context is useful for a number of reasons. We have put together with the help of the IFAU a data set which follows a cohort of unemployed for a number of years. The employment status data has been linked to earnings records allowing us to follow career outcomes of workers for a number of years, free from recall bias.

We find that training programmes seem to have no beneficial impact on the treated. On the contrary, they postpone exit from unemployment due to the lock-in effect, whereby treated are deterred from moving into employment while on the programme, which can be used to renew unemployment insurance eligibility. Subsidised employment seems to be more beneficial, particularly to high ability individuals. First, it speeds up transitions into employment although not enough to recover from the lock-in effect. Second, it seems to have some impact on wages although less than usual job experience. And third, treated individuals of high ability enjoy longer employment spells after treatment.

The next section discusses the Swedish institutional context, the essence of which we try to capture in our dynamic structural model, and describes the data used in our analysis. Section 3

[1]Forslund and Krueger (1997) and Sianesi (2001a,b and 2004).

sets up the model. Section 4 analysis the estimated effects of treatment and section 5 discusses the predicted outcomes of alternative policy scenarios. Finally section 6 concludes the paper.

2 Data and Institutional background

2.1 The Swedish labour market policy

Sweden runs one of the world's most generous welfare policies targeted at the unemployed. We briefly describe some of the most important features of Swedish labour market institutions of the late nineties that will set the ground for our model design choices.

The unemployment insurance in Sweden amounts to 80% of the individuals salary in the previous job up to a ceiling of about SEK16,500. To first become eligible to 14 months of UI benefits, an individual needs to have accumulated a minimum of 5 months of working experience in the past. After that, eligibility to UI can always be renewed through an additional 5 months on a regular job or in one or more of the many programmes offered to the unemployed.

There are a great number of alternative treatments being offered at any time to unemployed individuals. They include subsidised jobs (scheme job subsidies and trainee replacement initiatives), vocational training, work practice schemes and relief work among others. In this paper we distinguish between *subsidised jobs* and all other programmes in assessing their differential impact on labour market performance. In what follows, the latter will be called *training* programmes.

2.2 Data Set and Descriptive Statistics

The data set we use is drawn from four different administrative data sets which have been merged for the purpose of the study. The Unemployment Register "Händel" provides information from August 1991 onwards on unemployment spells, programme participation spells and the subsequent labour market status of those who are deregistered (employment, education, inactivity or 'lost' (attrition)). Information on unemployment compensation comes from the Akstat data base and is available from January 1994 onwards.

We combine information on monthly employment spell and wages from employer reports. This information is available from 1990 onwards. Finally, information on education levels is taken from the "Sysreg" data base which provides the highest education achieved by calendar year, starting in 1990.

The different data sets are merged together using each individual's unique social security number. The data covers the whole working age population in Sweden.

From these data we select the population of Swedish males becoming unemployed during 1996 and follow them up to December 1998. Selection was conditional on the following criteria: being aged between 25 and 30 years of age at their sample inflow; having completed at the most 1-2 years of high school and not upgrading during the observation window (this is true for 95% of the unskilled population at this age group); and not being disabled or self-employed. In each month from inflow to December 1998, the individual's activity is classified in one of the four alternatives, employment, unemployment, subsidised employment or training programme. The criterion we used in case of conflict was to select the state that lasted for longest in the month.

Programme occurrences were only considered if in long spells, lasting for more than 2 months. In such case, treatment spells are split in 4 months periods and considered as sequences of treatment events. The employment state includes part- and full-time employment. If no earnings are observed for an employment spell, it is re-classified as unemployment.[2]

Using the criterion selection described above, our data set contains 14,370 individuals who all start an unemployment spell in 1996. Estimation used a randomly selected 20% sub-sample. From these data we excluded individuals for whom the information from the unemployment

[2]Earnings information is reported by the employer.

registry and from the employer are incompatible. These are individuals who have a relatively long history of past employment as derived from the employer provided data but are not eligible for unemployment benefits as detailed in the unemployment registry data. About 20% of the sample has been excluded on these grounds. We have also dropped individuals eligible to unemployment insurance at sample inflow but with no previous employment history. These amount to less then 2% of the sample.

Table 1: Descriptive Statistics

	full sample (1)	20% subsample (2)	20% subsample excl incompatibilities (*) (3)
Number of individuals in 96	14370	2809	2249
Average labour market experience in 96 (yrs)	4.2	4.1	4.2
Proportion with previous Job Subsidy in 96	5.8%	5.9%	5.9%
Proportion with previous Training in 96	47.0%	48.0%	49.8%
Average number of mths UI eligibility in 96	10.2	10.1	12.6
Average time to first employment (mths)	6.4	6.5	6.6
Average number of U spells 96-Dec98	1.91	1.88	1.95
Average number of E spells 96-Dec98	1.61	1.56	1.64

(*) At entrance into the sample we assess whether there is incompatible information from different data sources. Individuals with incompatible information regarding past employment experience (as derived from the employer provided information) and eligibility to unemployment benefits (as derived from the unemployment registry) are excluded from the sample.

Table 1 provides a brief summary of the whole data (column (1)), the 20% sub-sample (column (2)) and sub-sample we use in estimation (column (3)). There seems to be no important sample selection problems created by our cleaning and selection rules. The only variable which is affected at inflow is, as expected, the number of months of UI eligibility. This is because the most drastic cleaning we have done was to exclude individuals that at inflow were not eligible to unemployment compensation (or to renew benefits eligibility through programme participation) despite having long employment records and *all* these have zero months of eligibility to UI at inflow. For all other variables, including the ones that reflect the individuals' behaviour throughout our observation window such as the average duration of the first unemployment spell and the average number of unemployment and employment spells, the three samples show very similar patterns.

Figure 1 displays the proportion of individuals in unemployment, employment or either active labour market programme. At the start of the data set, all individuals are unemployed. At the end of the sample, about 10% are unemployed. At any point in time, about 2.2% of individuals are in a training program and 0.6% are in a job subsidy program.

Figure 1: Labour market status over time

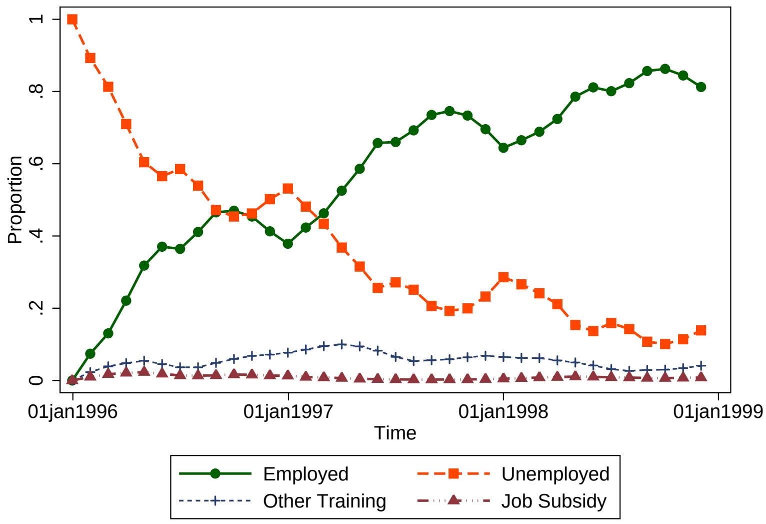
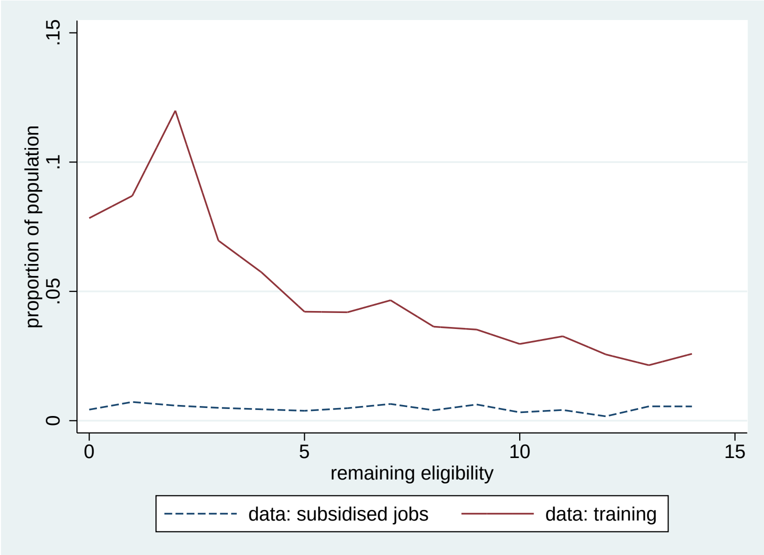


Figure 2 displays the enrolment rate into training or job subsidy programs as a function of the remaining eligibility to unemployment benefits. The enrolment in job subsidy program does not appear to be related to eligibility to UI. On the contrary, the enrolment in training programs is increasing in the remaining eligibility and peaks a few months before the individual looses the right to UI. This suggests that training programs are used to renew eligibility.

Figure 2: Participation in labour market programmes by remaining eligibility to UI



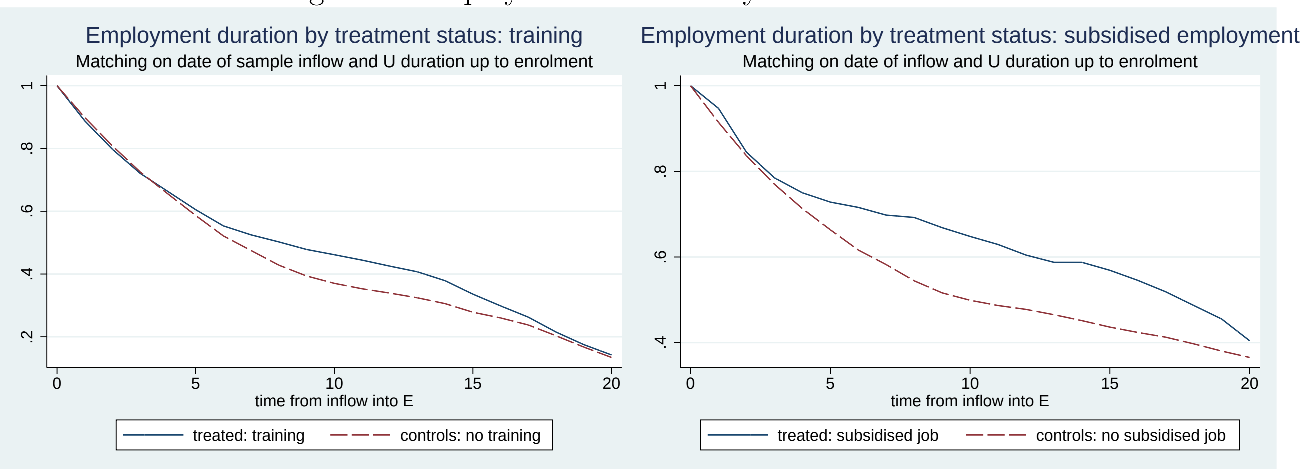
Figures 3 and 4 compare treated with matched controls with respect to two alternative outcomes: the remaining duration of unemployment from enrolment into treatment and the duration of the next employment spell. In both cases, treated are individuals enrolling into training or subsidised employment during their first 12 months in the sample while still in their first observable unemployment spell. We consider the first instance of treatment only. Controls are individuals remaining unemployed and without treatment for at least the time it took the treated to enrol into treatment. We match exactly on the period of sample inflow and time to treat. To compare the duration of employment spells we further condition on having a subsequent employment spell and the outcome is measured on the first employment spell after

Figure 3 shows an initial 4-month lock-in effect of both types of treatment. This is the minimum period the individuals remain in treatment. After that, training seems to reduce the speed at which individuals leave unemployment while subsidised employment seems to have the reverse effect. The impact is so large for individuals in subsidised employment that the lock-in effect is totally overcome by month 7 after enrolment into treatment.

Figure 4 suggests that both programs are beneficial with respect to the duration of future

Figure 3: Unemployment rate by treatment status

Figure 4: Employment duration by treatment status



employment although the effect of subsidised jobs seems to be much more substantial.

However, these results may be plagued with selection bias. Table 2 shows the characteristics at inflow of individuals that take and do not take treatment during the observational time window by type of treatment. It is clear from these figures that the treated are not a random sample of this population. The differences are particularly strong for individuals enrolling into training during the observational window. They have less accumulated experience and are more likely to have experienced treatment in the past.

Table 2: Treated versus non-treated within observational time window - characteristics at inflow

	Subsidized job		Training	
	non-treated	treated	non-treated	treated
past experience in months	51.1	49.0	52.4	47.3
% had subsidised jobs in the past	5.8%	6.3%	4.9%	8.7%
% participated in training in the past	49.6%	55.2%	46.0%	60.2%

Notes: Table shows characteristics at inflow of individuals that take and do not take treatment during observational time window, between January 96 and December 98, by type of treatment.

We now turn to wages in employment. Table 3 displays the coefficients of a regression of log wage on experience and dummies for having participated in either a subsidised job or a training program during the observational window. The analysis is conditional on having had no previous treatment. We compute the treatment effects using both OLS and a fixed effects regression. Cross section estimates (columns (1) and (2) in the table) suggest subsidised jobs have a large positive impact on wages of almost 11%. On the contrary, training seems to have a detrimental effect on wages of over 7%. However, these numbers are unlikely to be consistent estimates of the treatment effects if selection into treatment is non-random.

The next two columns in table 3 display the first differences estimates of a similar regression. By using first differences, we remove fixed differences in productivity at individual level. While individuals experiencing unemployment see a 2% decrease in their wage, the effect of both labour market programs are positive, 8% for subsidised jobs and 5.5% for training. These results suggest either that treatment improves the wages of participants or that selection into employment is important enough to generate these results. Indeed, programme participation does not only provide training, but also renews eligibility to UI. Hence, at the end of a programme individuals can choose between a further unemployment spell at 80% of the previous

Table 3: Determinants of log wages

	OLS		First differences	
	Coefficient	sd. err.	Coefficient	sd. err.
	(1)	(2)	(3)	(4)
experience (log)	0.1003	0.0022	-	-
Job subsidy	0.1083	0.0114	0.0798	0.0439
Training	-0.0730	0.0071	0.0556	0.0207
unemployment	-	-	-0.0239	0.0055
constant	9.1862	0.0088	0.0005	0.0012
observations	124,177		93,748	

Notes: Regressions are conditional on no program participation prior to first observation.

wage, or to accept a new job if one is offered. Programme participation may therefore increase the reservation wage, making individuals more selective about which jobs to accept.

The large differences between estimates obtained using OLS and fixed effects shows how important it is to take into account unobserved heterogeneity related to labour productivity. In the next section we develop a model that explicitly addresses the dynamic selection issues and allows for unobserved heterogeneity.

3 The model

3.1 An Overview

We model labour supply and programme participation for a group of workers who have become unemployed early on in their career. The model is forward looking and allows for the main institutional features of the Swedish active labour market programmes faced by this cohort in the late nineties. The framework we use has its origins in the seminal paper of Eckstein and Wolpin (1989).

The model is set in discrete time with one period corresponding to a month. Because the individuals are young when they enter the sample we solve their optimisation problem as if they were infinitely lived. In each time period, the individual chooses an activity (subject to constraints) to maximise the expected present value of rewards (utility) subject to constraints (e.g. "is an offer of a job available?") and to available information. Possible (mutually exclusive) activities are employment, unemployment and participation in one of two programmes - subsidised job and training.

Thus, while out of work, the individual may be offered a job or a place on a programme. The individual then assesses the relative costs and benefits of participation, including those expected in the future, and chooses the best option. Individuals receive offers at different rates, depending on their characteristics. These may change over time, as a result of the individual's actions. Once in a job, the individual receives a wage determined by her/his characteristics and subject to random shocks. Individuals who receive sufficiently bad stochastic shocks may move into unemployment.[3]

There are several sources of dynamics in the model: *(i)* participation in programmes affects future benefits while out of work, future earnings and the chances of receiving job and treatment offers; and *(ii)* employment affects experience, earnings and the benefits while out of work.

3.2 A Formal description of the model

3.2.1 The state space

The current position of the individual is described by a set of relevant variables. These include work experience (e); the remaining number of months of entitlement to UI benefits (u where u

[3]According to our estimates, we did not find it important to allow for exogenous job destruction.

is below a cap $\overline{u} = 14$ months); the accumulated number of periods working or in a programme since UI eligibility was last exhausted (m where m is below a cap $\overline{m} = 5$); the number of spells in subsidised employment and training programmes (p^J and p^T, respectively), and the number of such spells completed at the start of current out-of-work spell if applicable (s^J and s^T, respectively); the exogenous variables (x) including region of residence.[4] The set of possible values of these observable variables constitute the state space; the point in this space for individual i at time t is denoted Ω_{it}.

In each period the individual receives a number of unobservable (by the econometrician) innovations. We denote by Γ_{it} the set of shocks received by individual i at time t. These include a productivity innovation ν, which arrives with probability p, job and programme offers, which arrive with probabilities o^k for $k = E, J, T$, and three taste shocks, $(\epsilon^E, \epsilon^J, \epsilon^T)$, that affect the present return to each alternative activity (work, subsidised job and training).

Finally, we also allow for two sources of unobserved heterogeneity: θ^W explains permanent differences in productivity (wage) levels; θ^E explains permanent differences in job attachment. Both sources of heterogeneity have a discrete distribution. Following some experimentation the former has three points of support and the latter two.

3.3 The individual's problem

Let d_{it}^k, $k = U, E, J, T$, be a set of dummy variables describing the labour market status of individual i at time t.[5] These are the decision variables. $d_{it}^k = 1$ means that alternative k has been selected in period t, $d_{it}^k = 0$ otherwise. Each option is mutually exclusive and $\sum_{k \in K} d_{it}^k = 1$ for all i and t, where $K = \{U, E, J, T\}$.

The problem of individual i in period tau is to select the optimal sequence of feasible activities over the future, $\{d_{it}\}_{t=\tau,\ldots} = \left\{d_{it}^E, d_{it}^U, d_{it}^J, d_{it}^T\right\}_{t=\tau,\ldots}$, conditional on the contemporaneous

[4] s^J and s^T determine unemployment benefit while out of work, not p^J and p^T.

[5] U is unemployment, E is employment, J is a subsidised job and T training.

information set, $(\Omega_{i\tau}, \Gamma_{i\tau}, \theta_i)$,

$$\max_{\{d_{it}\}_{t=\tau,\ldots}} E_\tau \left[\sum_{t=\tau}^{\infty} \sum_{k \in K} \beta^{t-\tau} d_{it}^k R_{it}^k \left(\Omega_{it}, \Gamma_{it}, \theta_i\right) \middle| \Omega_{i\tau}, \Gamma_{i\tau}, \theta_i \right]$$

where β is the discount rate and R^k represents the per period reward or utility function when labour market option k is selected.

This maximisation problem is subject to a number of restrictions, including the law of motion of the state variables and the feasibility of the different labour market options in each period. We now describe the per-period reward functions and the restrictions to the maximisation problem.

3.4 Per period reward functions

Contemporaneous utility is assumed to be logarithmic in income. Income is modelled as a dynamic process. Working and programme participation affect future earnings while in employment and income while out of work given its link to the market wage.

The contemporaneous utility from employment The market wage for an individual of ability type θ^W with e periods of working experience and (p^J, p^T) treatments is $w(e_{it}, p_{it}^J, p_{it}^T, \theta_i^W)$. The actual earnings are also determined by the productivity shock, ν, so that

$$w_{it} = w(e_{it}, p_{it}^J, p_{it}^T, \theta_i^W) \exp(\nu_{it}).$$

Following the patterns in the data, we have modelled ν to have some persistence by including an additional parameter that determines the probability of receiving a wage innovation in each period (p).[6] So, for an individual that has two sequential employment periods,

$$w_{it+1} = \begin{cases} w_{it} & \text{with probability } p \\ w(e_{it+1}, p^J_{it+1}, p^T_{it+1}, \theta^W_i) \exp(\nu_{it+1}) & \text{with probability } 1-p \end{cases}$$

If a wage innovation is received while in employment, it is drawn from the distribution $\mathcal{N}(0, \sigma_1)$. While out of work, a new job offer is drawn from the distribution of wage innovations, $\mathcal{N}(0, \sigma_0)$.

The current reward of employment for individual i at time t can now be expressed as,

$$R^E(\Omega_{it}, \Gamma_{it}, \theta_i) = \ln\left(w\left(e_{it}, p^J_{it}, p^T_{it}, \theta^W_i\right) \exp(\nu_{it})\right) + \theta^E_i + \epsilon^E_{it}$$

where job attachment is captured by the unobserved heterogeneity term, θ^E. ϵ^E is the transitory taste shock, which is uncorrelated over time and follows a distribution $\mathcal{N}(0, \sigma^2_E)$.

The contemporaneous utility from unemployment The period utility from unemployment depends on the eligibility status to UI. An eligible individual ($u > 0$) is entitled to a proportion α of the market wage for a worker of similar characteristics up to a ceiling, $\overline{B}$. An ineligible individual ($u = 0$) is entitled to a flat social security rate, b. The contemporaneous utility function for an unemployed individual i at time t is

$$R^U(\Omega_{it}, \Gamma_{it}, \theta) = \begin{cases} \ln(UI_{it}) = \ln\left(\min\left\{\alpha w\left(e_{it}, s^J_{it}, s^T_{it}, \theta^W_i\right), \overline{B}\right\}\right) & \text{if } u_{it} > 0 \\ \ln(b) & \text{if } u_{it} = 0 \end{cases}$$

where $s^{J/T}$ measure the number of programmes the individual has participated in up to the beginning of the current out-of-work spell and UI_{it} is the amount of unemployment insurance the individual receives while entitled.

The contemporaneous utility from subsidised employment We define a subsidised employment spell to equal the number of months required for the renewal of benefit eligibility

[6] We have experimented with an AR(1) process for the innovation ν. However such model could not reproduce important patterns in the data such as the transitions from employment into other activities.

($\overline{m}$). An individual may have a number of consecutive spells. While in subsidised employment work experience is not increased - the productivity effects are completely reflected in the indicator of the number of spells in such a programme s_{it}^J. The other difference is that the individual does not obtain θ_i^E and the taste shock is specific to the programme. The reward function for the whole $\overline{m}$-months period on a subsidised job is,

$$R^J\left(\Omega_{it},\Gamma_{it},\theta\right) \quad = \quad \frac{1-\beta^{\overline{m}}}{1-\beta}\ln\left(w(e_{it},p_{it}^J,p_{it}^T,\theta_i)\exp\left(\nu_{it}\right)\right)+\epsilon_{it}^J$$

where t is the first period on the programme. ϵ^J is the transitory taste shock, assumed to be uncorrelated over time and following a distribution $\mathcal{N}(0,\sigma_J^2)$.

The contemporaneous utility from training Finally, the contemporaneous returns to training programmes depend on whether the minimum working experience requirement for UI has been fulfilled in the past. Again, we only consider long spells, lasting for at least $\overline{m}$ months, and the longer spells are split in subsequent spells of exactly $\overline{m}$ months. The per-period income is either the UI benefit of the social security flat rate subsidy, depending on whether e is larger or smaller than $\overline{m}$. The reward function for the whole $\overline{m}$ periods is,

$$R^T\left(\Omega_{it},\Gamma_{it},\theta\right) \quad = \quad \begin{cases} \frac{1-\beta^{\overline{m}}}{1-\beta}\ln(UI_{it})+\epsilon_{it}^T & \text{if } e_{it}\geq\overline{m} \\ \frac{1-\beta^{\overline{m}}}{1-\beta}\ln(b)+\epsilon_{it}^T & \text{if } e_{it}<\overline{m} \end{cases}$$

where ϵ_{it}^T is the transitory taste components, uncorrelated over time and following a distribution $\mathcal{N}(0,\sigma_T^2)$.

3.5 Transitions

The feasible set of activities in any period is restricted by the present activity and the arrival of offers for the alternative activities $k=E,J,T$. We follow the patterns observed in data, excluding direct transitions from employment into the programmes and from subsidised jobs into training. Conditional on receiving an offer, the individual will then decide whether to accept it or to remain (or become) unemployed. We assume the time intervals to be sufficiently small to ensure that at most one offer arrives in each period. The offer arrival rates are allowed to vary with the individual's characteristics. They are modelled as a logistic function of the activity in the previous period, past programme participation and region of residence. Treatment offers also depend on remaining eligibility time, to reflect the fact that the case officers in the job-centres will often prioritise finding a placement for those who are running out of benefits.[7] We represent the offer rate of option $k = E, J, T$ as $o^k(\Omega_{it})$.

3.6 The intertemporal value functions

The decision process of the individual, conditional on receiving an offer, is captured by the comparison of value functions for each alternative activity. We now describe these value functions. We denote by V_{it}^k the inter-temporal value of option k at time t for individual i. It is a function of all contemporaneous observable and unobservable variables but we omit this dependence for ease of notation.

The value of employment depends on its contemporaneous returns, $R^E\left(\Omega_{it}, \Gamma_{it}, \theta_i\right)$, and on future prospects as affected by current employment, assuming optimal decisions in the future. Employed individuals can always remaining employed for as long as the value of employment remains high enough. The outside option is to move into unemployment. The value of being employed can then be written as,

$$\begin{aligned} V_{it}^E \;=\; & R^E\left(\Omega_{it}, \Gamma_{it}, \theta_i\right) + \\ & \beta(1-p) E_{\epsilon^E}\left[\max\left\{V_{it+1}^U, V_{it+1}^E\right\}\middle|\, \theta, \Omega_{it}, w_{it+1} = w_{it}, d_t^E = 1\right] + \\ & \beta p E_{\epsilon^E, \nu}\left[\max\left\{V_{it+1}^U, V_{it+1}^E\right\}\middle|\, \theta, \Omega_{it}, w_{it+1} \neq w_{it}, d_t^E = 1\right] \end{aligned}$$

[7] Priority is given to individuals close to exhaust eligibility to UI in offering treatment.

The two last terms are distinguished by whether the individual received a wage shock or not. This happens with probability p. This function takes into account the laws of motion described later.

The value of unemployment While unemployed, the individual may receive an offer of any type (employment and the two programme types). The decision of what activity to engage in will depend on comparing the offered activity to unemployment. The value of unemployment at period t is,

$$\begin{aligned} V_{it}^{U} = \; & R^{U}\left(\Omega_{it}, \Gamma_{it}, \theta_{i}\right) + \\ & \beta o^{E}\left(\Omega_{it+1}, d_{it}^{U}=1\right) E_{\epsilon^{E},\nu}\left[\max\left\{V_{it+1}^{U}, V_{it+1}^{E}\right\}\middle|\, \theta, \Omega_{it}, d_{it}^{U}=1\right] + \\ & \beta \o^{J}\left(\Omega_{it+1}, d_{it}^{U}=1\right) E_{\epsilon^{J},\nu}\left[\max\left\{V_{it+1}^{U}, V_{it+1}^{J}\right\}\middle|\, \theta, \Omega_{it}, d_{it}^{U}=1\right] + \\ & \beta \o^{T}\left(\Omega_{it+1}, d_{it}^{U}=1\right) E_{\epsilon^{o}}\left[\max\left\{V_{it+1}^{U}, V_{it+1}^{T}\right\}\middle|\, \theta, \Omega_{it}, d_{it}^{U}=1\right] + \\ & \beta\left[1 - o^{E}\left(\Omega_{it+1}, d_{it}^{U}=1\right) - \o^{J}\left(\Omega_{it+1}, d_{it}^{U}=1\right) - \o^{T}\left(\Omega_{it+1}, d_{it}^{U}=1\right)\right] E\left[V_{it+1}^{U}\middle|\, \theta, \Omega_{it}, d_{it}^{U}=1\right] \end{aligned}$$

where each of the four last terms relates to the possibility of receiving an alternatve offer, with the last terms being the one where no offer is received and the individual has to remain unemployed.

The value of subsidised employment and training The current utility while on a subsidised job, $R^{J}\left(\Omega_{it}, \Gamma_{it}, \theta_{i}\right)$, accounts for the duration of the spell ($\overline{m}$ months). In $\overline{m}$ months time the individual will be weighing up the options and if possible will be deciding whether to move into employment or a new subsidised employment spell.[8] The value of a subsidised job

[8]Direct transitions into training programmes from subsidised jobs have been excluded as they are not observed in the data.

is,

$$
\begin{aligned}
V_{it}^{J} &= R^{J}\left(\Omega_{it},\Gamma_{it},\theta_{i}\right)+ \\
& \beta^{\overline{m}}\o^{E}\left(\Omega_{it},d_{it}^{J}=1\right)E_{\epsilon^{E},\nu}\left[\max\left\{V_{it+\overline{m}}^{U},V_{it+\overline{m}}^{E}\right\}\middle|\,\theta\Omega_{it},d_{it}^{J}=1\right]+ \\
& \beta^{\overline{m}}\o^{J}\left(\Omega_{it},d_{it}^{J}=1\right)(1-p)E_{\epsilon^{J}}\left[\max\left\{V_{it+\overline{m}}^{U},V_{it+\overline{m}}^{J}\right\}\middle|\,\theta\Omega_{it},w_{it+\overline{m}}=w_{it},d_{it}^{J}=1\right]+ \\
& \beta^{\overline{m}}\o^{J}\left(\Omega_{it},d_{it}^{J}=1\right)pE_{\epsilon^{J},\nu}\left[\max\left\{V_{it+\overline{m}}^{U},V_{it+\overline{m}}^{J}\right\}\middle|\,\theta\Omega_{it},w_{it+\overline{m}}\neq w_{it},d_{it}^{J}=1\right]+ \\
& \beta^{\overline{m}}\left[1-o^{E}\left(\Omega_{it},d_{it}^{J}=1\right)-o^{J}\left(\Omega_{it},d_{it}^{J}=1\right)\right]E\left[V_{it+\overline{m}}^{U}\middle|\,\Omega_{it},d_{it}^{J}=1\right]
\end{aligned}
$$

with a similar explanation to the one above. The value of the training option is similarly given by

$$
\begin{aligned}
V_{it}^{T} &= R^{T}\left(\Omega_{it},\Gamma_{it},\theta_{i}\right)+ \\
& \beta^{\overline{m}}o^{E}\left(\Omega_{it+1},d_{it}^{U}=1\right)E_{\epsilon^{E},\nu}\left[\max\left\{V_{it+1}^{U},V_{it+1}^{E}\right\}\middle|\,\theta,\Omega_{it},d_{it}^{U}=1\right]+ \\
& \beta^{\overline{m}}o^{J}\left(\Omega_{it+1},d_{it}^{U}=1\right)E_{\epsilon^{J},\nu}\left[\max\left\{V_{it+1}^{U},V_{it+1}^{J}\right\}\middle|\,\theta,\Omega_{it},d_{it}^{U}=1\right]+ \\
& \beta^{\overline{m}}o^{T}\left(\Omega_{it+1},d_{it}^{U}=1\right)E_{\epsilon^{o}}\left[\max\left\{V_{it+1}^{U},V_{it+1}^{T}\right\}\middle|\,\theta,\Omega_{it},d_{it}^{U}=1\right]+ \\
& \beta^{\overline{m}}\left[1-o^{E}\left(\Omega_{it+1},d_{it}^{U}=1\right)-\o^{J}\left(\Omega_{it+1},d_{it}^{U}=1\right)-\o^{T}\left(\Omega_{it+1},d_{it}^{U}=1\right)\right]E\left[V_{it+1}^{U}\middle|\,\theta,\Omega_{it},d_{it}^{U}=1\right]
\end{aligned}
$$

3.7 Dynamics of the information set

The rules governing the dynamics of the observable state variables depend on the present activity. Conditional on activity, they follow simple, deterministic rules.

Working experience is accumulated on the job only, each month in employment representing an additional period.

Eligibility to UI is determined by the variable u, which measures the remaining months of UI entitlement. u is limited by a maximum number of entitlement periods, $\overline{u}$, and is "used" while the individual is unemployed: for each period in unemployment, the individual loses entitlement to one period of UI benefits. The associated variable m defines the eligibility requirement. To first gain eligibility to the full $\overline{u}$ months of insured unemployment the individual must complete $\overline{m}$ months in regular employment. After that, full eligibility is regained by either completing a further $\overline{m}$ periods on a job or by participating in programmes for the same length of time. Since we are only considering long programme spells, lasting at least for $\overline{m}$ months, programme enrolment will always lead to full eligibility after the initial working requirement is fulfilled. Both m and u are zero at the start of working life.

Programme experience is accumulated through programme participation. We consider programme spells lasting for exactly $\overline{m}$ and split longer spells in sequences of treatments. We only consider the impact of the first treatment spell of each type.

3.8 Estimation Method

The full structural model is estimated by maximum likelihood using a nested optimisation algorithm where the inner routine solves the structural problem of the worker conditional on the model parameters and the outer routine maximises the likelihood function (see Rust, 1994, for a description of these sort of algorithms). To ensure stationarity, experience is assumed to have no impact on earnings after 20 years of work.

Unobserved heterogeneity is assumed to follow a discrete distribution. We allowed for 6 different unobserved types, resulting from a combination of 3 ability (or productivity) types and 2 preference types. Unobserved heterogeneity affects decisions through a number of dimensions, including wages, returns to experience and returns to treatment, employment and treatment offer rates and job attachment.

Because we select our sample to consist of the inflow into unemployment we have an initial conditions problem: work experience and accumulated programme participation at the point where our individuals join the sample are endogenous in the sense that they are correlated with unobserved heterogeneity. WE Deal with this problem by specifying a reduced form model for the initial conditions, which are a function of the same unobservables. The full likelihood function can be found in appendix B.

As described in the data section above, estimation was based on a random sub-sample of 20% of the individuals in the administrative data that start an unemployment spell during 1996.

4 Estimation Results

4.1 Estimated parameters

The model is fully described by a total of 40 parameters and all the estimates are presented in appendix A. Here we provide a brief description of some of the more meaningful parameters.

Table 4: Unobserved heterogeneity: composition

	Heter. in preferences	
	Low taste for E	High taste for E
Ability		
low	5.14%	3.02%
medium	17.80%	58.25%
high	15.72%	0.06%

Table 4 shows the distribution of unobserved heterogeneity over the population. Over 75% of our sample is concentrated in the "medium-ability" group, with most of them having "high job attachment" In contrast, we find few people in the tails with "lower" or "higher" ability. One interpretation is that unobservable characteristics are not playing a very important role in explaining observed behaviour.

Table 5: Estimates of the wage equation

	Coefficient	% Effect on Earnings
ln(experience)	0.039	0.30% (*)
Past subsidised jobs: 1	0.001	0.12%
Past training programmes	0.000	0.00%
constant: low productivity	8.749	
constant: medium productivity	9.909	
constant: high productivity	9.558	

(*) Impact of 4 extra months of work on the wage rate of an individual with 52 months of experience. This is the sample average experience for first time participants into subsidised employment at the time of enrolment. For training spells, the average past experience is slightly higher, at about 65 months).

The estimation results for the (log) wage are presented in Table 5. In the last column of this table we compare the impact of treatment with that of 4 additional months of working experience on the wage rate of an individual with 52 months of working experience (this is the average past experience at inflow into subsidised employment for first time participants). Subsidised jobs increase wages very modestly, for about 0.12%, amounting to less than half the impact of spending the same time employed in regular jobs at the same level of experience (0.3%), suggesting that the nature of these jobs is different from regular employment, possibly contributing less to human capital formation. Training has virtually no effect on wages.

In contrast with the results in column (1) of table 3, estimates of the wage equation within the model accounting for the full selection process show much smaller effects of working experience and both types of treatment on the wage rates. This seems to support the view that enrollment into treatment and employment is related to unobserved characteristics such as ability. Treatment effects on wages under the structural selection specification are also smaller than the fixed effects estimates in column (3) of the same table. This evidence suggests the treatment affects the selection mechanism into work: under the Swedish system, programme participation renews eligibility to UI, raising the reservation wage for the treated and consequently delaying entrance into employment.

Table 6: Estimates of offer rates

		Activity in period $t-1$				
		Unemployment				
		not treated	treated: sub. job	treated: training	Sub. empl.	Training
		(1)	(2)	(3)	(4)	(5)
		Job offer rates				
(1)	Residence: city	17.5%	15.9%	18.5%	35.2%	18.8%
(2)	Residence: rural	20.4%	18.7%	21.5%	39.6%	21.9%
(3)	Residence: other	18.2%	16.6%	19.2%	36.3%	19.6%
		Subsidised employment offer rates				
(4)	Residence: city	0.8%	0.3%	1.3%	15.9%	3.6%
(5)	Residence: rural	1.1%	0.5%	2.0%	20.1%	5.2%
(6)	Residence: other	0.8%	0.3%	1.3%	15.8%	3.6%
		Training offer rates				
(7)	Residence: city	4.8%	4.9%	11.5%	-	77.6%
(8)	Residence: rural	6.1%	6.3%	14.2%	-	73.0%
(9)	Residence: other	5.0%	5.1%	11.9%	-	76.8%

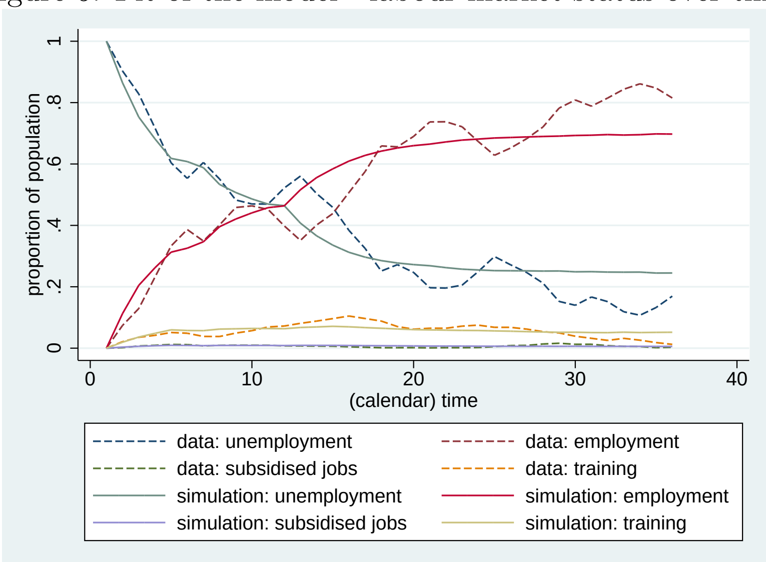
Table 6 presents estimates of job and treatment offer rates under alternative circumstances depending on previous activity, whether or not the individual has been in a programme in the past and region of residence.

Activity in period $t-1$ has a very strong effect on offer rates. In particular, having a subsidised job spell more than doubles the odds of being offered a job in the next period, probably reflecting a transformation of the subsidised job into regular employment. However, having had subidised jobs in the past does not seem to help job search. On the contrary, it has a negative impact on job offer rates, suggesting it might give a bad signal to potential employers. Training does not seem to affect offer rates other than those of training: past training spells make training offers more likely to arrive (column (3), rows (7)-(9)) while having been in training at $t-1$ makes it very probable to be able to continue(column 5).

4.2 Fit of the model

In this section we show some evidence on the fit of the model along with a discussion of the directly observable patterns of the data. In assessing the fit we use the distribution of initial conditions in our sample and simulate the individual decisions throughout the observable period. Each individual is simulated 30 times. We then compare the patterns created by the simulated data with what is observed in the real data.

Figure 5: Fit of the model - labour market status over time



Rows (5) and (10) in table 7 show the proportion of observations falling in each state and,

Table 7: Fit of Model - transitions between labour market states

		U	E	S	T
Real Data:					
(1)	unemployment (U)	0.781	0.177	0.005	0.038
(2)	employment (E)	0.064	0.936	0.000	0.000
(3)	subsidised job (S)	0.133	0.084	0.783	0.000
(4)	training (T)	0.142	0.039	0.003	0.826
(5)	*total*	*0.320*	*0.610*	*0.007*	*0.063*
Simulated Data:					
(6)	unemployment (U)	0.785	0.174	0.005	0.036
(7)	employment (E)	0.066	0.934	0.000	0.000
(8)	subsidised job (S)	0.133	0.080	0.787	0.000
(9)	training (T)	0.139	0.041	0.003	0.817
(10)	*total*	*0.325*	*0.607*	*0.008*	*0.060*

as expected, the simulations reproduce observable data very closely. This is confirmed in figure 5, which presents the proportion of individuals in each state over time from the moment of sample inflow. The doted and full lines stand for simulated and real data, respectively. The simulated data seems to reproduce the average evolution of labour market status quite closely but fails to capture the seasonal patterns (the current version of the estimates does not allow for seasonal variation).

Another particularly important feature is the pattern of transitions between different states. The remaining rows in table 7 present the data (rows (1) to (4) and model (rows (6) to (9)) transition rates. Again, the simulated patterns are very closed to the observed ones.

Figures 6 and 7 compare data and model regarding the rates of inflow into treatment and employment by remaining months of eligibility to unemployment benefit. While we are able

Figure 6: Fit of the model - Transitions into treatment by remaining eligibility time

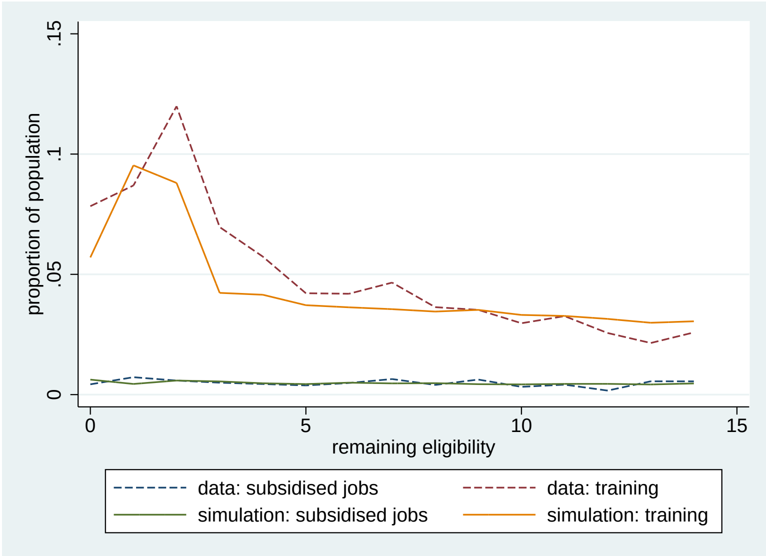
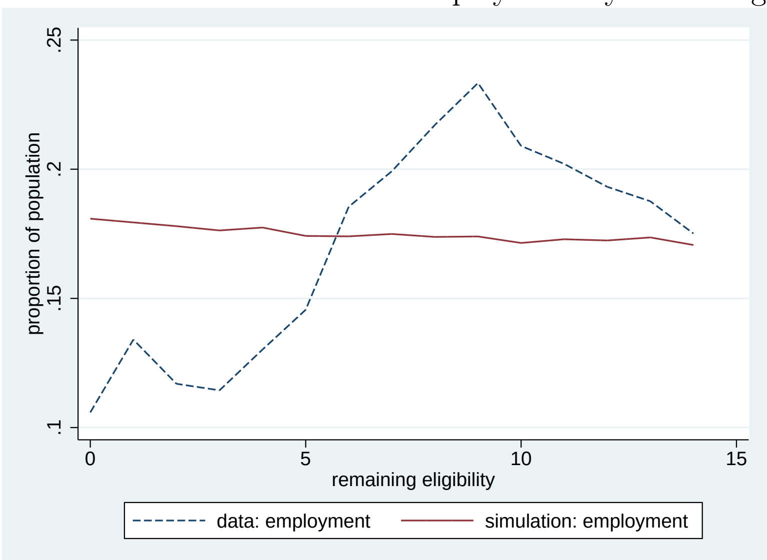
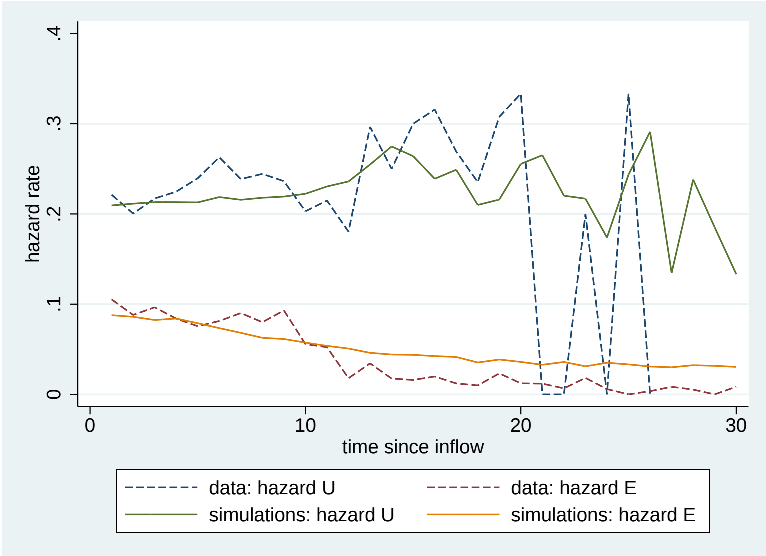


Figure 7: Fit of the model - Transitions into employment by remaining eligibility time



to reproduce the inflows into treatment quite closely, the model does very badly in accounting for the inflows into employment. Instead of the generally upward sloping curve displayed by the data, which suggests compositional changes in the pool of unemployment by eligibility

Figure 8: Fit of the model - Hazard rates from employment and unemployment



time, the model captures a slightly downward curve due to the increasing costs of remaining unemployed as eligibility approaches exhaustion. This means that heterogeneity related with job attachment is not enough to counteract the change in the relative value of unemployment due to exhaustion of the benefit. This aspect of the model requires more careful attention in future work.

Instead, heterogeneity related to job attachment is much more effective in capturing duration dependence on the job. Figure 8 shows that the evolution of the hazard rates from both employment and unemployment are captured quite well by the model.

Tables 8 and 9 show how close the model reproduces the data on wages. Table 8 shows that the distribution of the wage rates among workers is very close in the two datasets. Table **??** then assesses the correlation between wage rates among the employed and different individual characteristics. The results are very similar in the actual and simulated data although the size of the correlation between training programmes and wages is significantly larger in the data than in the model.

Table 8: Fit of the Model - Distribution of the logarithm of observed wages

	Data	Model
Mean	9.68	9.69
St. deviation	0.42	0.52
Percentile:		
1	8.00	8.35
5	8.92	8.81
25	9.57	9.36
50	9.72	9.71
75	9.89	10.04
95	10.24	10.53
99	10.62	10.89

Table 9: Fit of the Model - (Log) Wage equations

	Data		Model	
	Coefficient	Std. Error	Coefficient	Std. Error
log(experience)	0.024	0.001	0.023	0.002
Past Job Subsidy	0.012	0.002	0.016	0.002
Past Training	-0.012	0.001	-0.003	0.001
Constant	9.596	0.006	9.605	0.007

4.3 Effects of treatment

Using our model estimates, we can now simulate the impact of programme participation on individual outcomes. We compute both the average treatment effect (ATE) and the average effect of treatment on the treated (ATT). The ATE compares the regular path of individuals through unemployment and potential subsequent employment with what they would have done had they been forcefully assigned to treatment at inflow in our sample, when they start a new unemployment spell. This is done separately for subsidised employment and training. The ATT compares the life paths of individuals joining their first treatment spell within the first 2 years in the sample while still on their first unemployment spell (the treated) with what they would have done if (artificially) deterred from enroling in that first instance of treatment (the controls). This treated group is similar to the one used to plot the impact of treatment on the duration of unemployment and subsequent employment spells as displayed in figures 3 and 4. For both the ATE and the ATT, we then simulate individuals choices over the next 3 years in both treatment scenarios (being and not being treated) and compute the effects by comparing treated and controls. The effects arise as a combination of impacts of treatment in productivity levels, job offer rates and a change in the returns to unemployment due to the way treatment affects eligibility to unemployment benefits.

Table 10: Impact of treatment on income and activity over the 3 years after treatment

		Average Treatment Effect		Average Treatment on the Treated	
		Subsidised job	Training	Subsidised job	Training
(1)	Income	-0.8%	-1.1%	+1.3%	+0.4%
(2)	Time in employment	-0.2%	-4.8%	+0.2%	-2.7%
(3)	Time in subsidised jobs	+0.7%	+0.2%	+0.5%	+0.1%
(4)	Time in training	-0.6%	+2.2%	-0.5%	+1.2%

The first two columns of Table 10 display the ATE on income and activity over the 3 years that follow completion of treatment. Both programmes have a negative effect on wages, especially training with a decrease of 1.1%. Training also substantially decreases time in employment (of a magnitude of about 5%). This arises partly because training induces individuals to participate in further training and subsidised employment programmes and partly because it raises time in unemployment. On the other hand, a subsidised employment spell leads to less training programmes and further spells of subsidised employment, most likely with the same employer, as these spells frequently last for longer than a period of 4 months, the minimum period defined in our model.

These effects are less positive than the comparable ATT effects presented in the last two columns in table 10. This shows that the treated are not a random sample of the population. Instead, selection on future gains seems to play a role on the participation decision and the returns from treatment are not homogeneous. This seems to be true for both programmes. We now investigate the extent of the selection mechanism.

4.4 Average effects of treatment on the treated: unobserved heterogeneity

Table 11 presents the proportion of individuals in each programme by unobserved heterogeneity types. Participation in subsidised employment seems to be independent of type and driven mainly by the availability of places. On the contrary, enrolment into training is more frequent among individuals who have a relatively low taste for employment but is not affected by productivity levels.

Table 12 displays the ATT by types of unobserved heterogeneity. All types of individuals benefit from treatment in terms of income but these effects arise through different channels depending on the individual's characteristics and type of treatment.

Subsidised employment leads individuals with lower taste for employment to reduce future employment participation and gains arise essentially from the prolonged eligibility to unemployment insurance and improved chances of further subsidised employment spells. Individuals with higher taste for employment increase future time in regular and subsidised employment

Table 11: Selection into treatment by unobserved heterogeneity - proportion of treated in group

		Low taste for E			High taste for E		
		Ability			Ability		
	All	low	medium	high	low	medium	high
% in Subsidised job	2.2%	2.0%	1.9%	2.2%	2.6%	2.2%	0.0%
% in Training	15.7%	21.8%	22.5%	22.3%	10.7%	11.6%	10.5%

by over 1% of their time over the following three years (or about 11 days), independently of productivity level and this is the main source of additional income. In both cases, future take up of training is reduced as this is mostly a substitute for subsidised employment in the attempt to prolong eligibility to unemployment benefits.

In contrast, training has a smaller but still positive impact on future income, of about 0.4% (row (2)). If we break up this impact by remaining eligibility time, the impact is larger, at about 1.6%, for individuals within six months of benefit exhaustion but is negative, about -0.5%, for individuals farther away from exhaustion. Individuals with higher taste for employment are less likely to participate in training programmes and they also benefit less in terms of future income. The four months of training are more costly for them as they are more likely to miss acceptable job opportunities than individuals with lower taste for employment. Participation in training has also a strong effect on further treatment take up, particularly training, suggesting the scheme induces individuals to cycle between unemployment and treatment.

To better understand the impact of treatment on time allocation we plot its evolution over time. Figure 9 shows the impact of treatment on employment probabilities over time. There are very strong negative effects of both types of treatment immediately after enrolment, the lock-in effect. But as treatment finishes, individuals in subsidised employment flow into regular

Table 12: Heterogeneity in the impact of treatment on the treated over the 3 years after treatment

			Low taste for E			High taste for E		
				Ability			Ability	
		All	low	medium	high	low	medium	high
Impact on income								
(1)	job subsidy	+1.3%	+3.7%	+0.6%	+0.7%	+0.2%	+1.7%	-
(2)	training	+0.4%	+1.1%	+0.7%	+0.3%	-0.1%	+0.2%	+3.3%
Impact on time in employment after treatment								
(3)	job subsidy	+0.2%	-0.4%	-0.3%	-0.3%	+0.5%	+0.5%	-
(4)	training	-2.7%	-1.7%	-2.2%	-2.1%	-3.4%	-3.5%	-8.3%
Impact on time in subsidised employment after treatment								
(5)	job subsidy	+0.5%	+1.2%	+0.4%	+0.3%	+0.7%	+0.6%	-
(6)	training	+0.1%	+0.1%	+0.1%	+0.1%	+0.2%	+0.2%	0.0%
Impact on time in training after treatment								
(7)	job subsidy	-0.5%	-0.9%	+0.4%	-0.6%	-0.2%	-0.7%	-
(8)	training	+1.2%	+1.4%	+1.6%	+1.4%	+1.2%	+0.8%	+6.7%

employment very fast and become more likely to be employed after 1 year of enrolment. The recovery from the lock-in effect is much slower for individuals in training and they are always less likely to be employed in the future than if they had not participated in the training programme. As training raises the value of unemployment but does not change the value of employment, it will lead individuals to remain out of work for longer.

Figures 10 to 12 show how the duration of unemployment and employment spells are affected by treatment. Figure 10 plots the remaining duration if the first unemployment spell after enrollment into treatment. The graph displays the behaviour of treated and comparable

Figure 9: Re-employment probabilities over time after treatment

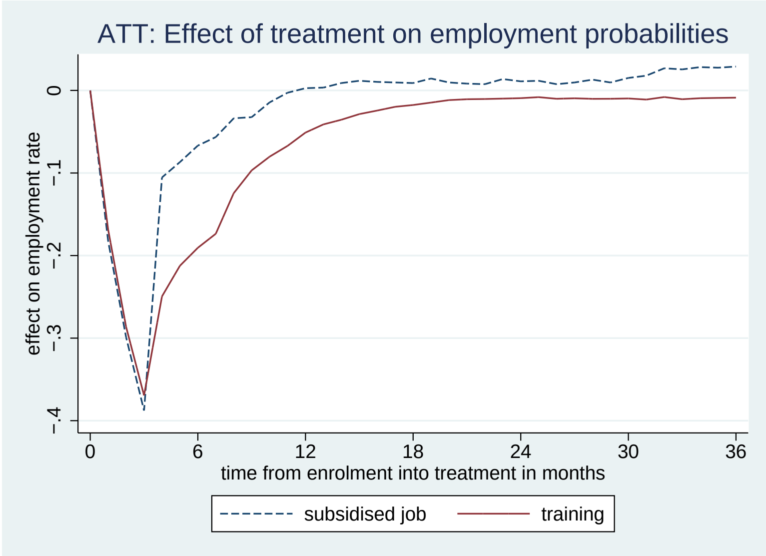
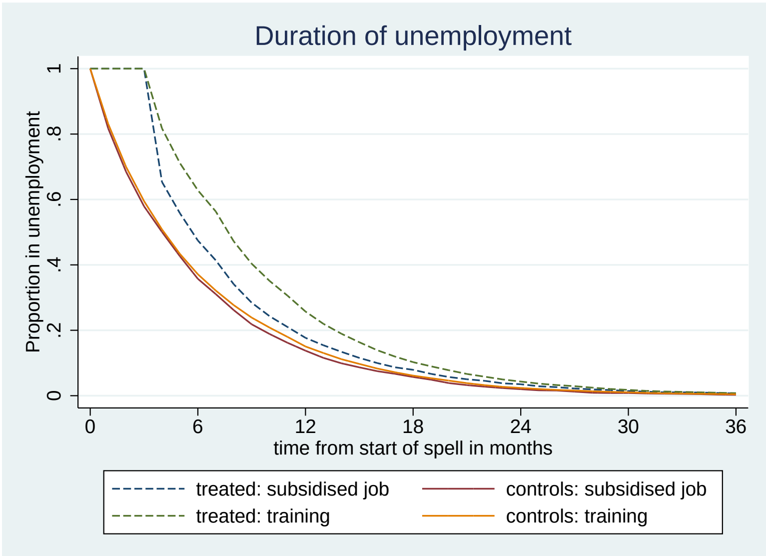


Figure 10: Duration of unemployment from time of enrolment into treatment by type of treatment: comparison between treated and controls



controls. It shows that both types of treatment have a positive impact on the duration of unemployment. In the case of subsidised jobs, the increased speed at which treated move into

Figure 11: Duration of first employment spell after treatment by type of treatment: comparison between treated and controls

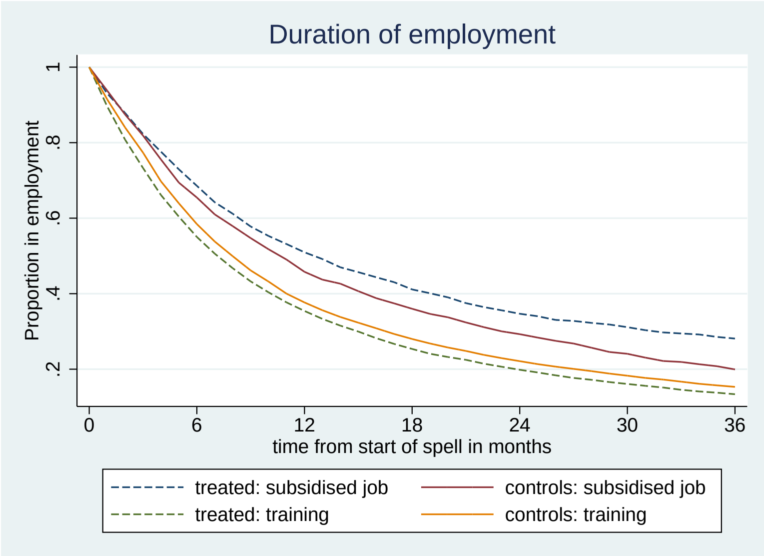
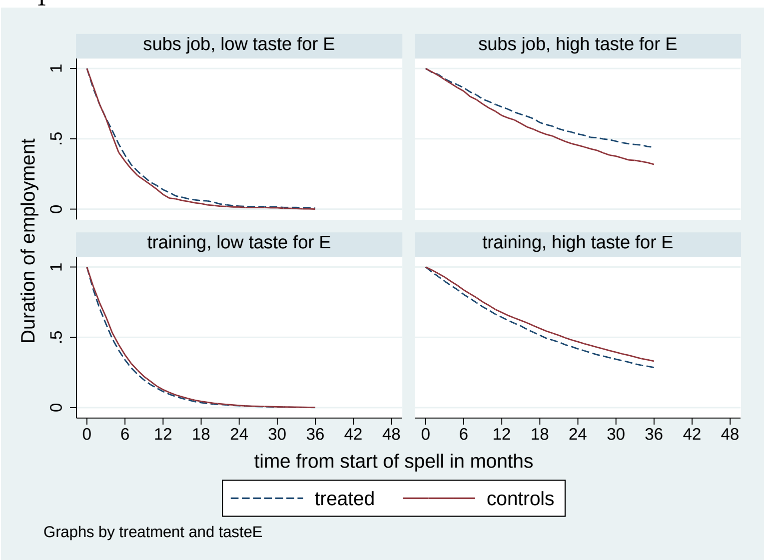


Figure 12: Duration of first employment spell after treatment by type of treatment and taste for employment: comparison between treated and controls



jobs is not enough to compensate for the lock-in effect of treatment. Training, however, if anything has a zero effect on the speed at which unemployed find jobs, thus further prolonging time out of work. On average, treated taking subsidised jobs experience an out-of-employment spell 2.1 months longer than had they not been treated. The similar figure to training is 3.4 months.

Figures 11 and 12 compare the duration of the first employment spells after treatment for individuals that find jobs in both scenarios, depending on whether or not they have been treated. Compared to participants in training programmes, the figures show that participants in subsidised employment have a stronger job attachment and enjoy a positive impact of treatment on job attachment, explaining the positive effect on time in employment identified in table 10. However, the effect of subsidised employment on job attachment is not homogeneous. Figure 12 shows that it is very positive among individuals with the highest job attachment, who are over 6% more likely to remain employed after 1 year of finding a job, but is nil for other individuals, who benefit from participation mainly through its effect on eligibility time and additional chances of participation in subsidised employment. In its turn, training seems to have a small negative effect on job attachment for the same group that seems to benefit more from subsidised employment. Driving this effect are the zero returns to productivity of training and the higher value of unemployment due to renewed eligibility to unemployment insurance.

4.5 Average effects of treatment on the treated: observed characteristics

The results above show that the impact of treatment is heterogeneous and selection on unobserved gains is important (although not so much for subsidised employment, maybe because it is in such low offer). However, these are not very useful for the policy maker, who cannot observe unobservable types and therefore, cannot target interventions more effectively. We now discuss how selection and treatment affects vary with observable characteristics.

Table 13: Selection into treatment by observable characteristics - proportion of treated in group

		% in subsidised employment	% in training
By experience at inflow			
(1)	lowest quartile	2.7%	18.7%
(2)	2nd quartile	2.4%	16.3%
(3)	3rd quartile	1.9%	14.6%
(4)	highest quartile	1.6%	13.1%
By duration of unemployment up to enrolment			
(5)	less than 5 months	1.4%	9.8%
(6)	6 to 12 months	11.7%	88.3%
(7)	over 12 months	8.6%	91.1%
Total		2.2%	15.7%

Table 13 shows how treatment take-up changes with work experience and duration of unemployment. Individuals with higher levels of experience and shorter unemployment durations are less likely to participate. This is particularly the case among individuals who participate in training. Rows (6) and (7) shows the extent to which training is used to renew eligibility to unemployment benefits.

Tables 14 and 15 display the impact of treatment by past experience and duration of the unemployment spell. The first two rows in table 14 show that, although less likely to participate, individuals with high experience that end up in subsidised employment benefit both in terms of income and employment. Experience is positively related with job attachment and productivity, and these positive impacts are partly a consequence of such compositional differences. On the contrary, the impact of training is more negative among high-experience

Table 14: Impact of treatment on the treated over the 3 years after treatment - by working experience at enrolment

		Outcome variable			
		Income	time in E	time in J	time in T
Impact of subsidised employment					
(1)	low experience	+1.5%	+0.1%	+0.7%	-1.0%
(2)	high experience	+4.0%	+0.3%	+0.6%	-0.3%
Impact of training					
(3)	low experience	+0.7%	-2.3%	+0.1%	+0.8%
(4)	high experience	-0.1%	-3.7%	+0.2%	+2.3%

Notes: Experience is measured at inflow in data. "Low experience" corresponds to the first quartile in the distribution of experience. "High experience" corresponds to the 4th quartile in the distribution of experience.

Table 15: Impact of treatment on the treated over the 3 years after treatment - by duration of unemployment until enrolment

		Outcome variable			
		Income	time in E	time in J	time in T
Impact of subsidised employment					
(1)	duration of U: below 6 months	+0.9%	+0.3%	+0.7%	-0.3%
(2)	duration of U: above 12 months	+3.5%	-0.1%	+0.8%	-0.6%
Impact of training					
(3)	duration of U: below 6 months	-0.1%	-2.7%	+0.1%	+1.1%
(4)	duration of U: above 12 months	+2.3%	-3.3%	+0.2%	+1.4%

individuals, who have higher foregone earnings and higher odds of missing acceptable job offers while in training.

Table 15 shows how treatment effects vary with duration of unemployment until enrolment. The time of participation is a consequence of individual choices, being determined by other individual characteristics that will affect treatment outcomes. For both training and subsidised employment, income gains are very pronounced for individuals who decide to participate only after 1 year of unemployment. This is a consequence of the institutional rules, which allow individuals to re-gain access to unemployment compensation through participation. However, these individuals lose in terms of time in employment, partly at the expense of further treatment, a reflection of the compositional changes in the unemployment pool in terms of job attachment as unemployment duration increases.

5 The impact of alternative policies

In this final section we experiment with two alternative policy scenarios and compare them to the one in operation at the time represented in the data and the alternative of having no available treatments while unemployed. The first alternative policy (*policy 1*) removes the link between UI eligibility and programme participation. In this case, only regular employment can lead one to regain access to fully subsidised unemployment. The second policy alternative (*policy 2*) sanctions the refusal to participation in an offered treatment by cutting eligibility to unemployment compensation until the individual regains eligibility through treatment or employment. We denote by *baseline* the scenario where no treatment is available and by *current policy* the scenario used in estimation characterised by both treatments being available, the possibility to renew eligibility through treatment and the absence of sanctions.

To construct the data we use the initial distribution of observable characteristics from the data and simulate the labour market behavior of these individuals for three years from inflow.

In all cases we compute the additional cost per capita of providing treatment as compared to a baseline where only unemployment benefits are available. Our estimates of the costs of unemployment include the income paid to individuals while out of work and the cost of programmes as reported in Carling and Richardson (2001). We then simulate the effect of the different scenarios on labour market outcomes under the assumption that the required additional funding to support the alternative policies comes from sources other than the tax payments of the target group.

Table 16: Effects of alternative policies on outcomes over the first 3 years after inflow

			Effects of alternative policies		
		Baseline	Current policy	Policy 1: no renew	Policy 2: sanction
(1)	Time in unemployment	33.5%	-1.05%	-1.82%	-4.63%
(2)	Time in employment	66.5%	-5.33%	-3.69%	-2.44%
(3)	Utility	110.4(**)	+1.33%	+0.89%	-2.62%
(4)	Income	579.9(*)	-0.53%	-0.88%	-5.18%
(5)	Income from employment	447.4(*)	-8.32%	-5.77%	-4.05%
(6)	Programme costs	132.5(*)	+31.45%	+20.32%	-2.91%

(*) Values in 1000s SEK and are per capita over the 3 years.
(**) Accumulated utility over the 3 years.

Table 16 shows how the three alternative policies compare with the scenario where no treatment is available. All policies imply less unemployment *and* less employment, with the difference being taken up by programmes. However, it is quite clear that in this respect the policy that reduces employment most is the *current* policy. The removal of the link between eligibility and the sanctions increase employment relative to the current policy.

Both the current policy and policy 1 have positive effects on the well-being of these individuals (row (3)) despite the reduction in income(row (4)). The reduction in earnings (row (5)) is compensated from an increase in subsidies. The reason for the increase in welfare may be due to the reduction in income volatility - our individuals are risk averse with a log utility.

Row (6) displays the change in government costs to support the change in policy. These include direct costs with unemployment benefits and the provision of treatment but not changes in revenue due to changes in employment choices and, therefore, due taxes on income. The second and third columns in row (6) show that making treatment available is very expensive, increasing expenses with unemployment compensation and provision of treatment by up to 30% (the impact would be even more negative if we account for losses in revenue due to decreased taxable income). However, excluding the possibility of renewing eligibility through programme participation allows for important savings as compared with the current policy without substantially affecting wellbeing or income.

The introduction of sanctions reduces utility and income much more dramatically because it induces very short subsidised unemployment spells. Employment income is higher rlative to the other two policy alternatives. As a consequence of the substantial reductions in transfers to the unemployed, the introduction of sanctions could actually lead to government savings as compared to the baseline scenario. This, however, is at the expense of large losses in welfare and income for this group.

Figure shows that the reduction in employment rates due to the availability of treatment is persistent over time, particularly for the current policy and policy 1. Out-of-work rates under policy 2 seem to catch up with those of the baseline as unemployment becomes much less attractive under this policy. The strong penalty that sanctions impose on unemployment is confirmed in figure 14, which shows that policy 2 is the only one to positively affect the duration of employment as compared to the baseline.

Figure 13: Out of employment rates over time

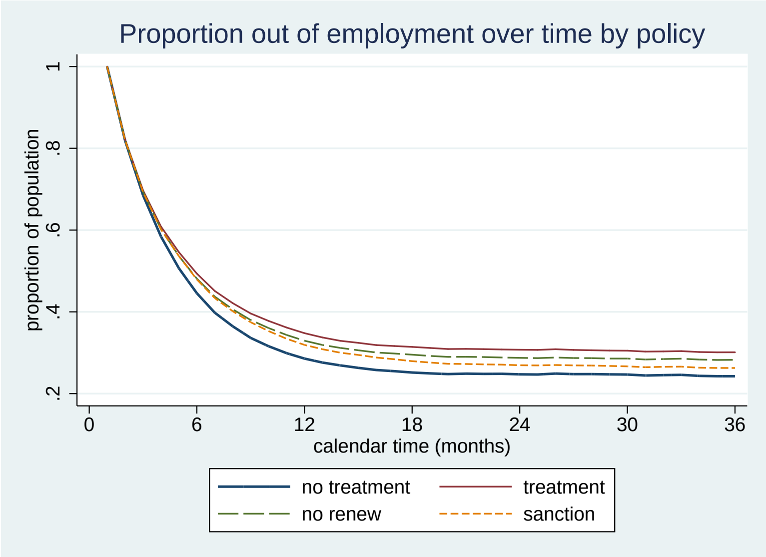
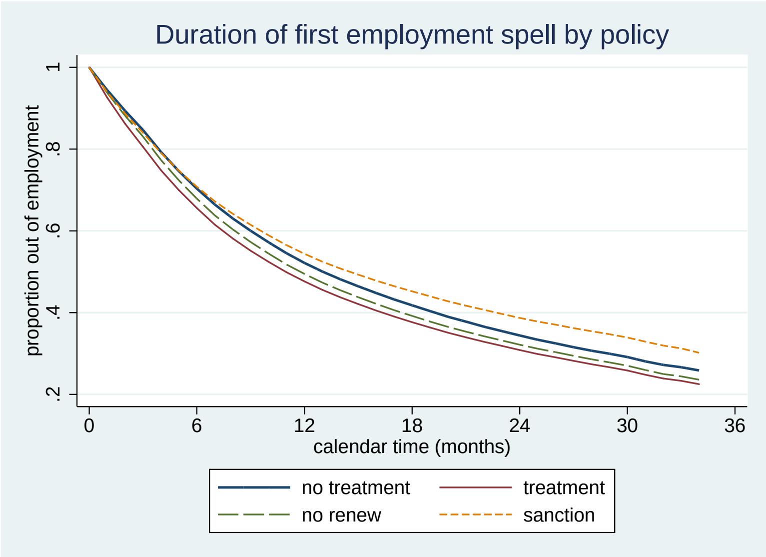


Figure 14: Duration of employment spells



6 Conclusion

In this paper we have built a model of programme participation and labour market transitions so as to capture the essential elements of the Swedish programmes, as they operated in the mid 90s. Our model also accounts for UI eligibility and how this relates both to work and programme spells. Contrary to earlier evaluations our model captures all the important dynamic interactions and considers both short term and longer term outcomes including wages. Questions we consider include the effectiveness of job training programmes and subsidised job placements in reducing unemployment, improving job attachment and increasing earnings. To achieve this we model transitions between unemployment, programmes and work, jointly with wages for a cohort of individuals who became unemployed in 1996. The model is of the dynamic discrete choice forward looking type and is estimated on a rich administrative data source which we put together for this purpose with the help of the IFAU in Sweden.

Our results are sobering. The current policy reduces employment quite substantially by increasing programme participation (including subsidised jobs). There is practically no effect on wages - training leaves them unchanged, while a spell in subsidised employment has a third of the effect on wages than does a normal job. However the current programme, despite the decline in income does seem to increase welfare; the reason for this is likely to be the reduction in income volatility.

A substantial improvement over the current policy is obtained if programmes cannot be used to renew eligibility for unemployment insurance: while the positive welfare gains are maintained there is a substantial increase in employment, relative to the current programme. Further increases in employment, but this time at the expense of a decline in overall welfare for this group can be achieved by imposing sanctions on those who refuse to participate in a programme.

The results seem to show that the programme component of the Swedish active labour market system is at best a costly and ineffective approach. The insurance element of the system seems important for welfare purposes. The large costs of the programme would seem to be better spent on other interventions. One element of the programmes that could perhaps be thought useful are subsidised placements. So if anything, the training component should be reduced and the subsidy programmes expanded, with some of the funds channelled to firms so they can ensure they train workers in an effective way.

Appendix A: Estimates

Tables 17 and 18 present the full set of estimated parameter of the model together with the respective standard errors.

Appendix B: Likelihood function

The contribution to the likelihood of each type of transition conditional on unobserved heterogeneity is described below. In the end, we set up the overall liklihood function.

Let $\widetilde{V_{it}^E}$ be the present value of the employment option for individual i at time t excluding the contemporary transitory taste shock. Thus, $\widetilde{V_{it}^E} = V_{it}^E - \epsilon_{it}^E$. Similarly define $\widetilde{V_{it}^J} = V_{it}^J - \epsilon_{it}^J$ and $\widetilde{V_{it}^T} = V_{it}^T - \epsilon_{it}^T$. For ease of notation, we omit the arguments from the value functions in what follows, namely $(\Omega_{it}, \Gamma_{it}, \theta_i)$. However, for clarity we include the productivity shock when relevant. Finally, let L_{it} be the contribution to the likelihood of the transition observed between period $t-1$ and t for individual i.

Transitions from employment into employment

- If there is no innovation the wage in period t is the same as in period $t-1$ and the productivity shock ν_{it} is such that $w_{it} = w_{it-1}$. Let $\widetilde{V}^E$ be evaluated at such point and denote it by $\widetilde{V}_{it}^E(\nu_{it} : w_{it} = w_{it-1})$. Then the contribution to the likelihood function is,

$$L_{it} = (1-p)\left[1 - \Phi\left(\frac{V_{it}^U - \widetilde{V}_{it}^E(\nu_{it} : w_{it} = w_{it-1})}{\sigma_E}\right)\right]$$

- If there is an innovation then the new productivity shock ν is drawn from the distribution $\mathcal{N}(0, \sigma_1)$. Let $\widetilde{V}^E$ be evaluated at the drawn innovation and denote it by $\widetilde{V}^E_{it}(\nu_{it})$. Then the contribution to the likelihood function is,

$$L_{it} = p\left[1 - \Phi\left(\frac{V^U_{it} - \widetilde{V}^E_{it}(\nu_{it})}{\sigma_E}\right)\right]\phi\left(\frac{\nu_{it}}{\sigma_1}\right)\frac{1}{\sigma_1}$$

Transitions from employment into unemployment The contribution to the likelihood in this case weights the two possibilities: having or not experienced a wage innovation. Using the same notation as above,

$$\begin{aligned} L_{it} &= (1-p)\Phi\left(\frac{V^U_{it} - \widetilde{V}^E_{it}(\nu_{it} : w_{it} = w_{it-1})}{\sigma_E}\right) + \\ & p\int_{-\infty}^{+\infty}\Phi\left(\frac{V^U_{it} - \widetilde{V}^E_{it}(\nu)}{\sigma_E}\right)\phi\left(\frac{\nu}{\sigma_1}\right)\frac{1}{\sigma_1}d\nu \end{aligned}$$

Transitions from subsidised employment into employment We assume there is always an innovation in this case, which is consistent with the data. We use the same notation as above. We also omit the arguments from the offer rates for simplicity of notation except for the previous labour market status,

$$L_{it} = o^E_{it}\left(d^J_{it-1} = 1\right)p\left[1 - \Phi\left(\frac{V^U_{it} - \widetilde{V}^E_{it}(\nu_{it})}{\sigma_E}\right)\right]\phi\left(\frac{\nu_{it}}{\sigma_1}\right)\frac{1}{\sigma_1}$$

Transitions from subsidised employment into subsidised employment Again, there are two possibilities depending on whether there is an innovation. However, there is never an innovation in the data so we consider the case of no innovation only. We use a similar notation to the explained above.

$$L_{it} = o^J_{it}\left(d^J_{it-1} = 1\right)(1-p)\left[1 - \Phi\left(\frac{V^U_{it} - \widetilde{V}^J_{it}(\nu_{it} : w_{it} = w_{it-1})}{\sigma_J}\right)\right]$$

Transitions from subsidised employment into unemployment In this case we consider the possibility of having or not received a wage innovation if another instance of subsidised employment is offered (and rejected),

$$\begin{aligned}
L_{it} \;=\; & o^E_{it}\left(d^J_{it-1}=1\right) p \int_{-\infty}^{+\infty} \Phi\left(\frac{V^U_{it}-\widetilde{V}^E_{it}(\nu)}{\sigma_E}\right)\phi\left(\frac{\nu}{\sigma_1}\right)\frac{1}{\sigma_1}d\nu + \\
& o^J_{it}\left(d^J_{it-1}=1\right)(1-p)\Phi\left(\frac{V^U_{it}-\widetilde{V}^J_{it}(\nu_{it}:w_{it}=w_{it-1})}{\sigma_J}\right) + \\
& o^J_{it}\left(d^J_{it-1}=1\right) p \int_{-\infty}^{+\infty} \Phi\left(\frac{V^U_{it}-\widetilde{V}^J_{it}(\nu)}{\sigma_J}\right)\phi\left(\frac{\nu}{\sigma_1}\right)\frac{1}{\sigma_1}d\nu + \\
& \left(1-o^E_{it}\left(d^J_{it-1}=1\right)-o^J_{it}\left(d^J_{it-1}=1\right)\right)
\end{aligned}$$

Transitions from training or unemployment into employment Let l denote the labour market status in period $t-1$, either training T or unemployment U. In this case, transitions to employment can only occur if there is an offer and this is a draw from the wage distribution determined by the productivity shocks following a distribution $\mathcal{N}(0,\sigma_0)$. Transitions into employment make the following contribution to the likelihood function,

$$L_{it} = o^E_{it}\left(d^l_{it-1}=1\right)\left[1-\Phi\left(\frac{V^U_{it}-\widetilde{V}^E_{it}(\nu_{it})}{\sigma_E}\right)\right]\phi\left(\frac{\nu_{it}}{\sigma_0}\right)\frac{1}{\sigma_0}$$

Transitions from training or unemployment into subsidised employment Following the same notation as above,

$$L_{it} = o^J_{it}\left(d^l_{it-1}=1\right)\left[1-\Phi\left(\frac{V^U_{it}-\widetilde{V}^J_{it}(\nu_{it})}{\sigma_J}\right)\right]\phi\left(\frac{\nu_{it}}{\sigma_0}\right)\frac{1}{\sigma_0}$$

Transitions from training or unemployment into training These are also conditional on receiving an offer,

$$L_{it} = o^T_{it}\left(d^l_{it-1}=1\right)\left[1-\Phi\left(\frac{V^U_{it}-\widetilde{V}^T_{it}}{\sigma_T}\right)\right]$$

Transitions from training or unemployment into unemployment Following the same notation as before,

$$\begin{aligned}
L_{it} &= o^E_{it}\left(d^l_{it-1}=1\right)\int_{-\infty}^{+\infty}\Phi\left(\frac{V^U_{it}-\widetilde{V}^E_{it}(\nu)}{\sigma_E}\right)\phi\left(\frac{\nu}{\sigma_0}\right)\frac{1}{\sigma_0}d\nu + \\
&\quad o^J_{it}\left(d^l_{it-1}=1\right)\int_{-\infty}^{+\infty}\Phi\left(\frac{V^U_{it}-\widetilde{V}^J_{it}(\nu)}{\sigma_J}\right)\phi\left(\frac{\nu}{\sigma_0}\right)\frac{1}{\sigma_0}d\nu + \\
&\quad o^T_{it}\left(d^l_{it-1}=1\right)\Phi\left(\frac{V^U_{it}-\widetilde{V}^T_{it}}{\sigma_T}\right) + \\
&\quad \left(1-o^E_{it}\left(d^l_{it-1}=1\right)-o^J_{it}\left(d^l_{it-1}=1\right)-o^T_{it}\left(d^l_{it-1}=1\right)\right)
\end{aligned}$$

Overall likelihood The overall likelihood for the conditional sample of individuals entering unemployment at time $t=1$ is

$$L = \prod_{i=1}^{N}\int_{\theta\in\Theta}\prod_{t=2}^{T}\prod_{l=U,E,J,T}\left[\begin{array}{l} P\left[d_{it}=l|\Omega_{it},\Gamma_{it},d_{it-1},\theta\right]^{\mathbf{1}(d_{it}=l)} * \\ f_{\Omega_t|\Omega_{t-1},d_{t-1},\theta}\left(\Omega_{it}|\Omega_{it-1},d_{it-1},\theta\right) * f_{\Gamma_t|\Gamma_{t-1},d_{t-1},\theta}\left(\Gamma_{it}|\Gamma_{it-1},d_{it-1},\theta\right) * \\ f_{\Omega_1|d_0,d_1,\theta}\left(\Omega_{i1}|d_{i0}=E,d_{i1}=U,\theta\right) * f_{\theta|d_0,d_1}\left(\theta|d_{i0}=E,d_{i1}=U\right) \end{array}\right]d\theta$$

In the present case we consider a discrete distribution for the unobserved heterogeneity. This means that the integral in the above expression can be replace by a summation. At this stage we are also taking the initial conditions as exogeneous so that $f_{\Omega_1|d_0,d_1,\theta}\left(\Omega_{i1}|d_{i0}=E,d_{i1}=U,\theta\right)$ is not included in the likelihood function. We also consider a deterministic evolution of the observable variables conditional on the previous period information, so $f_{\Omega_t|\Omega_{t-1},d_{t-1},\theta}\left(\Omega_{it}|\Omega_{it-1},d_{it-1},\theta\right)$ is also excluded. So the likelihood function simplifies to,

$$L = \prod_{i=1}^{N}\int_{\theta\in\Theta}\prod_{t=2}^{T}\prod_{l=U,E,J,T}\left[\begin{array}{l} P\left[d_{it}=l|\Omega_{it},\Gamma_{it},d_{it-1},\theta\right]^{\mathbf{1}(d_{it}=l)} * \\ f_{\Gamma_t|\Gamma_{t-1},d_{t-1},\theta}\left(\Gamma_{it}|\Gamma_{it-1},d_{it-1},\theta\right) * \\ f_{\theta|d_0,d_1}\left(\theta|d_{i0}=E,d_{i1}=U\right) \end{array}\right]d\theta$$

where the product of the first two terms is the L_{it} functions defined above.

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Table 17: Parameter estimates

	estimates	st. errors
Wage equation		
intercept: low productivity	8.749	0.010
intercept: medium productivity	9.558	0.010
intercept: high productivity	9.909	0.010
log experience	0.039	0.001
previous subsidised employment	0.001	0.001
previous training	0.000	0.000
Unobserved heterogeneity: tastes for employment		
low taste for employment(*)	53.610	102.692
high taste for employment(*)	136.730	469.323
Job offers		
previous labour market status: unempl.	-1.552	0.001
previous labour market status: subs. empl.	-0.504	0.065
previous labour market status: training	-1.531	0.011
region 1: rural	0.188	0.001
region 2: other (not city or rural)	0.048	0.001
past subs. job spells	-0.107	0.001
past training spells	0.069	0.000
Subsidised employment offers		
previous labour market status: unempl.	-4.675	0.093
previous labour market status: subs. empl.	-0.194	0.958
previous labour market status: training	-3.656	0.276
region 1: rural	0.432	0.071
region 2: other (not city or rural)	0.019	0.066
past subs. job spells	-0.932	0.207
past training spells	0.577	0.068

(*) Although these parameters appear as insignificant, we have added a set of parameters at a time and the likelihood ratio test showed they are statistically significant (for a discussion of the problems with the estimation of standard errors for non-linear functions by the maximum likelihood method, see Gregory and Veale, 1985).

Table 18: Parameter estimates (cont.)

	estimates	st. errors
Training offers		
previous labour market status: unempl.	-2.777	0.020
previous labour market status: training	-18.293	- (**)
region 1: rural	0.308	0.015
region 2: other (not city or rural)	0.051	0.016
past subs. job spells	-0.000	0.039
past training spells	0.986	0.020
remaining eligibility time: less than 3m	0.860	0.023
Distribution of the error terms		
st. error prod. shock if out of empl.(inverse)	2.012	0.000
st. error prod. shock if in empl.(inverse)	2.331	0.000
probability of wage innovation	0.098	0.000
st. error taste shock to empl. (inverse)	0.003	0.000
st. error taste shock to subs. empl. (inverse)	0.002	0.000
st. error taste shock to training (inverse)	0.004	0.000
Distribution of unobserved heterogeneity(***)		
low prod / low taste for E group	0.051	0.000
low prod / high taste for E group	0.032	0.000
medium prod / low taste for E group	0.234	0.001
high prod / low taste for E group	0.171	0.001
high prod / high taste for E group	0.001	0.000

(**) This parameter leads to an offer rate of 1 and it becomes impossible to estimate the standard error.
(***) These are the parameters determining the weights, not the actual weights.