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 programmes 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 incorporates 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 programmes - which account for a large proportion of programmes - have little effect on future outcomes, whereas job experience programmes have a beneficial effect.

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1 Introduction

Active labour market programmes have become increasingly important in a number of OECD countries as a way of combating unemployment and helping workers reallocate to new sectors in the wake of 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 programmes 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, 2006). 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 programmes by Greenberg et al. (2004). Using similar data as in this paper and based on a non-parametric matching approach, Sianesi (2001a,b) 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 than 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 on earnings, and to be in a position to study policy reforms the underlying dynamics have to be modelled.

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 to 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 programme participation or work. We allow for selection on unobserved heterogeneity and model explicitly the dynamic selection choices of forward-looking 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 the effects of alternative policies.

The Swedish labour market programmes have been considered before[1], though never in such a systematic way as we propose here. Furthermore, we have put together a detailed 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 sets up the model. Section 4 presents the estimated effects of treatment and section 5 discusses

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

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 the prevalent and most relevant features of Swedish labour market institutions of the late nineties (1996-1998, corresponding to the time period covered by the data) that will set the ground for our model.

Unemployment insurance (UI) in Sweden amounts to 80% of the individuals salary in the previous job up to a ceiling of about SEK16,500 per month. To first become eligible to 14 months of UI benefits, an individual needs to have worked for a minimum of 80 days over 5 calendar months during the previous 12 months.[2] After meeting such requirement, eligibility to UI can always be renewed through an additional 80 days over 5 calendar months of work or treatment through 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, in particular job subsidies, trainee replacement schemes, vocational labour market training (AMU), relief work, and work practice schemes (including work experience replacement, ALU, and workplace introduction, API). In this paper we distinguish between *subsidised employment*, which includes the first two treatments mentioned above, and all the other programmes in assessing their differential impact on labour market performance. In what follows, the latter will be called *training programmes*.[3]

[2] There is also a membership condition, requiring payment of the (almost negligible) membership fees to the UI fund for at least 12 months prior to the claim. However, opting out of membership seems to be a rare event and we deal with UI membership as if it was compulsory.

[3] Although alternative aggregate rules could have been used and argued for, our choice was to classify the programmes according to their compensation regime as this reflects their relative closeness to the labour market.

There have been numerous policy changes although the 1996-1998 period has been remarkably stable. Notwithstanding, reforms occurred in July 1997, regarding the eligibility rules to unemployment compensation, and in September 1997, regarding the compensation level. These have been minor changes and we disregard them in the model. Perhaps the major policy change after our observational time window occurred in February 2001 when the possibility to renew eligibility to UI through programme participation was abolished. Using our model and results, we will assess the potential impacts of such policy change.[4]

2.2 Data

This section briefly discusses the main data related issues. More details can be found in Appendix C.

Data sources 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 (e.g. employment, education, inactivity or 'lost' (attrition)).
- The *Akstat* data base provides information on unemployment compensation from January 1994 onwards.
- The *Kontrolluppgifts-registry* provides employment information by employer from January 1990 onwards. This is employer provided data for tax purposes and is reported

A finer classification could have disclosed more detailed information about the programmes and will be the subject of further work.

[4]In future work we plan to explore the use of the most relevant policy changes to validate a structural model.

yearly. It includes the period of employment and the total earnings (which we also designate by wages) over the period by employer. Reported earnings are equally split over working period on a monthly basis. These are total earnings, not adjusted for hours worked.

- The *Sysreg* dataset provides information on educational achievement (highest educational level) by calendar year, starting in 1990.

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

Sample selection From the data we select the group individuals becoming unemployed during 1996 and follow them up to December 1998. For simplicity, we focus on a relatively homogeneous group. Selection was ruled by two main criteria: *(i)* the relative importance of the group in terms of size and expected returns from treatment and *(ii)* the nature of the decision process among the individuals of the group. Our final sample is composed of individuals with the following characteristics:

- Males - by excluding females we avoid having to deal with fertility decisions.
- Unskilled - these are disproportionately represented among the unemployed. We choose individuals having completed no more than 1 to 2 years of high school and not upgrading during the observation period (this is true for 95% of the unskilled population of the age group being considered - see below).
- Aged 26 to 30 at the time of their sample inflow - young individuals have been the object of attention of both policies and empirical research for two reasons: *(i)* they are to become the major labour force group in the near future and *(ii)* their perceived plasticity facilitates learning and adaptation to new conditions or environments. We focused on a young group outside the educational years to avoid dealing with the educational decisions.

- Not disabled or self-employed - these individuals face different conditions and policies.

Using these selection criteria, our data set contains 14,370 individuals who all start an unemployment spell in 1996. From these data we have excluded individuals for whom the information from the unemployment register and from the employer is incompatible. These are individuals who have a relatively long history of past employment as derived from the employer-provided data, but who are not eligible for unemployment benefits as detailed in the unemployment registry data. About 20% of the sample has been excluded on these grounds.[5] 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. Estimation used a randomly selected 20% sub-sample of these cleaned and selected data.

Labour market activity In each calendar 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. When more than one activity is present in any given month, we selected the one that lasted longest in that month. Since the employer-provided data is not as reliable as the unemployment register, we gave preference to unemployment information in case of conflict. This means that employment is the residual activity whenever a positive wage is simultaneously observed.

We do not distinguish between part- and full-time employment. While on part-time employment, individuals may still be entitled to UI (a share of the full amount) and have priority access to treatment as compared to unregistered individuals. However, part-time employment contributes towards renewing UI eligibility, just as full time employment does. We therefore decided to classify both types of jobs in the "employment" state.

[5] Although membership to UI funds is voluntary and is a pre-requisite to eligibility, it is unlikely that it explains this disparity between eligibility and employment history as the number of workers that opt out from UI funds seems to be small.

Programme occurrences were only considered if in long spells, defined as lasting for more than 2 months. In such case, treatment spells are split in 4 months periods and considered as sequences of treatment events. While such simplification reduces the dimensionality of our problem, it also corresponds to the patterns found in the data. Descriptive analysis has shown that the duration of the treatment spells peaks at 3 to 4 months.[6]

However rich and effective the data is in following individuals over their working life, it sometimes happens that we lose contact with one individual in a given month during our observational time window, meaning that the agent is neither registered as unemployed, in a treatment spell or in paid work. This may happen because, for example, the individual moves into education, out of the country or into inactivity (unregistered unemployment). We censor the history of affected individuals from that moment onwards. This affects 30% of the individuals in the sample.

Variables Based on the historical information back to 1990, we constructed a number of variables to characterise the individuals' state: *(i)* working experience, which is simply the cumulated number of months in employment since January 1990; *(ii)* remaining eligibility to UI in months, which varies from 0 to 14, is used up while in unemployment and can be recovered through employment or programme participation; and *(iii)* the criterion to renew full eligibility to UI (14 months), which measures the time in work or treatment since the last unemployment spell.

[6]It should be noticed that although the policy requirement to renew UI eligibility is 5 months in either employment or treatment, we will use a 4-month rule in the model discussed below. Such choice reflects the different criteria used by the employment services and in our study in measuring time in each labour market status. Calendar months are used in both cases. As explained before, the employment services require the agent to work for 80 days over 5 months, meaning that in some of these months the agent may work for as little as 1 day. Our criterion, however, is to use the predominant labour market status over the calendar month and to require 4 months of employment/treatment. By being more demanding, our measure will under-predict the accumulated experience towards renewing eligibility.

2.3 Descriptive statistics

Table 1 provides a brief summary of the whole data (column (1)), the data excluding individuals with incompatible information from the employer and unemployment registry (column (2)) and the 20% sub-sample we use in estimation (column (3)). There seems to be no important sample selection problems created by our cleaning and selection rules. For all 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.

Table 1: Descriptive Statistics

	full sample		20% subsample
	all observ.	excl. incomp.(*)	excl. incomp.(*)
	(1)	(2)	(3)
Number of individuals in 96	14,370	11,609	2,249
Average labour market experience in 96 (yrs)	4.2	4.3	4.3
Proportion with previous Job Subsidy in 96	5.8%	5.9%	5.9%
Proportion with previous Training in 96	47.1%	48.9%	49.8%
Average remaining time in UI in 96 (mths)	11.6	12.6	12.6
Average time to first employment (mths)	5.8	5.9	6.0
Average number of U spells 96-Dec98	1.91	2.00	1.97
Average number of E spells 96-Dec98	1.61	1.70	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.

In what follows we use the full sample excluding incompatibilities (described in column (2) of table 1) to estimate a few descriptive statistics. Results are very similar to what we obtained using the 20% subsample but are more precise.

Figure 1 displays the proportion of individuals in unemployment, employment and 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 programme and 0.6% are in a job subsidy programme.

Figure 1: Labour market status over time

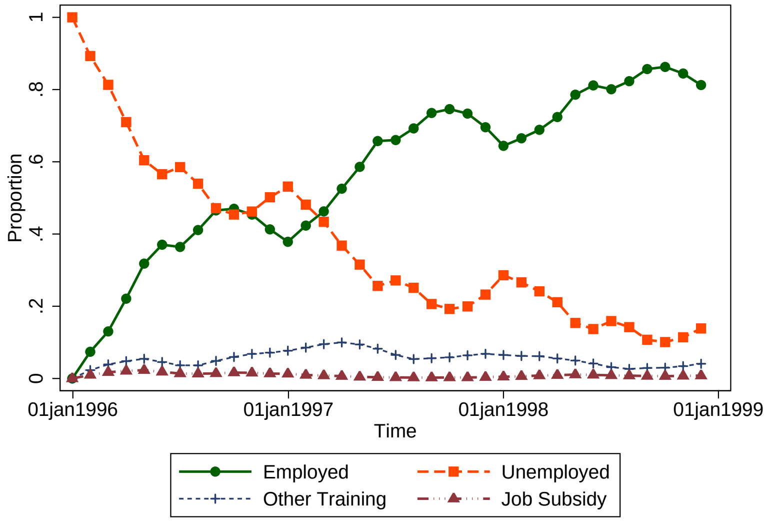
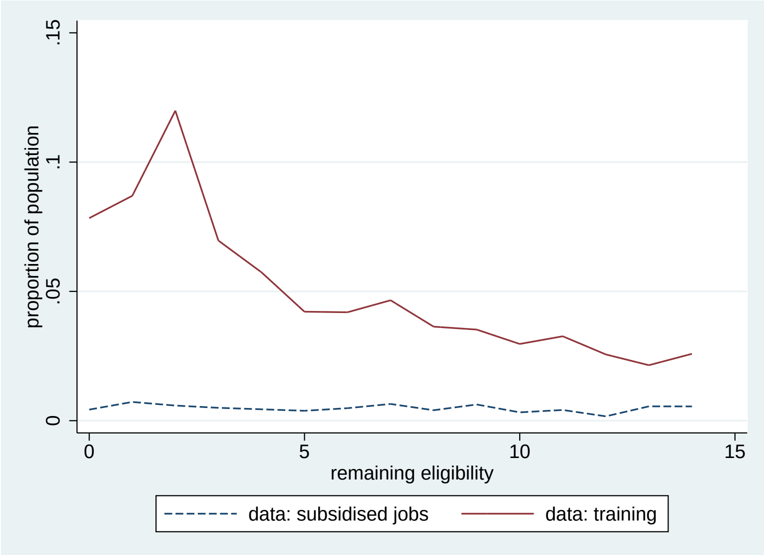


Figure 2 displays the enrolment rate into training or job subsidy programmes as a function of the remaining eligibility to unemployment benefits. Enrolment in a subsidised job does not appear to be related to eligibility to UI. On the contrary, enrolment in training programmes is increasing in the remaining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

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 and

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



restrict the analysis to individuals observed up to the end of the observational time window, December 1998. 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 treatment. 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 the treatment period.

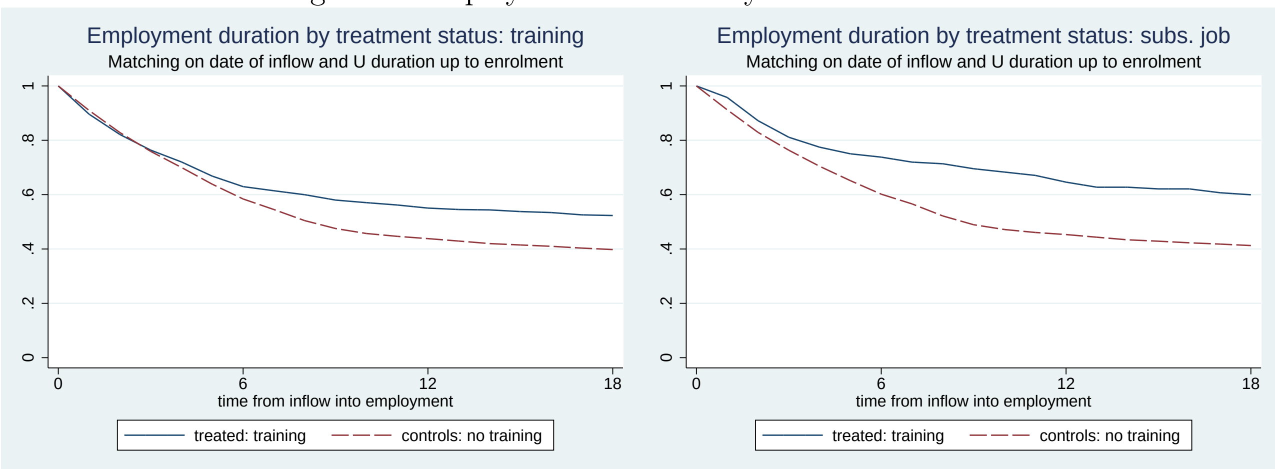
Figure 3 shows an initial 4-month lock-in effect of both types of treatment. This is the minimum period the individuals remain in treatment. After that, training seems to reduce the speed at which individuals leave unemployment while subsidised employment seems to have the reverse effect. The impact is so large for individuals in subsidised employment that the lock-in effect is totally overcome by month 6 after enrolment into treatment.

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

Figure 3: Unemployment rate by treatment status

Figure 4: Employment duration by treatment status



window by type of treatment. It is clear from these figures that the treated are not a random sample of this population. Individuals with previous treatment spells are always more likely to take further treatment and more so of the same type they have previously experienced. They have also accumulated less experience, particularly those that have undergone some training prior to inflow.

We now turn to earnings 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

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	49.6	52.4	47.3
% had subsidised jobs in the past	5.7%	10.3%	5.4%	7.3%
% participated in training in the past	48.6%	57.4%	45.0%	60.5%

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

training programme during the observational window. The analysis is conditional on having had no treatment prior to inflow. We compute the treatment effects using both OLS and a fixed effects regression. Cross section estimates (columns (1) and (2) in the table) suggest that subsidised jobs have a positive impact on earnings of almost 3.5%. On the contrary, training seems to have a detrimental effect on earnings of over 9%. However, these numbers are unlikely to be consistent estimates of the treatment effects if selection into treatment is not 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 effects of both labour market programmes are positive, 7.5% for subsidised jobs and 5.9% for training. There are at least three possible explanations for these results. The first, of course, is that treatment genuinely improves the earnings of participants. The second is that some mechanism like the Ashenfelter's dip rules participation: agents that have suffered a drop in earnings before becoming unemployed are more likely to enrol into treatment. However, a simple comparison of the earnings growth rates of treated and non-treated before an unemployment spell does not support this hypothesis. The third explanation is that programme participation affects

Table 3: Determinants of log earnings

	OLS		First differences	
	Coefficient	sd. err.	Coefficient	sd. err.
	(1)	(2)	(3)	(4)
experience (log)	0.155	0.011	-0.610	0.353
Job subsidy	0.035	0.014	0.075	0.044
Training	-0.093	0.007	0.059	0.021
unemployment	0.011	0.007	-0.023	0.005
constant	8.963	0.045	0.0089	0.005
observations	98,843		93,748	

Notes: Regressions are conditional on no programme participation prior to first observation. The observations in these regressions are the months in employment of all individuals included in the selected sample with no incompatibilities. This is why there are many more observations used in these regressions than individuals in the sample. The regression in first differences discards the first working observation for each individual with at least one employment spell over the observational window.

selection into employment and the selection process generates these results. Programme participation provides treatment *and* renews eligibility to UI. As a consequence, unemployment may become a more valued option after treatment, increasing the reservation wage and making individuals more selective about which jobs to accept.

The large differences between estimates obtained using OLS and fixed effects show 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 incorporates the main institutional features of the Swedish active labour market programmes faced by this cohort in the late nineties. Individuals are assumed to be forward looking and to make fully informed decisions about their working lives. The framework we use has its origins in the seminal work by Eckstein and Wolpin (1989a and b).

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 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. We do not separate between voluntary and involuntary job separations because the data does not seem to support such distinction. According to previous estimates of our model, where a job destruction probability was introduced instead of allowing for some permanent taste from employment, the job destruction probability is zero and the model is incapable of reproducing the transitions into employment, both from unemployment and the programmes. Accordingly, we also do not account for differences between quits and layoffs in terms of eligibility to UI while in reality the former would not be eligible. This is also in line with the fact that UI sanctions are rare in Sweden. We therefore abstract from this aspect of the unemployment policy.

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

In each period the individual decides about labour market status. We consider four possible alternatives, employment (E), unemployment (U), subsidised employment (J) and training (T). The decision at each point in time is determined by the information set at the individual's disposal. We assume the relevant information is described by a set of relevant variables, some observable and others unobservable by the econometrician.

The observable state space includes work experience (e); the remaining number of months of entitlement to UI benefits (u where u 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 $\overline{m} = 4$);[7] 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 the current out-of-work spell if applicable (s^J and s^T, respectively); the exogenous variables (x) including

[7] Although the true policy parameter is $\overline{m} = 5$ we choose to use $\overline{m} = 4$. See the data section for a justification of this choice.

region of residence.[8] The set of possible values of these observable variables constitute the state space Ω; at each point in time, t agent i draws a point in this state space, Ω_{it}.

The state space for the unobservable variables is denoted by Γ where Γ_{it} is the point drawn by individual i at time t. Γ includes a number of variables: *(i)* a productivity innovation, ν, which arrives with probability π if the agent is employed or in a subsidised job and is also realised by non-employed individuals receiving a job offer; *(ii)* job and programme offers, which arrive with probabilities o^l for $l = E, J, T$; and *(iii)* the transitory taste shocks, ϵ^l for $l = E, J, T$.

Finally, we also allow for two sources of unobserved heterogeneity: θ^W, which explains permanent differences in productivity (wage) levels; and θ^E, which explains permanent differences in job attachment. In what follows we call the former *ability* and the latter *taste for employment*. We denote by θ the 2-factor unobserved heterogeneity, $\theta = \left(\theta^W, \theta^E\right)$. 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} describe the labour market status of individual i at time t with possible values $l = U, E, J, T$. This is the decision variable. $d_{it} = l$ means that alternative l has been selected in period t.

The problem of individual i in period τ is to select the optimal sequence of feasible activities over the future, $\{d_{it}\}_{t=\tau,\ldots}$, conditional on the contemporaneous information set, $(\Omega_{i\tau}, \Gamma_{i\tau}, \theta_i)$,

$$\max_{\{d_{it}\}_{t=\tau,\ldots}} E_\tau \left[\sum_{t=\tau}^{\infty} \sum_{l\in\{U,E,J,T\}} \beta^{t-\tau} \mathbf{1}(d_{it} = l) R^l_{it} \left(\Omega_{it}, \Gamma_{it}, \theta_i\right) \middle| \Omega_{i\tau}, \Gamma_{i\tau}, \theta_i \right]$$

where β is the discount rate, R^l represents the per period reward or utility function when

[8] s^J and s^T determine the amount of compensation while in unemployment, not p^J and p^T.

labour market option l is selected and E_τ is the expectations operator conditional on the available information at time τ.

This maximisation problem is subject to a number of restrictions, including the laws of motion for 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, as well as 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 $w(e_{it}, p^J_{it}, p^T_{it}, \theta^W_i)$. The actual earnings are also determined by the transitory productivity shock, ν, so that

$$w_{it} = w(e_{it}, p^J_{it}, p^T_{it}, \theta^W_i)\exp(\nu_{it}).$$

Following the patterns in the data, we model the persistence in ν through a positive probability but smaller than 1 probability of receiving a wage innovation in each period (π).[9] So, for an individual who has two sequential employment periods,

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

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, $\mathcal{N}(0, \sigma_0)$.

[9] 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.

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

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

where the taste for employment is captured by the unobserved heterogeneity term, θ^E. The transitory taste shock, ϵ^E, is uncorrelated over time and has 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, $\overline{B}$.[10] 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

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

where s^J and s^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 ($\overline{m}$). An individual may have consecutive spells in subsidised emplyment. This treatment does not change the individual's work experience. Instead, the productivity effects are measured by an indicator of the number of past treatment spells, p^J_{it}. The two other differences to regular employment are that subsidised employment does not accrue utility θ^E_i and the taste shock is specific to the programme. The reward function for the whole $\overline{m}$-months period on a subsidised

[10]This is a simplification of the actual policy, which states that the individual is entitled to a proportion α of the earnings in the last employment up to a ceiling, $\overline{B}$.

job is,

$$R^J\left(\Omega_{it}, \Gamma_{it}, \theta\right) \;=\; \frac{1-\beta^{\overline{m}}}{1-\beta} \ln\left(w(e_{it}, p^J_{it}, p^T_{it}, \theta_i) \exp\left(\nu_{it}\right)\right) + \epsilon^J_{it}$$

where t is the first treatment period. The transitory taste shock, ϵ^J, is assumed to be uncorrelated over time and has distribution $\mathcal{N}(0, \sigma^2_J)$.

In consecutive subsidised employment spells, the productivity innovation is allowed to exhibit some persistence in a fashion similar to what is described above for consecutive employment periods.

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 into subsequent spells of exactly $\overline{m}$ months. The per-period income is either the UI benefit or 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,

$$R^T\left(\Omega_{it}, \Gamma_{it}, \theta\right) \;=\; \begin{cases} \frac{1-\beta^{\overline{m}}}{1-\beta} \ln(\mathrm{UI}_{it}) + \epsilon^T_{it} & \text{if } e_{it} \geq \overline{m} \\ \frac{1-\beta^{\overline{m}}}{1-\beta} \ln(b) + \epsilon^T_{it} & \text{if } e_{it} < \overline{m} \end{cases}$$

where the transitory taste component, ϵ^T_{it}, is uncorrelated over time and has distribution $\mathcal{N}(0, \sigma^2_T)$.

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 $l = E, J, T$. 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 probabilities, o^l for $l = E, J, T$, 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.[11]

3.6 The intertemporal value functions

Conditional on receiving an offer, the individual's decision is based on the comparison of the present and future value of each option. This process is described by the comparison of value functions for each alternative activity. We now describe these value functions. We denote by V_{it}^l the inter-temporal value of option l 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, $R^E(\Omega_{it}, \Gamma_{it}, \theta_i)$, and on future prospects as affected by current employment while assuming optimal decisions in the future. Employed individuals can always remain 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,

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

where the two last terms represent the continuation values under the two alternatives depending on the realisation or not of a wage innovation. An innovation occurs with probability π

[11] In offering treatment, priority is given to individuals close to exhausting their eligibility to UI.

(3rd line in the equation). The operators E_{ϵ^E} and $E_{\epsilon^E,\nu}$ stand for the expectations with respect to ϵ^E or (ϵ^E, ν) at time $t+1$, respectively. In all that follows, E_α represents the expected value with respect to the random variable α at $t+1$. The expectations are conditional on the present (time t) information and use the laws of motion described below to learn about the state space at $t+1$ which is the (omitted) argument of V^l_{t+1} for $l = U, E$. The notation we use below is in line with the one just discussed.

The value of unemployment While unemployed, the individual may receive an offer of any type (employment and the two programme types). The decision of whether or not to move will depend on the relative value of the two alternatives, where unemployment is always a possibility. Thus, the value of unemployment at period t is

$$\begin{aligned} V^U_{it} \;=\; & R^U(\Omega_{it}, \Gamma_{it}, \theta_i) + \\ & \beta o^E(\Omega_{it+1}, d_{it} = U)\, E_{(\epsilon^E,\nu)}\left[\max\left\{V^U_{it+1}, V^E_{it+1}\right\}\middle|\, \theta_i, \Omega_{it}, d_{it} = U\right] + \\ & \beta o^J(\Omega_{it+1}, d_{it} = U)\, E_{(\epsilon^J,\nu)}\left[\max\left\{V^U_{it+1}, V^J_{it+1}\right\}\middle|\, \theta_i, \Omega_{it}, d_{it} = U\right] + \\ & \beta o^T(\Omega_{it+1}, d_{it} = U)\, E_{\epsilon^T}\left[\max\left\{V^U_{it+1}, V^T_{it+1}\right\}\middle|\, \theta_i, \Omega_{it}, d_{it} = U\right] + \\ & \beta\left[1 - o^E(\Omega_{it+1}, d_{it} = U) - o^J(\Omega_{it+1}, d_{it} = U) - o^T(\Omega_{it+1}, d_{it} = U)\right] E\left[V^U_{it+1}\big|_i\, \theta_i, \Omega_{it}, d_{it} = U\right] \end{aligned}$$

where the terms in lines 2, 3 and 4 correspond to the possibility of receiving a job, subsidised employment or training offers, respectively. The last term deals with the possibility that no offer to start at $t+1$ arrives, in which case the individuals has no option but to remain unemployed.

The value of subsidised employment and training The current utility while on a subsidised job, $R^J(\Omega_{it}, \Gamma_{it}, \theta_i)$, 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.[12] The value of a subsidised job

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

is

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

The value of the training option is similarly given by

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

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 up" 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. At the start of our observational time window, however, they will generally be different from zero as individuals have had time to accumulate some working and treatment experience.

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 types and 2 preference types. Unobserved heterogeneity affects decisions through a number of dimensions, including earnings, returns to experience and returns to treatment, employment and treatment offer probabilities and job attachment. We estimate the distribution of unobserved herogeneity using non-parametric maximum likelihood following (see Heckman and Singer, 1984).

The sample selection process, which chooses 25-30 years old males flowing into unemployment during 1996, creates an initial conditions problem: working experience and accumulated programme participation at entrance are endogenous in the sense that they are correlated with unobserved heterogeneity. While we do not deal with it here, we plan to do so in the future. 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: joint distribution of the two factors

	Heterogeneity 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 taste from employment". 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 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 estimated parameters on the (log) earnings equation 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 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 earnings very modestly. At about 0.12%, the impact of subsidised jobs on earnings amounts to less than half the impact of spending the same time in regular jobs at the same level of experience (0.3%). This suggests that the nature of these jobs is different from regular employment, possibly contributing less to human capital formation. Training has virtually no effect on earnings.

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 earnings. This seems to support the view that enrolment into treatment and employment is related to unobserved characteristics such as ability. Treatment effects on earnings under the structural selection specification are also smaller than the fixed effects estimates in column (3) of table 3. This evidence suggests that 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 probabilities by previous activity, treatment status and region of residence

		Activity in period $t-1$				
		Unemployment				
		not treated	treated: sub. job	treated: training	Sub. empl.	Training
		(1)	(2)	(3)	(4)	(5)
		Job offer probabilities				
(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 probabilities				
(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 probabilities				
(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%

These are estimates of the functions o^l for $l = U, J, T$ being the previous activity. Apart from previous activity, these functions also depend on treatment status and region of residence. The table presents the probabilities of being offered a job or a treatment placement for the different combinations of these variables.

Table 6 presents estimates of job and treatment offer probabilities under alternative circumstances depending on previous activity, whether or not the individual has been treated in the past and region of residence. Activity in period $t-1$ strongly affects offer probabilities. Being in a subsidised job spell more than doubles the probability of being offered a job in the next period (column (4) as compared with the remaining columns, rows(1)-(3)). This probably reflects a transformation of the subsidised job into regular employment where the individual remains in the same firm, possibly doing a similar task but now in the regular workforce. However, having had subidised jobs in the past does not seem to help job search. On the contrary, it has a small negative impact on job offer probabilities, suggesting it might give a bad signal to potential employers (column (2) versus columns (1) and (3), rows (1)-(3)). Training does not seem to affect offer probabilities 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), rows (7)-(9)). These estimates together with the also high offer probabilities of subisdised employment for agents in subsidised employment are partly determined by the continuation of the same treatment spell over 4 months.

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.

Table 7 displays the data and simulated month-to-month transition probabilities between alternative labour market states. Rows (5) and (10) show the proportion of observations falling in each state and, 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

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*

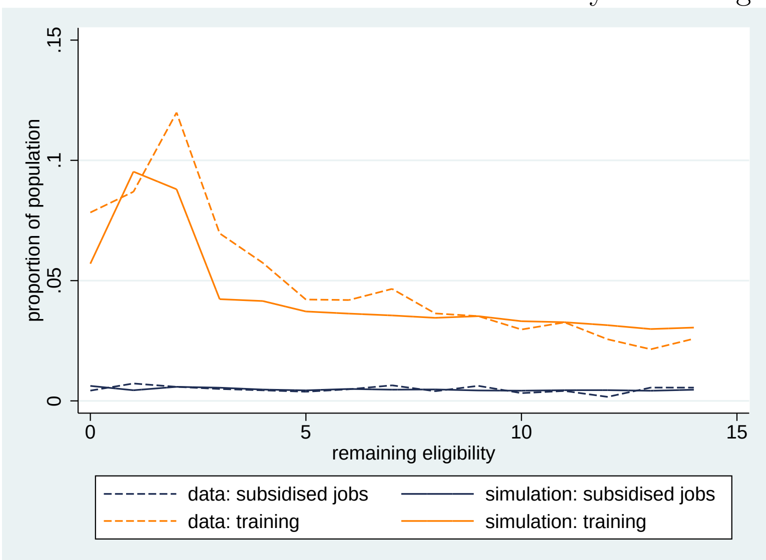
from the moment of sample inflow. The dashed and full lines stand for simulated and real data, respectively. The simulated data seem to reproduce the average evolution of labour market status quite closely but fails to capture the seasonal patterns (the current version of the estimates does not allow for seasonal variation but this will be incorporated in future versions of the model).

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 probabilities. Again, the simulated pattern is very closed to the observed one.

Figures 6 and 7 compare data and model regarding the probabilities of inflow into treatment and employment by remaining months of eligibility to unemployment benefit. While we are able to reproduce the inflows into treatment quite closely, the model does very badly in accounting

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

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



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 time, the model captures a slightly downward curve due to the increasing costs of remaining

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

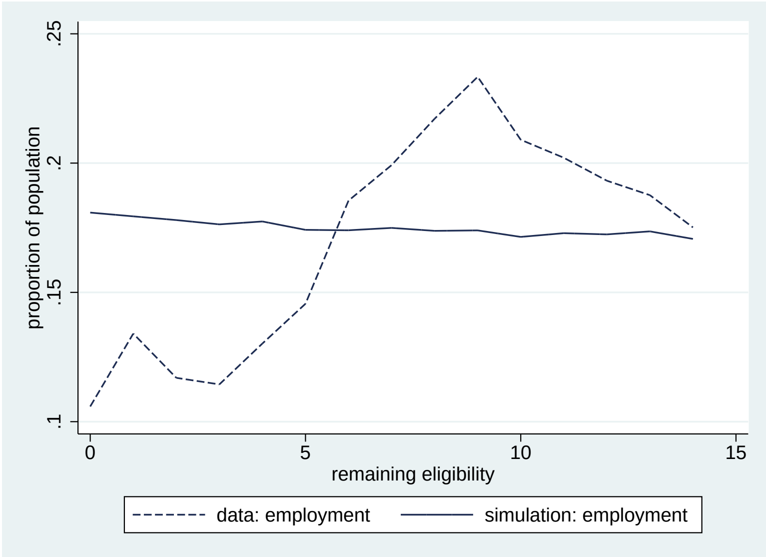
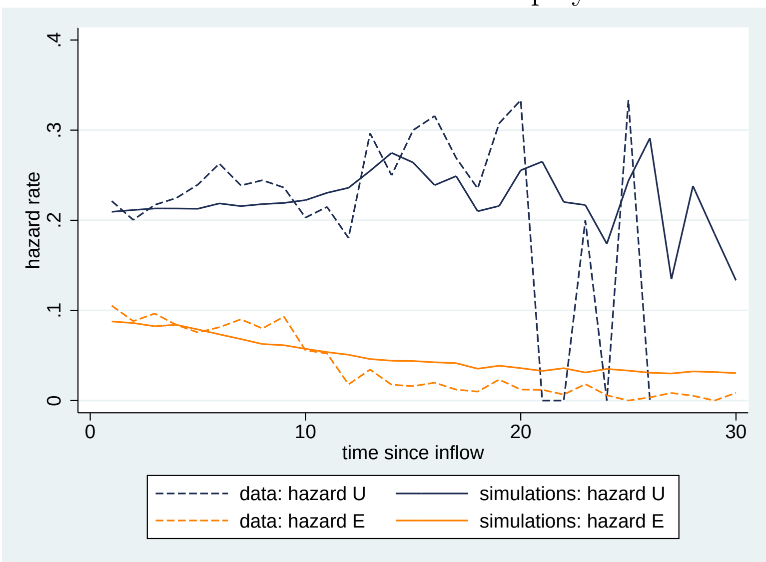


Figure 8: Fit of the model - Hazard rates from employment and unemployment



unemployed as eligibility approaches exhaustion. This means that heterogeneity related with the taste for employment is not enough to counteract the change in the relative value of unemployment due to exhaustion of the benefit. This pattern of the simulated data suggests that an additional source of heterogeneity might be needed and requires careful attention in future work.

Instead, heterogeneity related to the taste for employment 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 is captured quite well by the model. Figure 8 also shows a peak in the outflows from unemployment around a duration of 14 months, which is captured by the model as a response to benefit exhaustion. According to figures 6 and 7, such peak arises from the transitions into training near or at benefit exhaustion, not from transitions into employment.

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

	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

Tables 8 and 9 show how close the model reproduces the data on earnings. Table 8 shows that the distribution of earnings among workers is very close in the two datasets. Table 9 then assesses the correlation between earnings among the employed and different individual

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

characteristics. The results are very similar in the actual and simulated data although the size of the correlation between training programmes and earnings is significantly larger in the data than in the model.[13]

4.3 Effects of treatment

Using our model estimates, we can now simulate the impact of programme participation on individual outcomes. As before, all simulations use the distribution of initial conditions observed in the data. Given the solution to the dynamic problem and conditional on a random draw of the unobservables in the model we can then simulate the optimal labour market decisions of these individuals. We simulate the labour market history of each individual 50 times and use these simulations to compute both the average treatment effect (ATE) and the average effect of treatment on the treated (ATT).

The *ATE* is obtained from the comparison between: *(i)* the simulated labour market histo-

[13]Table 9 uses all data and simulated observations to compute the correlation between earnings and some of the observables affecting earnings. It is different from table 3, where observations were selected and two of the most widely used methods were used to support the discussion about the identification of the causal impact of treatment.

ries of individuals flowing into unemployment during 1996 and *(ii)* their simulated histories had they been forced into treatment at inflow into unemployment in 1996. We do this separately for both subsidised employment and training.

The ATT is obtained from the comparison between: *(i)* the simulated labour market histories of individuals flowing into unemployment during 1996 and joining a programme at some point during the first 2 simulated years and *(ii)* the simulated labour market history of the same subgroup of individuals had they been refused participation on that first treatment they intended to take. That is, the ATT measures the impact on individuals that are observed in the simulations to select into treatment.[14]

For both the ATE and the ATT, we then simulate individual 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 on productivity levels, job offer probabilities and a change in the returns to unemployment due to the way treatment affects eligibility to unemployment benefits.

There are two substantial differences between the ATE and the ATT. First, of course, is the nature of the parameter: ATE is the average impact on a randomly selected individual while ATT is the impact on individuals that self-select into treatment. And second, different definitions of treatment are used in each case: the ATE measures the impact of treatment at inflow into unemployment while ATT measures the impact of treatment at a moment in the first unemployment spell selected by the individual.

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 earnings. This is especially true for training, which reduces earnings by 1.1%. Training also substantially decreases time in employment (by about 5%). Two factors explain this effect: training induces

[14]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.

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%

individuals to participate in further treatment and raises time in unemployment. On the other hand, subsidised employment reduces future time in training but increases future time in subsidised employment, most likely with the same employer as these spells frequently last for longer than our standard length of treatment of 4 months.

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 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%

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 a 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 a higher taste for employment increase future time in regular and subsidised employment by over 1% of their time during 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.

By 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.[15] Individuals with a higher taste for employment are less likely to participate in training programmes and they also benefit less in

[15]These results are not in the table and can be obtained from the authors under request.

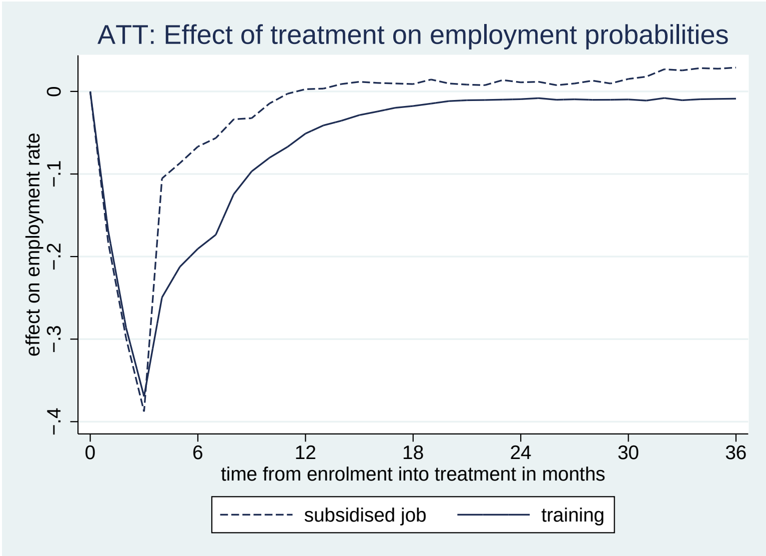
Table 12: Heterogeneity in the impact of treatment on the treated over the 3 years after treatment

			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%

terms of future income (notice that the group “high taste for employment / high ability” is extremely small and so the values for this category are very sensitive to strange outliers). The four months of training are more costly for them as they are more likely to miss acceptable job opportunities than individuals with a 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.

Figure 9: Re-employment probabilities over time after treatment



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 employment very fast and become slightly more likely to be employed after 1 year from enrolment than if they had not been treated. 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 of the first unemployment spell after enrolment into treatment. The graph displays the behaviour of treated and comparable 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 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

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

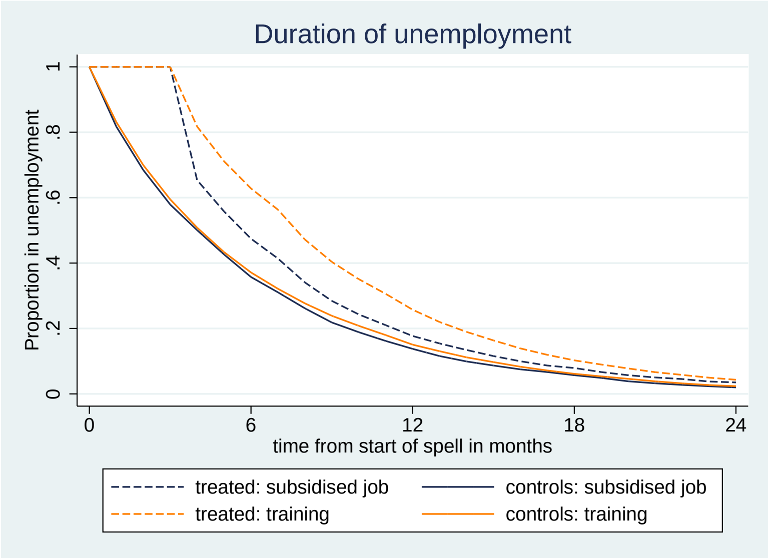
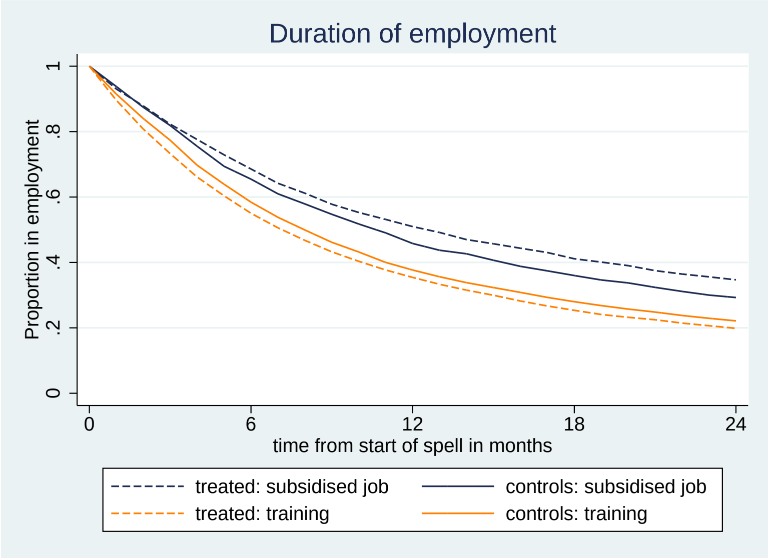
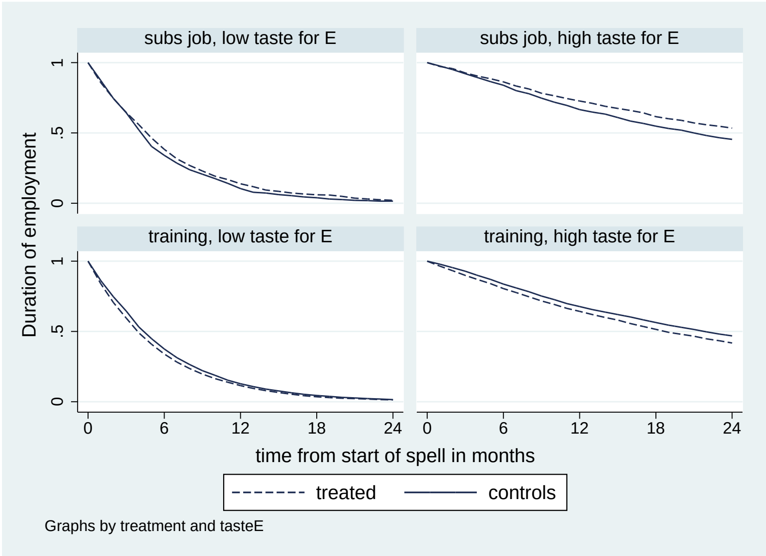


Figure 11: Duration of first employment spell after treatment by type of treatment: comparison between treated and controls



time out of work. On average, treated taking subsidised jobs experience an out-of-employment

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



spell 2.1 months longer than if they had not been treated. The similar figure for training is 3.4 months.

Figures 11 and 12 compare the duration of the first employment spell after treatment for individuals who 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 longer employment spells and enjoy a positive impact of treatment on the duration of the subsequent employment spells, explaining the positive effect on time in employment identified in table 10. However, the effect of subsidised employment on the duration of future employment spells is not homogeneous. Figure 12 shows that it is very positive among individuals with the highest taste for employment, 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 turn, training seems to have a small negative effect on the duration of employment spells among the agents that most benefit 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, perhaps 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 use this information to target interventions more effectively. We now discuss how selection and treatment effects 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) show the extent to which training is used to renew eligibility to unemployment benefits.

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.

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 the taste for employment 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 individuals, who have higher foregone earnings and higher odds of missing acceptable job offers

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%

while in training.

Table 15 shows how treatment effects vary with the 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 taste for employment 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 policy alternative (*policy 1*) removes the link between UI eligibility and programme participation. In this case, only regular employment can allow one to regain access to fully subsidised unemployment. This policy scenario reproduces the design introduced in February 2001.

The second policy alternative (*policy 2*) sanctions the refusal to participate in an offered treatment by cutting eligibility to unemployment compensation until the individual regains eligibility through treatment or employment. While refusal to take up adequate treatment or employment is sanctioned in Sweden, this seems to happen only on the paper, being seldom used in practiced. In this policy scenario we enquire what would happen if treatment were to become compulsory as has been implemented in other countries such as the UK with the New Deal for Young People.

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.

In all this analysis we are abstracting from potential indirect effects. This is a reasonable assumption if the policy affects a small proportion of individuals but is not as credible if we are discussing large policy reforms. In particular, the transition from our baseline scenario to one of the alternative policies could arguably involve important changes in the functioning of the labour market that would change the parameters we take as structural. However, to study the labour market responses to the change in policy scenarios is outside the scope of this paper. Instead, our impacts can be understood at an individual level as if others would continue to face the policy scenario used in estimation.

To construct the simulated data we use the initial distribution of observable characteristics from the real data and simulate the labour market behaviour 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 (2004). 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)	Gov't expenditure	132.5(*)	+31.45%	+20.32%	-2.91%

(*) Values are in 1000s SEK and 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 by 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 of unemployment benefits and the provision of treatment but not changes in revenue due to changes in employment choices and, therefore, in income tax revenue. The second and third columns in row (6) show that making treatment available is very expensive, increasing expenditure on unemployment compensation and the 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, and does so 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 relative 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 13 shows that the reduction in employment probabilities due to the availability of treatment is persistent over time, particularly for the current policy and policy 1. Out-of-work probabilities 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 probabilities over time

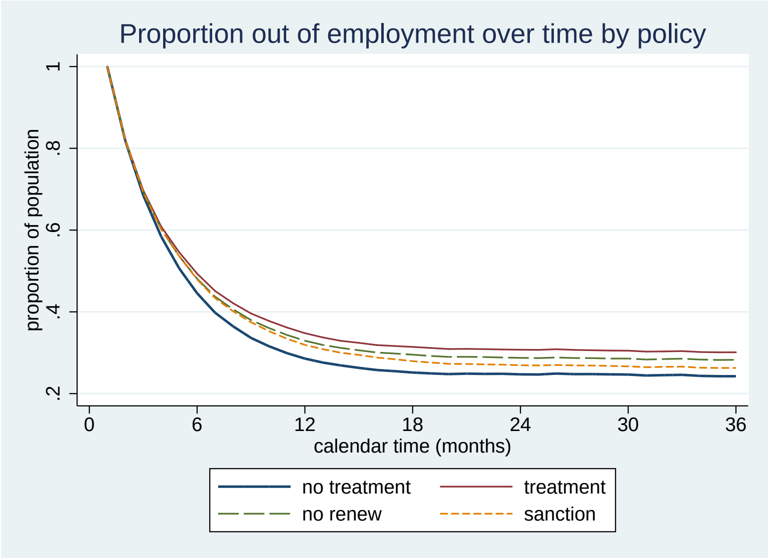
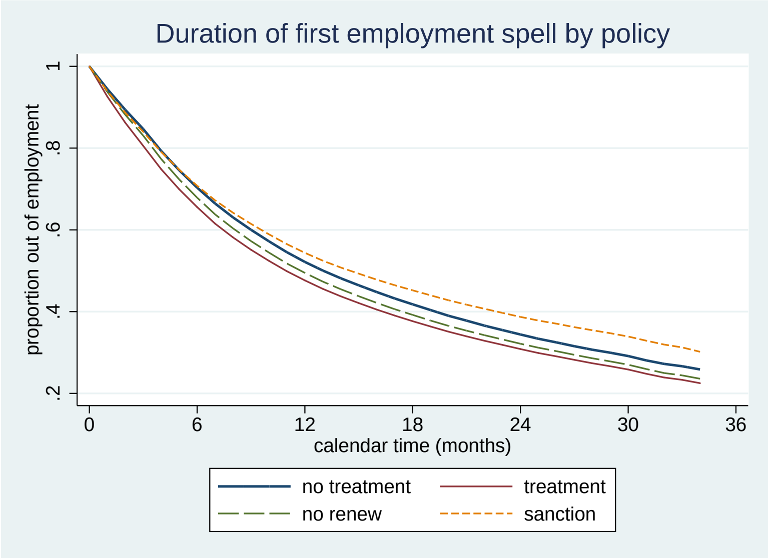


Figure 14: Duration of employment spells



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 to late 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 the important dynamic interactions and considers both short term and longer term outcomes including earnings. 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 earnings, for a cohort of individuals who became unemployed in 1996. The model is of the dynamic, discrete choice, forward-looking type and is estimated for the population of unskilled males aged 26 to 30 who have a period of unemployment starting during 1996. We use rich administrative data which have been put together for this purpose.

Our results are sobering. The current policy reduces employment quite substantially by increasing programme participation (including subsidised jobs). There is practically no effect on earnings - training leaves them unchanged, while a spell in subsidised employment has a third of the effect on earnings than does a normal job. However the current policy, 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 policy. 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 programmes 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.

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 likelihood 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 $(\Omega_{it}, \Gamma_{it}, \theta_i)$ as defined in the main text. However, for clarity we include the productivity shock when relevant. Finally, let $L_{it}(l, l')$ be the contribution to the likelihood a transition from activity l to activity l' observed between period $t-1$ and t for individual i. It may or may not include a model of earnings depending on the type of transitions. This is made explicit in what follows.

Transitions from employment into employment

- No wage innovation occurs with probability $1 - \pi$, in which case 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 of such transitions and wage draw is

$$\begin{aligned} L_{it}(E,E) &= g_{(d,w)}\left(d_{it}=E, w_{it}|d_{it-1}=E, \nu_{it-1}, \Omega_{it}, \theta_i\right) \\ &= (1-\pi)\left[1-\Phi\left(\frac{V_{it}^U - \widetilde{V}_{it}^E(\nu_{it}: w_{it}=w_{it-1})}{\sigma_E}\right)\right] \end{aligned}$$

where $g_{(d,w)}$ is the conditional joint density of present labour market activity and earnings given the particular state space realisation.

- A wage innovation occurs 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 $\widetilde{V}_{it}^E(\nu_{it})$. Then the contribution to the likelihood function of such transition and wage draw is

$$\begin{aligned} L_{it}(E,E) &= g_{(d,w)}\left(d_{it}=E, w_{it}|d_{it-1}=E, \Omega_{it}, \theta_i\right) \\ &= \pi\left[1-\Phi\left(\frac{V_{it}^U - \widetilde{V}_{it}^E(\nu_{it})}{\sigma_E}\right)\right]\phi\left(\frac{\nu_{it}}{\sigma_1}\right)\frac{1}{\sigma_1} \end{aligned}$$

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 we have

$$\begin{aligned} L_{it}(E,U) &= g_d\left(d_{it}=U|d_{it-1}=E, \nu_{it-1}, \Omega_{it}, \theta_i\right) \\ &= (1-\pi)\Phi\left(\frac{V_{it}^U - \widetilde{V}_{it}^E(\nu_{it}: w_{it}=w_{it-1})}{\sigma_E}\right) + \\ &\quad \pi\int_{-\infty}^{+\infty}\Phi\left(\frac{V_{it}^U - \widetilde{V}_{it}^E(\nu)}{\sigma_E}\right)\phi\left(\frac{\nu}{\sigma_1}\right)\frac{1}{\sigma_1}d\nu \end{aligned}$$

where g_d is the conditional probability of the present labour market activity given the particular state space realisation.

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 probabilities for simplicity of notation except for the previous labour market status,

$$\begin{aligned} L_{it}(J,E) &= g_{(d,w)}\left(d_{it}=E, w_{it}|d_{it-1}=J,\Omega_{it},\theta_i\right) \\ &= o_{it}^{E}\left(d_{it-1}=J\right)\left[1-\Phi\left(\frac{V_{it}^{U}-\widetilde{V}_{it}^{E}(\nu_{it})}{\sigma_E}\right)\right]\phi\left(\frac{\nu_{it}}{\sigma_1}\right)\frac{1}{\sigma_1} \end{aligned}$$

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.

$$\begin{aligned} L_{it}(J,J) &= g_{(d,w)}\left(d_{it}=J, w_{it}|d_{it-1}=J,\nu_{it-1},\Omega_{it},\theta_i\right) \\ &= o_{it}^{J}\left(d_{it-1}=J\right)(1-\pi)\left[1-\Phi\left(\frac{V_{it}^{U}-\widetilde{V}_{it}^{J}(\nu_{it}:w_{it}=w_{it-1})}{\sigma_J}\right)\right] \end{aligned}$$

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),

$$\begin{aligned} L_{it}(J,U) &= g_{d}\left(d_{it}=U|d_{it-1}=J,\nu_{it-1},\Omega_{it},\theta_i\right) \\ &= o_{it}^{E}\left(d_{it-1}=J\right)\int_{-\infty}^{+\infty}\Phi\left(\frac{V_{it}^{U}-\widetilde{V}_{it}^{E}(\nu)}{\sigma_E}\right)\phi\left(\frac{\nu}{\sigma_1}\right)\frac{1}{\sigma_1}d\nu + \\ &\quad o_{it}^{J}\left(d_{it-1}=J\right)(1-\pi)\Phi\left(\frac{V_{it}^{U}-\widetilde{V}_{it}^{J}(\nu_{it}:w_{it}=w_{it-1})}{\sigma_J}\right) + \\ &\quad o_{it}^{J}\left(d_{it-1}=J\right)\pi\int_{-\infty}^{+\infty}\Phi\left(\frac{V_{it}^{U}-\widetilde{V}_{it}^{J}(\nu)}{\sigma_J}\right)\phi\left(\frac{\nu}{\sigma_1}\right)\frac{1}{\sigma_1}d\nu + \\ &\quad \left[1-o_{it}^{E}\left(d_{it-1}=J\right)-o_{it}^{J}\left(d_{it-1}=J\right)\right] \end{aligned}$$

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, which follow a distribution $\mathcal{N}(0,\sigma_0)$. Transitions into employment make the following contribution to the likelihood function,

$$\begin{aligned} L_{it}(l,E) &= g_{(d,w)}\left(d_{it}=E, w_{it}|d_{it-1}=l,\Omega_{it},\theta_i\right) \\ &= o_{it}^{E}\left(d_{it-1}=l\right)\left[1-\Phi\left(\frac{V_{it}^{U}-\widetilde{V}_{it}^{E}(\nu_{it})}{\sigma_E}\right)\right]\phi\left(\frac{\nu_{it}}{\sigma_0}\right)\frac{1}{\sigma_0} \end{aligned}$$

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

$$\begin{aligned} L_{it}(l,J) &= g_{(d,w)}\left(d_{it}=J, w_{it}|d_{it-1}=l,\Omega_{it},\theta_i\right) \\ &= o_{it}^{J}\left(d_{it-1}=l\right)\left[1-\Phi\left(\frac{V_{it}^{U}-\widetilde{V}_{it}^{J}(\nu_{it})}{\sigma_J}\right)\right]\phi\left(\frac{\nu_{it}}{\sigma_0}\right)\frac{1}{\sigma_0} \end{aligned}$$

Transitions from training or unemployment into training These are also conditional on receiving an offer but no wage is drawn,

$$\begin{aligned} L_{it}(l,T) &= g_{d}\left(d_{it}=T|d_{it-1}=l,\Omega_{it},\theta_i\right) \\ &= o_{it}^{T}\left(d_{it-1}=l\right)\left[1-\Phi\left(\frac{V_{it}^{U}-\widetilde{V}_{it}^{T}}{\sigma_T}\right)\right] \end{aligned}$$

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

$$\begin{aligned}
L_{it}(l,U) &= g_{(d,w)}\left(d_{it}=U|d_{it-1}=l,\Omega_{it},\theta_i\right) \\
&= o_{it}^{E}\left(d_{it-1}=l\right)\int_{-\infty}^{+\infty}\Phi\left(\frac{V_{it}^{U}-\widetilde{V}_{it}^{E}(\nu)}{\sigma_E}\right)\phi\left(\frac{\nu}{\sigma_0}\right)\frac{1}{\sigma_0}d\nu + \\
&\quad o_{it}^{J}\left(d_{it-1}=l\right)\int_{-\infty}^{+\infty}\Phi\left(\frac{V_{it}^{U}-\widetilde{V}_{it}^{J}(\nu)}{\sigma_J}\right)\phi\left(\frac{\nu}{\sigma_0}\right)\frac{1}{\sigma_0}d\nu + \\
&\quad o_{it}^{T}\left(d_{it-1}=l\right)\Phi\left(\frac{V_{it}^{U}-\widetilde{V}_{it}^{T}}{\sigma_T}\right) + \\
&\quad \left[1-o_{it}^{E}\left(d_{it-1}=l\right)-o_{it}^{J}\left(d_{it-1}=l\right)-o_{it}^{T}\left(d_{it-1}=l\right)\right]
\end{aligned}$$

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

$$L = \prod_{i=1}^{N}\int_{\theta\in\Theta}\prod_{t=2}^{T}\prod_{l,l'=U,E,J,T}\left[\begin{array}{l} L_{it}\left(l,l'\right)^{\mathbf{1}(d_{it}=l',d_{it-1}=l)} * f_{\Omega_t|\Omega_{t-1},d_{t-1},\theta}\left(\Omega_{it}|\Omega_{it-1},d_{it-1},\theta\right) * \\ f_{\Omega_1|d_0,d_1,\theta}\left(\Omega_{i1}|d_{i0}=E,d_{i1}=U,\theta\right) * f_{\theta|d_0,d_1}\left(\theta|d_{i0}=E,d_{i1}=U\right)\end{array}\right]d\theta$$

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. 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 excluded from the likelihood function. 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. This will be relaxed in future work. So the likelihood function simplifies to,

$$L = \prod_{i=1}^{N}\sum_{\theta\in\Theta}\prod_{t=2}^{T}\prod_{l,l'=U,E,J,T}L_{it}\left(l,l'\right)^{\mathbf{1}(d_{it}=l',d_{it-1}=l)}f_{\theta|d_0,d_1}\left(\theta|d_{i0}=E,d_{i1}=U\right)$$

Appendix C: Data

Data sources

The estimation of the structural model relies on the availability of a particularly rich data set, which follows workers through a long period and allows one to link earnings information to employment, programme and unemployment spells. We exploited a uniquely comprehensive combination of both new and updated series of datasets. This involved linking the various types of available information, summarised in Table C1, both over time (from January 1990 to December 1998) and across labour market states (spells in education, employment, compensated and uncompensated unemployment, programme participation and inactivity).

Unemployment and programme participation histories are provided by the various databases of Händel, the unemployment register. This longitudinal event history dataset, available from August 1991 to June 2000, has information on all unemployed individuals registered at the public employment offices and provides labour market status information over time (e.g. unemployed, on a given programme, temporarily employed), together with important personal characteristics of the job-seeker and the reason for leaving the employment office (e.g. obtained employment, gone on regular education or left the workforce).

Akstat, available from January 1994 to June 2000, originates from the unemployment insurance funds and provides information on spells of unemployment benefits, including the type (UI or KAS where KAS is cash assistance and is unrelated to previous earnings) and amount of compensation paid out.

Employment information by employment and calendar year is available from the Kontrolluppgifts-registry from 1990 to 1998. This information is provided by each employer for tax purposes and contains the first and last calendar months where the worker has been employed by that employer as well as the corresponding employment income paid out to him during that period.

The highest educational qualification achieved within a given calendar year (1990 to 1998) together with other demographic information is obtained from Statistics Sweden.

The end result is a very large and representative dataset, with information about the duration of stay in a labour market state, employment earnings, an array of demographic and human capital variables and, for entitled individuals, additional information on type of entitlement, unemployment benefit recipiency and previous working conditions.

Data issues

Despite the comprehensiveness of the data, a number of important shortcomings had to be dealt with to construct the dataset for analysis.

The first problem relates to the availability of information while out of the unemployment register (Händel). Händel is the most reliable data source but it contains no additional information about individuals labour market status in between registration periods beyond the initial state to which the individual moves upon leaving the office. Furthermore, the attrition/misclassification problem of individuals being recorded as having left simply because "contact ended" means that we do not know whether they have found a job they did not report, or are still in (unregistered) unemployment (cf. Bring and Carling, 2000, and Sianesi, 2004).

The employment information reported by employers has been used to fill in such gaps. However, it is in itself not free of problems. First, employment spells recorded in the data are not necessarily uninterrupted; we only know that an individual has been paid at least in the first and last months recorded by that employer but we cannot ascertain for sure whether the worker has been paid in the intermediate period unless he/she re-registers as unemployed or participates in a programme. Second, and potentially more serious, is the occurrence of employment spells with missing start and end dates and whose income is thus unallocated over the calendar year. The incidence of such spells is low (2-3% of total spells) but they affect 20% of our sample individuals. Based on a number of exploratory analysis, our preferred procedure has been to spread these spells over the whole year for as long as the worker is not reported as being in registered unemployment or on a programme. A third problem with the employment data relates to the suspected over-reporting of January-to-December spells. Again, these spells have been interrupted for eventual periods in registered unemployment or on programmes.

We detect participation in education using outflows from registered unemployment into education and from upgrades to the highest qualification. However, the incidence of missing information for the "reason to leave registered unemployment" together with the fact that educational data are censored at the end of 1998 (and therefore, ongoing investments cannot be determined) imply that some upgrades and educational spells will be missed.

Once cleaned and merged, the data suffer from the following shortcomings:

- Low consistency of information from the various sources, in particular: *(i)* time in employment according to Händel and to the employer-provided data (10% of employment spells in the latter are not compatible with unemployment or programme participation reported in Händel); *(ii)* monthly income from Akstat and the one derived from the annual payments reported by employers; *(iii)* highest educational attainment at the time of registering as unemployed from Händel and in that calendar year from Statistics Sweden (good correspondence at the compulsory and secondary levels, but not at the tertiary one); and *(iv)* unemployment compensation according to Akstat and Händel (21% of monthly spells where individuals receive compensation are not compatible with states measured in Händel).

  To deal with these inconsistencies, priority has been given to the most reliable data source in a given case, and further decisions taken on the basis of exploratory and cross-checking analyses which also involved the use of additional data sources (in particular, Louise and education data from compulsory school Grundskola).

- Definition of an individual's labour market state in a given month: it is not straightforward to reliably specify the state in which an individual is in a given month, this being especially the case for education and employment, for which no monthly data is available. Further conceptual issues relate to how to treat part-time employment whilst registered at the unemployment office. Based on exploratory analysis (e.g. the income they earn is substantial compared to income earned on other employment spells) and the institutional treatment of part-time employment (which counts towards renewing eligibility to UI just as full-time employment does), we have decided to treat part-time employment as full-time employment. However, part-time employed workers do receive unemployment compensation and have preferential access to programmes as compared to deregistered individuals.

- Computation of monthly employment income: while employment income would be perfectly apportioned over a calendar year (confirmed also by the very good correspondence between total employment income in that calendar year and income from the Louise dataset), it is difficult to apportion employment income exactly over calendar months due to the lack of reliable measures of the spell durations mentioned above.

Data preparation and set-up

Obvious mistakes giving rise to negative spells in Händel have been corrected and the remaining individuals with at least a negative spell have later been dropped from the sample (this amounted to less than 4% of the original sample). Before being merged, the data has been reshaped into calendar month history, taking the labour market state that lasted longest in a month as the reference state for that month. The employer-provided data on employment spells has been corrected based on unemployment and programme spells information in Händel. Monthly income from employment has then been calculated based on the corrected employment spells and taking into account overlapping spells with different employers.

The following adjustments have also been made to set-up the data for estimating the model:

- Treatment spells: we only consider "long" programmes, i.e. those lasting more than 2 months. If a programme spell lasts 2 or fewer months, it is considered as time in unemployment; if it lasts 3 months, one extra month on the programme is added; and if it lasts more than 4 months, it is split up into shorter programme spells of 4 months each.

- Direct employment-to-programme transitions: these occur in less than 0.2% of the transitions on a monthly basis and are therefore prevented by including an intermediate period in unemployment.

- Employment with no income: given the data limitations highlighted above, employment is a residual category for when an individual is not registered as unemployed or taking part in a programme. In terms of history before inflow, employment spells with no corresponding income are set to unemployment; after inflow, employment or subsidised employment spells with no corresponding income are censored from the moment the individual enters the spell.

- Entitlement to unemployment insurance: over our analysis window, we consider individuals as becoming eligible to 14 months of UI after being in employment or treatment for 4 months. The following variables have been created to capture these factors:

  - Work experience: set to 0 in January 1990, experience is then calculated as the cumulated number of months in employment till then.

  - Months in employment or treatment to count towards renewing full eligibility: number of months in employment or treatment since the last time the individual has started an unemployment spell being fully entitled to the 14 months of UI.

– Remaining months of UI eligibility: varies between 0 to 14 and is used up while in unemployment.

Sample selection

The original dataset covered the population registering at an unemployment office between 1 August 1991 and 31 December 1998, with no occupational handicap and aged 16 to 30 (age being defined as year of registering minus year of birth).

For our analysis we have selected the population of Swedish males registering at an unemployment office during 1996 (note that from January 1996 individuals can no longer become eligible to UI for the first time via a programme) as either full-time unemployed or to take part in a programme. Individuals are then followed until December 1998, and their history is known back to January 1990. Additionally, at the time of registering individuals had to be aged 26-30 and have either compulsory education or 1-2 years of high school (60% of the full inflow sample; educational attainment has been derived from Statistics Sweden under the assumption that courses finish in May). The selected individuals are further observed not to upgrade their educational level during the analysis window (representing over 93% of the low-education individuals), never to have an occupational handicap (over 98% of original sample), never to be self-employed or sailors, never to have a negative spell (after corrections of obvious mistakes, over 96% of the original sample), and never to be in programmes for older, disabled or immigrant workers, in vocational rehabilitation or in self-employment grants. We have further dropped from the sample individuals with UI at inflow but no compensation left (less than 2%), as well as individuals not entitled to UI compensation at inflow but who fulfil the eligibility criteria (20% of the sample).

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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 probability of 1 and it becomes impossible to estimate the standard error.
(***) These are the parameters determining the weights, not the actual weights.