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Identifying treatment effects of active labour market programmes for Norwegian adults*

By Tao Zhang

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Abstract

We investigate treatment effects of active labour market programmes for Norwegian adults for the 1990 to 2000 period. Three types of active labour market programmes are evaluated within a competing risks hazard rate model. Non-parametric specifications on both duration dependence and unobserved heterogeneities are used. By utilising rich administrative data, we find that active labour market programmes do have intended effects on enhancing the transition probability to employment *after* the completion of programmes participation, but *during* the participation, the transition probability is low relative to that for non-participants. There is some evidence of heterogeneity of treatment effects with respect to observed individual characteristics, and effects for training programmes and wage subsidy programmes are pro-cyclical and more favourable at boom time. The positive treatment effects of labour market programmes are long lasting, at the same time diminish gradually over time when individuals remain in unemployment after completion of programmes. The net impact of active labour market programmes in terms of reduced total amount of unemployment exposure is estimated to be about 6.42%.

Keywords: labour market programmes, treatment effects, competing risk, non-parametric estimation.
JEL Classification: C41, J24, J64.

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1. Introduction

Active labour market programmes have been widely applied in attempts to combat rising unemployment during the past decades. In most OECD countries, active labour market programmes have been used extensively when the economy has been at slump. In continental Europe, particularly in the Nordic countries, labour market programmes have a long tradition and major status in government policy consideration.

Evidence on the impact of active labour market programmes displays a mixed picture. In the US, no clear conclusion has been made on the effects of programmes in terms of enhanced employment opportunity and job perspective. In Europe, some encouraging results regarding the success of programmes have been seen lately. But equally many empirical studies have showed no or even negative effects. For a general survey, see e.g. Heckman et al (1999) and Fay (1996). Some recent evaluation literature on the European active labour market policies can be found in e.g. Fertig et al (2002) and Gerfin and Lechner (2002). It is notable that quite a few studies have showed that the Swedish model, which is associated with the most ambitious active labour market policy of all, has failed to produce convincing evidence of favourable treatment effects, see e.g. Ackum et al (2001) and Calmfors et al (2001).

Recent studies on the evaluation of Norwegian active labour market programmes have, however, produced some encouraging results. Raaum et al. (2002) have found that with income as a measure for post programmes success, labour market training programmes have a significant positive treatment effect. They also find that the effect is strongly influenced by business cycle conditions and is strongest when job opportunities are favourable. Røed and Raaum (2003) have evaluated the total effects of participation in active labour market programmes and also found positive impacts on the transition probability from unemployment to employment. Aakvik et al (2000) have provided some positive evidences on the Norwegian rehabilitation training programmes.

In this paper, we evaluate the Norwegian active labour market programmes within the model framework of unemployment duration analysis. We model the assignment of treatment in terms of hazard rates, and evaluate the resulting changes of transition probability to job *during* and *after* programmes participation as a measure for success. We apply a 5-state competing risks model, non-parametric specification for both duration dependence and unobserved heterogeneity. The econometric approach used in this paper starts out from the dependent competing risks treatment evaluation framework provided by Røed and Raaum (2003). However, we extend their model in three directions: First, while Røed and Raaum (2003) view the "treatment" as a single one-dimensional state, we model the selection into and the causal effects resulting from programme participation separately for three different types of programmes. Second, while Røed and Raaum (2003) treat the duration of the programmes as exogenous, we model the duration of the programmes as part of the competing risks structure. And finally, while Røed and Raaum (2003) model the treatment effects as constant at individual level (except from a "dying out" effect after completion), we model the treatment effects as varying freely from month to month, both through the participation phase and afterwards. Our findings suggest that in general, the basket of active labour market programmes has a significant positive impact on the probability of employment.

The difficulty that lies beneath all studies on the labour market programmes effects is that in the studies on observational data, assignment of treatment is unlikely to be totally random due to the population heterogeneity. In evaluation of treatment effects, the fundamental problem is thus the unobserved heterogeneity (Heckman et al 1999). If the treatment is assigned to a subpopulation with systematically different characteristics than the population as a whole, we would inevitably have a sample selection problem. Heckman (1979) was the first to analyse the impact of such selectivity bias due to population heterogeneity. It is well conceived that participants who receive treatment may have some unobserved characteristics that researchers cannot assess, e.g. that they are more inclined to participate and more responsive towards the treatment. If the assignment of treatment is not random, the outcome of such treatment can be driven by the same factors that influence the probability of receiving treatment itself. Fail to controll the unobserved heterogeneity in the form of self-selection into the treatment, the effect of treatment is obviously estimated with bias.

The ideal way to avoid such self-selection bias (also administrative selections) is to randomise the assignment of treatment to identically assembled sample such that the outcome is not conditional on factors that influence the assignment. This is a common practice in experimental studies such as in medicine and biology. Rubin has done an extensive research on the causal effect of treatment within the experimental settings (e.g. Rubin (1974), Holland (1986)), and maintained that causal effect can only be identified through experiments (Holland (1986), also see Lalonde (1986)).

Some methods have been developed to minimise the risk of selection bias in analysing non-experimental data. Matching techniques have been applied widely in evaluating treatment effects (Heckman et al. (1997)). A central assumption behind the matching technique is the conditional independence assumption, which means that conditional on observed heterogeneity, the effect of treatment does not depend on the assignment probability of such treatment. Under this assumption, by matching treated with untreated who has "similar" observed characteristics, the estimated effect is unbiased. Nevertheless, in practice, it is not always possible to ensure that observed characteristics catch up all the population heterogeneity. In addition, the conditional independence assumption is a rather strong assumption and justification is not without difficulty in practice.

Another method in tackling independence of treatment assignment is the exclusion assumption. This means that by utilising some instrumental variables that enter the determination of treatment assignment but do not affect the outcome, the probability of assignment and effect of the treatment are not perfectly correlated. It is however difficult in practice to find such instrumental variables and justification of independence is often questionable. Some other methods such as difference-in-difference have been developed in the evaluation literature. A comprehensive reference is Heckman et al. (1999).

Most of such methods have a style of "binary-choice and binary-effect". This means that the assignment of treatment is modelled by a binary (or multivariate) choice model and the effect of treatment is modelled in a similar way. They are mostly static evaluation practices and the time until treatment and the time until outcome are usually ignored. Abbring and van den Berg (2003b) have argued that it is precisely the time until treatment and time until outcome that convey important information in capturing the selection into the treatment and selection towards outcome. They suggest that duration modelling framework is suitable in treatment evaluation, and prove that the treatment effect is non-parametrically identified within the context of a mixed proportional hazard rate model. Richardson and van den Berg (2002), Lalive et al. (2001), and Røed and Raaum (2003) are recent applications in evaluating treatment effects using duration model framework. In this paper, we adopt identification results of Abbring and van den Berg (2003b), also identifications based on time-varying covariates suggested by McCall (1994) and Brinch (2000). We propose here a dynamic analysis of treatment evaluation within the context of duration model with unobserved heterogeneity.

The rest of this paper is organised as follows: Section 2 gives a brief introduction to the institutional settings of Norwegian active labour market programmes, also describes the data at hand and estimation strategies. Section 3 gives an account of econometric theory and modelling of the treatment evaluation problem. Focus is given to the identification of treatment effects in competing risks model and advocate the use of duration modelling. Section 4 presents main results. We will show the estimation of determinants of programmes participation, also present estimated treatment effect in a dynamic setting. Section 5 concludes and offers some policy implications.

2. Norwegian labour market programmes and data used in this analysis

Norwegian active labour market programmes have been important policy tools to combat rising unemployment for many years and have been applied extensively during the past decades. One of the stated goals of active labour market programmes is to increase the employability of the participants. In addition to its primary intention, the active labour market programmes also have a number of welfare implications. By admitting unemployed workers to programmes with some form of allowance or economic compensation, it may prevent poverty and avoid individuals from dropping out of labour market, and maintain their social network.

Active labour market policy also serves as an incentive scheme particularly for unemployment benefit claimants. For most of the period covered by the analysis in this paper, unemployment benefit claimants were entitled to benefit for a maximum duration of

186 weeks (about 47 months), but with a possible cut-off period of 13 weeks after the first 80-week period (18-20 months). If the unemployed fails to meet certain criteria for active job search after the exhaustion of the first benefit period, the benefit is cut-off for a quarantine period. Although strict enforcement rules of cut-off were rarely applied, benefit claimants have often been required to participate in some programmes in order to maintain the benefit entitlement during or after the quarantine period.

The scope and volume of active labour market programmes are adjusted according to the overall unemployment situation. When in the slump time, a wide range of programmes are offered to unemployed, while in boom time the programmes are scaled down. All programmes evaluated here are offered and organised by the public employment services – some of them in cooperation with other agents, both private and public.

Since the one of the primary goals of active labour market programmes is to increase the employability of unemployed persons, it is natural in this paper to define the success of programmes by the enhancement of the employment probability. We use the term *treatment* to denote the participation in the active labour market programmes. The *causal effects* of programmes are measured by the changes in transition probability from unemployment to employment for programme participants. For a systematic study of programme effects, we classify the Norwegian active labour market programmes into 3 groups[1]:

1. Labour market training programmes. This group mainly consists of formal training courses offered by the public employment services. It is mainly a qualification scheme. By participating in courses in different areas including general and occupational specific trainings, the participants are able to improve their individual qualifications for either their existing occupations, or the new careers. Also, some special courses are offered to immigrants in order to improve their language skills. The duration of these programmes varies, but most of them last for 1-5 months. Some courses are preparatory, leading to some more advanced courses next term. Thus we may observe periods of programme participation last for up to 10 months. Admission usually takes place in the start of spring and autumn seasons. But in reality, exceptions are often made to suit the individual's particular needs. Training

[1] For a description of Norwegian active labour market programmes, see e.g. Torp (1995).

programmes constitute almost half of active labour market programmes in Norway. They are in principle open for all unemployed jobseekers, and no specific qualification is required for participation.

2. Temporary employment in public sectors (including voluntary sector). This group of programmes is targeted at the long-term unemployed, or those who are particularly "hard-to-employ". Duration of programmes is normally up to one year. By offering temporary placement in public sectors, the programmes aim to prevent unemployed from dropping out of the labour force. The employment programmes were offered in large scale during the last slump period in early 1990's, but reduced dramatically as labour market conditions became favourable in late 1990's. From the year 2000, the employment programmes have no longer been offered.

3. Wage subsidy, stand-in jobs, courses in active job search, etc. The wage subsidy programmes work with private establishments to employ jobseekers, while part of the wages are subsidised by governmental employment offices. Stand-in jobs are on temporary basis, but are normal employments by nature. Courses in active search are aimed to provide information about job market and personal adjustments to fit in, etc. We group these programmes together under the name "wage subsidy programmes". This group of programmes is aimed to assist ready-to-work jobseekers by enhancing their competitiveness in the job market, hence the participants are usually more qualified than those in other programmes.

The motivation for us to focus on these 3 groups of programmes and evaluate effects of participation in these programmes separately is this: it is obvious from the design of ordinary active labour market programmes that the targeted participants of different programmes are different. The wage subsidy programmes are targeted to those ready-to-employ jobseekers with higher qualification, while the employment programmes are targeted long-term unemployed who have the most difficulties in the job market. Thus admission to different programmes is selective both in terms of individual characteristics, and in terms of administrative admission requirement (administrative selection), see e.g. Røed et al. (2000) for a detailed exposure. Secondly, the treatment effects of different labour market programmes are likely different due to different selection mechanisms into the programmes. If evaluating various programmes aggregately, the total effects would be driven by shares and compositions of participants of different programmes.

The data we use in this analysis is from a wide range of official administrative registers collected at the Ragnar Frisch Centre for Economic Research. They include unemployment registers for the whole Norwegian unemployment population from 1989 to 2000, combined with detailed demographic information for the Norwegian population collected in 1993-1997, and detailed labour market experiences from 1967 to 1999.

In this analysis we focus on the core of the labour force, i.e. adult male and female job seekers, aged 25-50, not temporarily laid off, who have been full time employed for at least 12 months prior to entering the registers as unemployed. All of them are entitled to unemployment benefits (i.e. they are entitled to about 62.4 per cent compensation of previous before-tax earnings up to a ceiling for a period about 47 months). The reason for putting these restrictions on the sample is to have a pretty homogenous analysing population when it comes to preferences and labour market options. For unemployed members of the core of the labour force, gainful employment is supposed to be the preferred and dominant transition. For very young and senior unemployed, other options as well - such as education and retirement - are possibly both preferred and available. Restricting the analysis to the core of the labour force enables us to identify the effects of the evaluated programmes on the employment for participants who are motivated for returning to employment. At the same time we are essentially excluding out-of -labour-force as a possible transition state. The purpose of restricting our attention to those entitled to unemployment benefits is due to registration phenomena. Without unemployment benefit, the incentive to register with public employment service is weak; therefore the unemployment spells are likely not correctly measured for non-benefit-claimants. To avoid the contamination of data due to incomplete unemployment registration, we censor the spell once the jobseeker loses his or her unemployment benefit.

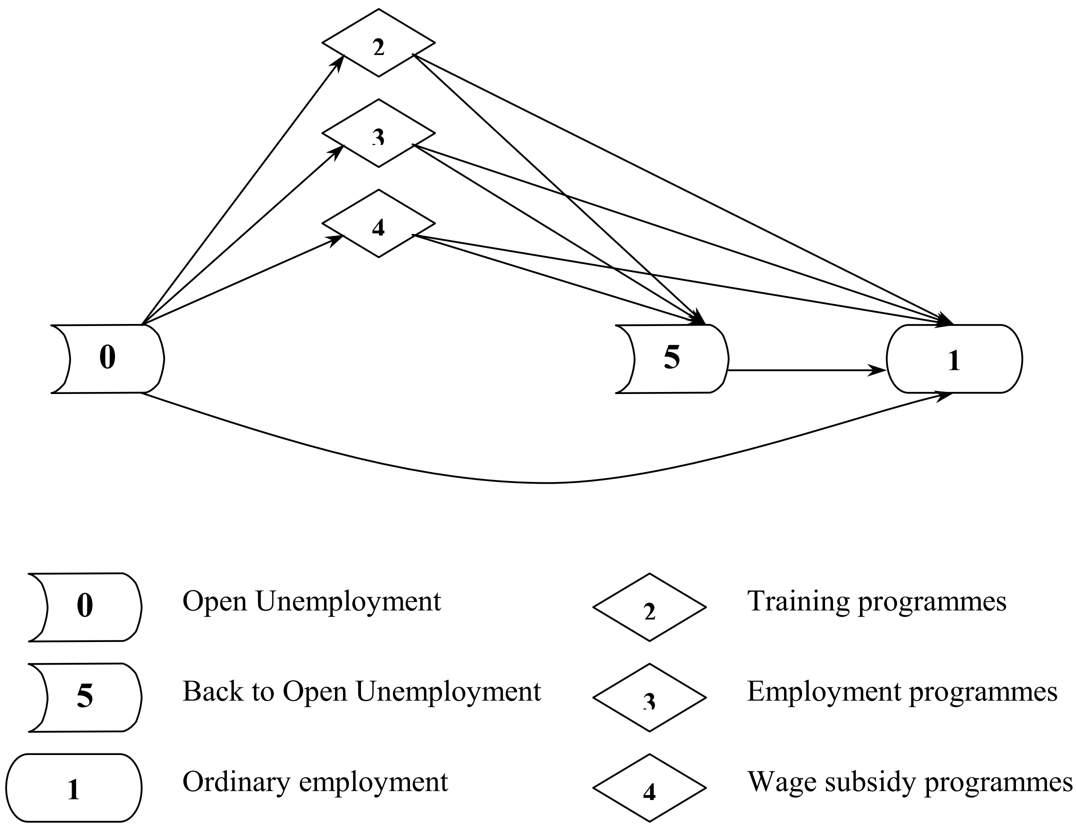
Our observational window is set from January 1990 to December 2000. Since employment programmes ceased to exist from year 2000, and there were very few participants already from 1998, we censor the employment programmes from January 1998. For each month, we record the status of unemployment, along with observed individual characteristics. All observed individual characteristics are in principle time-varying if their values change during the spell.

Each individual enters our analysing data as a new entrant to open unemployment. We define 4 possible transitions from the entrance to open unemployed: to ordinary employment and to 3 labour market programmes defined above. The duration of the unemployment spell is defined in the following way: the spell starts as open unemployment with 4 possible transitions (after January 1998, there are only three possible transitions: ordinary employment, labour market training programmes and wage subsidy programmes). We follow the spell until there is a consecutive two months of registered part-time job observed, or a consecutive three months absence from the unemployment register[2]. We define it as a successful transition to employment. If a transition to any of the 3 programmes has occurred, we then followed the spell further until a termination (defined below) is observed. When the individual is participating in labour market programmes, we only allow two possible transitions: back to open unemployment or to ordinary employment. If individual completes a labour market programmes and returns to open unemployment with unemployment benefit, we only allow one possible transition: to ordinary employment.

To better illustrate the dynamics of transitions between unemployment, labour market programmes and ordinary employment, Figure 1 provides a flowchart for these complex processes. The arrow lines indicate the directions of possible transitions an individual can take from the current state he or she is occupying. Let j be the origin states and k be the destination states for transitions. The individual enters open unemployment as state $j=0$ and facing 4 possible transitions indicated by four arrow lines ($k=1,2,3,4$). Once a transition to one of the programmes is made, e.g. in Figure 1, if the individual is at state $j=1$, the only possible transition is $k=5$ (back to open unemployment after completing the programmes) or to state $k=1$ (ordinary employment). If the individual is at state $j=5$, then the only possible transition is to job ($k=1$), indicated by the single arrow line.

[2] The part-time jobs are registered in the unemployment register. However, we do not have the complete employment register for the whole analysing period. Therefore, we have to rely on such criteria to define transition to employment.

Figure 1: Flowchart of dynamic transitions between unemployment, active labour market programmes and ordinary employment.



Spells are terminated either due to transition to ordinary employment, or censored. Spells are censored after 36 months of the total length, as the observed frequencies of transitions are too low for a precise estimation after 36 months. Also we restrict our attention to only one treatment at a time. This means that if an individual has taken a transition from one programme to another, we censor the spell accordingly at the transition month. This is because we are interested in evaluating each treatment effect on the transition probability to job alone. If we allow multiple programmes participation, the estimated effects may be the joint effects of multiple programmes. Our censoring scheme allows us to isolate the pure effect on transition probability to job from each and one programme alone, and avoid complicated joint effects of multiple treatments.

After careful preparation, we have to our disposal 115,557 individuals with 126,034 spells. The total number of monthly observations in our estimation sample is 664,250. Table 1 gives a summarizing view of analysing data. A quick glance of Table 1 reveals that there are more men (57%) than women in our sample, probably as a result of the previously full-time work requirement. Average age is around 35. We find that those with low educational attainment (less than high school) are in majority with 78%. Average time spent in unemployment is approximately 5.27 months. For those eventually participating in some labour market programmes, time spent before participation is on average 7.53 months. Mean duration of programmes is 3.45 months. Those remaining unemployed after participation would have on average 4.41 more months before a possible job transition (or being censored). Of all 126,034 spells, 93,528 have a successful transition to ordinary employment. Among these, 6,624 make the transition with the assistance of participations in the labour market programmes.

3. Econometric model and identification of treatment effect.

We consider a mixed proportional hazard rate model with *k* competing destination states of transitions from origin state *j* over a continuous time τ. The transition specific hazard rate can be defined by

$$(1)\quad \theta_{jk}\left(\tau \mid \mathbf{X}_{jk\tau}, v_k\right) = \lim_{\Delta t \to 0} \frac{P(\tau \le T_{jk} \le \tau + \Delta\tau, K = k \mid T_{jk} \ge \tau, \mathbf{X}_{jk\tau}, v_k)}{\Delta\tau} = \lambda_{jk}(\tau) \cdot \phi(\mathbf{X}_{jk\tau}) \cdot v_k$$

here $\lambda_{jk}(\tau)$ is the underlying duration baseline associated with transition *k*; $\phi(\mathbf{X}_{jk\tau})$ is the structure term of covariates affecting the transition specific hazard rate. Note the subscript τ and *k*, which indicate that the effects of covariates can be transition specific and time-variant. v_k is meant to capture the unobserved transition specific heterogeneity with unknown distribution. We assume v_k is constant throughout the spell duration. In applied research, we often encounter discrete time units, which might be due to the observational or data sampling practice. In Norwegian official registers for unemployment, the available data is commonly updated at the end of each calendar month, which implies that

Table 1: Statistics of estimation data.

# of individuals	115,557	
# of spells	126,034	
# of monthly observations	664,250	
Means*	**mean**	**std**
Gender (1=male)	0.5744	0.4944
Age (years)	34.9793	7.3265
Married (1=yes)	0.4499	0.4975
Having children under 18 years (1=yes)	0.5682	0.4953
Non-OECD immigrants (1=yes)	0.0529	0.2238
Immigrants with Norwegian citizenship (1=yes)	0.0266	0.1609
Having relevant experience for intended job	0.9274	0.2595
Having relevant training for intended job	0.8107	0.3917
County of residence		
Akershus, Hedmark, Oppland, Buskerud	0.2358	0.4245
Vestfold, Telemark, Aust-Agder, Vest-Agder	0.1803	0.3845
Rogaland, Hordaland	0.1333	0.3399
Sogn og Fjoldane, Møre og Romsdal, Sør-Trondlag, Nord-Trondlag	0.1507	0.3578
Nordland, Troms, Finnmark.	0.1077	0.3101
Education attainment (percent)		
up to 9 years	0.7812	0.4134
10 years	0.1568	0.3636
11-12 years	0.0616	0.2405
13-16 years	0.0002	0.0138
17 or more years	0.0002	0.0146
Occupational Background		
Technical, physical science, humanistic and artistic	0.2178	0.4127
Administrative executive work, clerical work and sales work	0.2979	0.4574
Agriculture, forestry, fishing and related work	0.0177	0.1319
Manufacturing work, mining, quarrying, building and construction work (reference)	0.2767	0.4474
Service work, transport and communication	0.1817	0.3856
Unspecified	0.0081	0.0898
Transitions (# of spells)	**#**	
To Job	93,528	
Have not participated in Active labour market programmes	86,904	
Have participated in Active labour market programmes	6,624	
To Training programmes	10,732	
To Employment programmes	2,106	
To Wage subsidy programme	7,533	
Back to open unemployment after participation in programmes	6,978	
Censored	26,538	
Durations (months)**	**mean**	**std**
Average total spell durations	5.2704	5.7098
Average durations until programmes	7.5313	6.0819
Average durations after programmes	4.4110	4.2507
Average durations of programmes	3.4599	2.8795

Note: * means are calculated on spell basis. ** means are calculated within relevant groups.

the smallest reliable time unit is month. In the case of some discreteness, a convenient assumption is that the competing hazard rates are constant within each time unit. This is probably an innocent assumption, provided that the time unit is small. In our case, let *d* be discrete time unit (e.g. month, $d = 1, 2, \ldots$), we can for example define the integrated hazard rate within interval $[d - 1, d]$ as (for transition from *j* to *k*):

$$\int_{d-1}^{d} \theta_{jk}(u \mid \mathbf{X}_{jk\tau}, v_k) du = \int_{d-1}^{d} \lambda_{jk}(u) \cdot \phi(\mathbf{X}_{jk\tau}) \cdot v_k du$$

As in the dynamic transition process depicted in Figure 1, we define origin and destination states as:

$j,k = 0$ open unemployment
$j,k = 1$ ordinary employment
$j,k = 2$ training programmes
$j,k = 3$ employment programmes
$j,k = 4$ wage subsidy programmes
$j,k = 5$ back to open unemployment

In our context of programmes evaluation, we start by model a four-state competing risk model from origin state of open unemployment, with mixing unknown distributions for unobserved heterogeneity for each state. We follow the spell until a transition to either of the four states has occurred. Note however that, once a transition to one of the labour market programmes has taken place, the possible transitions from labour market programmes are restricted to job and back to open unemployment again. Here we do not allow cross programmes transitions. While the individual is participating in the programme, the competing risks are reduced to only two possible transitions, *k=1* and *k=5* (back to open unemployment), with origin state be *j=2,3,4,* (participating in programmes). If the individual has finished participation in labour market programmes and nevertheless still remains unemployed, we define the origin state be *j=5* (have participated, but still unemployed after the participation), and the only possible transition is reduced to job (*k=1*).

We also introduce an important model term: the calendar variation, as time-varying dummy variables σ_t, to denote the calendar months *t* at which each individual is at the risk set. These are meant to capture the aggregate labour market conditions and business cycle and seasonal effects on the transition probabilities out of unemployment. There are totally 132 such dummies. The estimation of calendar dummies itself can be proven of great interest. Røed and Zhang (2003) have showed that the predicted hazard rate (from estimation of a single risk model) on each calendar dummies can have the convenient interpretation as the cyclical variation in the transition. Røed (2002) gives a detailed account on the properties of such estimates and possible business cycle interpretation of these.

We are only interested in treatment effects on job probability in this paper. Therefore we model the treatment effects only in the hazard rate for job transition. The total treatment effects are modelled by

(2) $\Delta_{kt} = \delta_{0k}(\mathbf{D}_{0kt} + \mathbf{x}_{\mathbf{0}kt} + b_t) \cdot I_0 + \delta_{1k}(\mathbf{D}_{1kt} + \mathbf{x}_{1kt} + b_t) \cdot I_1,\ \ \Delta_{kt}=0\ \textit{if}\ \ k \neq 1.$

The (exponential of) Δ_{kt} is the aggregated treatment effect in calendar month *t* which affects hazard rate proportionally. Note that Δ_{kt} by definition only affects transitions to job. In order to fully assess the treatment effects of labour market programmes, we have made some decomposition of aggregated effects Δ_{kt}. First, we let effects vary *during* the participation and *after* the participation. δ_{0k} is the effect of labour market programmes while under the participation; δ_{1k} is the effect after the participation. We denote accordingly *while-treatment effects* and *after-treatment effects* respectively. I_0 and I_1 are indexing functions, which indicate if the individual is currently under participation and if the individual has participated in the labour market programmes earlier in the same spell, respectively.

Second, we allow the treatment effects to vary over time. In (2), $\mathbf{D}_{0kt}$ is a set of dummies to indicate 1,2, … months after the *start* of treatment, while $\mathbf{D}_{1kt}$ is a set of dummies to indicate 1,2, … months after the *completion* of treatment. By interacting treatment effects with these two sets of dummies, we can then fully examine the time pattern of treatment effects on an individual's transition probabilities, both while under treatment and after treatment.

We introduce further heterogeneous treatment effects for various demographic observables by letting while-treatment effects and after-treatment effects to be dependent on observed covariates such as gender, age and education, by introducing interactive terms. In (2)

$\mathbf{x}_{0kt}$ and $\mathbf{x}_{1kt}$ are vectors of individual characteristics that we wish to interact with treatment effects.

It is also conceivable that treatment effects may vary with respect to job opportunities and labour market conditions. Raaum et al (2002) find that the impact of labour market programmes varies over the business cycle. At least for training programmes, a strong pro-cyclical tendency has been found. Therefore it is of importance to look into the treatment effects within the context of business cycle. We also wish to investigate here how the while-treatment effects and after-treatment effects of programmesparticipation would be affected by business cycle conditions. To facilitate that, we let the treatment effects be interacted with business cycle indicators b_t. The business cycle indicator is taken from Gaure and Røed (2003). It is a vector of smoothed calendar time parameters for each calendar month from 1989 to 2002, estimated from a comprehensive hazard rate models for transitions from unemployment to employment. Similar usage of estimated outflow rates as business cycle indicators can be found in e.g. Raaum et al. (2002) and Røed and Zhang (2003). For a more detailed discussion of this set of business cycle indicators, see Gaure and Røed (2003).

Let $\lambda_{jkd} = \log(\int_{d-1}^{d} \lambda_{jk}(u)du)$, $\phi(\mathbf{X}_{jkt}) = \exp(\mathbf{X}_{jkt}'\beta_k)$, $\mu_k = \log(v_k)$, the integrated hazard rate for interval $[d-1, d]$ is thus

$$\varphi_{jk}(d,t,\mathbf{X}_{jkt},\mu_k) = \exp(\lambda_{jkd} + \mathbf{X}_{jkt}'\beta_{jk} + \sigma_{kt} + \Delta_{jkt} + \mu_k)$$

and the monthly transition probability from origin *j* to destination *k* is given by

$$(3)\ \ h_{jk}(d,t,\mathbf{X}_{jkt},\mu_k) = \left[1 - \exp(-\sum_k \varphi_{jk}(d,t,\mathbf{X}_{jkt},\mu_k))\right] \cdot \frac{\varphi_{jk}(d,t,\mathbf{X}_{jkt},\mu_k)}{\sum_k \varphi_{jk}(d,t,\mathbf{X}_{jkt},\mu_k)}$$

for relevant *j* and *k*.

One important feature of our model framework in (3) is the dynamic definition of risk sets. Depending on which transition is realised, the subsequent risk sets an individual occupies are endogenously defined. Once a transition to a labour market programme has occurred, a new possible transition (back to open unemployment) is added, and the individual finds himself within another risk sets. In our model framework, we open for interdependence of different transitions by allowing unobserved heterogeneity μ_k to be dependent across transitions, i.e. $\text{cov}(\mu_k, \mu_m) \neq 0$ for $k \neq m$.

Equation (3) has a familiar form of complementary loglog model. It has the advantage of flexibility, which we find is very suitable for non-parametric duration analysis. There is an obvious advantage to adopt non-parametric specification because in reality, the economic theories and observational data do not provide convincing arguments towards using any particular parametric functional form specifications. Arbitrary chosen functional form would involve the risk of misspecification, particularly for unobserved heterogeneity. Heckman and Singer (1984) have warned about the danger of "overparameterising" the unobserved heterogeneity, and suggested the approach of specifying a discrete distribution with support of unknown number of points to non-parametrically estimate the unknown mixing distribution. They have proved consistency of such non-parametric maximum likelihood estimators. Baker and Melino (2000) provide Monte Carlo evidence for single risk models. Their conclusions are more in favour of semi-parametric specification, where the unobserved heterogeneity is modelled by discrete mass points, while the duration dependence is modelled by some parametric family. Zhang (2003) has done an extensive Monte Carlo study on models where both duration dependence and unobserved heterogeneity are specified non-parametrically. He found that non-parametric specified duration dependence and unobserved heterogeneity can be consistently estimated. Further more, even when the true underlying distribution is parametric, non-parametric estimation can still produce reasonable approximations. He also showed the evidence of consistent estimation for competing risks model with bivariate normal distributed unobserved heterogeneity. In our model, we have 5 distinct competing states and 5 mixing distributions for unobserved heterogeneity. We find it difficult to apply any parametric functional form on all duration dependences, not to mention combinations for unobserved heterogeneity. Therefore the non-parametric specification is especially suitable in our context. We have chosen to model the duration dependence and unobserved heterogeneity non-parametrically by using step functions for λ_{jkd} and μ_k in equation (3).

The calendar time of commencing and elapsed spell duration can function as additional identification source for unobserved heterogeneity. The intuition behind this is as follows:

In applied study, it is typical that local or macro economic environments will have effects on the transitions from unemployment to work. Consider two individuals that are identical in every observed aspect and have the same length of elapsed unemployment spell. Given the assumption of proportional hazards, these two should experience the same hazard rate if they have the same value of unobserved heterogeneities. But if one experiences unemployment during a slump period when “everyone” is hit by the unemployment risk while the other starts unemployment in a boom time when job opportunity is good and the overall outflow rate is high, it is intuitively plausible that the individual being unemployed at the boom time should have a better job opportunity and shorter duration than that of the “identical twin” in the slump time. The fact that they have the exact length of spell can then only be accredited to the unobserved differences between them (plus random factor). It is therefore likely that the one unemployed in boom time might have somewhat unfavourable personal characteristics that comparing to the one in the slump time with the same spell length, which implies lower chance of getting employed, even though the observed characteristics are identical. The same argument can apply on the transitions to different labour market programmes as well. Given the same length of elapsed spells, the different hazard rates for transition to one type of labour market programmes of two otherwise identical individuals must reflect different unobserved characteristics associated with the programme transition. This is to say that, time of the unemployment spell taking places and undergoing is the only source of hazard rate variation, cerates paribus. Therefore by including control for such exogenous variations of calendar time within the hazard rate formulation, the identifiability of unobserved heterogeneity should be greatly improved.

Identification of such competing risks model has been a focal point in the hazard rate model literature, see Heckman and Honoré (1989), McCall (1997) and Abbring and van den Berg (2003a). The general review on identification of competing risks duration model with time-varying covariates can be found in e.g. van den Berg (2001). Abbring and van den Berg (2003a) have proved that under proportionality and some regularity assumptions, the dependent competing risks model is non-parametrically identified. McCall (1996, 1997) has showed some identification results when models possess time-varying covariates. Brinch (2000) has proved that with time-varying covariates, the proportionality assumption can be relaxed, and the mixed hazard model is identified non-parametrically. Zhang (2003) provides Monte Carlo evidences both for single risk and competing risk models showing the advantages of including time-varying calendar variations as identification sources for unobserved heterogeneity.

Abbring and Van den Berg (2003b) have discussed and proved that under some regularity conditions, the treatment effect is identified non-parametrically within the duration model framework. The *timing-to-event approach* is suitable for treatment effect estimation in several aspects: 1. *Randomness in treatment assignment*: Though in practice the determinants that affect the assignment of treatment are never fully known, they are modelled in the form of competing risks hazard rates, therefore whether an individual is receiving the treatment is characterised by a transition probability, which by definition of probability itself ensures the randomness in assignment. 2. *Selection problems:* as elaborated earlier, it is the unobserved population heterogeneity that produces selection biases on the evaluation of treatment effects. Control of the observed heterogeneity can minimise the impact of selection on treatment effect, but never fully eliminate the source. In the mixed hazard rate model, not only the observed heterogeneity is fully modelled, but also the unobserved heterogeneity is taken into account by mixing its distribution with the hazard rate. Moreover, by allowing the unobserved heterogeneity associated with different transitions to be correlated, the selection is captured by the correlation coefficients of unobserved heterogeneity across transitions. By ensuring randomness in treatment assignment and controlling for selection bias due to unobserved population heterogeneity, the causal effect of treatment can be successfully revealed in hazard rate model framework, see Abbring and van den Berg (2003b).

The model is estimated with maximum likelihood method. Due to the complexity of transition processes, we find it convenient to divide the total duration of a spell into 3 segments: duration before possible transitions to labour market programmes, duration while participating, and duration of post-programme period. Let

$\kappa_t = 0$ if $j = 0, k = 1,2,3,4$

$\kappa_t = 1$ if $j = 2,3,4, k = 1,5$

$\kappa_t = 2$ if $j = 5, k = 1$

Define $d = \sum_{\kappa_t} d_{\kappa_t}$, where d_{κ_t} is the duration associated with each spell segment according to κ_t.

We use spells, rather than individuals as the basic unit for unobserved heterogeneity as well as likelihood formulation. This implies that we have ignored the information provided by multiple spells of the same individual. Although repeated spells are valuable sources for identification of unobserved heterogeneity (Honoré (1993)), we find several reasons to use spells after all. First, it is not likely that the unobserved characteristics for an individual would remain constant across spells, especially since we have conditioned the entrance to our data on the 12 months absence rule. Thus treating repeated spells from the same individual as independent spells in our context is more reasonable. Second, persons with repeated spells are not likely to be representative. This is because the length of the second spell is inversely related to the length of the first spell, given the observational window. This might have imposed some possible selection problem that persons with multiple spells are likely to have shorter earlier spells. Also from the statistics showed in Table 1, there are relatively few individuals with repeated spells. Therefore we feel using spell as unit for unobserved heterogeneity is justified.

We model the unobserved heterogeneity in the form of a discrete distribution with w different mass points. Let p_w be the probability of a particular combination of unobserved variables, $\sum_w p_w = 1$. Also note that since calendar time and spell duration effects are varying from month to month, we have to divide each spell into many one-month long subspells, which sum up to original spell length. This is a known technique in dealing with time-varying covariates.

Let $Z_{\kappa t}$ be an dummy indicator variable that:

$Z_{0t} = 1$ if $\kappa_t = 0,\ Z_{0t} = 0$ otherwise
$Z_{1t} = 1$ if $\kappa_t = 1,\ Z_{1t} = 0$ otherwise
$Z_{2t} = 1$ if $\kappa_t = 2,\ Z_{2t} = 0$ otherwise

This implies that $Z_{z+1} = 1 \Rightarrow Z_z = 1$, for $z = 0,1$. Further let i be spell id, the segmental likelihood for duration d_{κ_t} of spell i is then given by

$$(4)\quad L_{i\kappa_t} = \left[\prod_k h_{jk}(d_i, t_i, \mathbf{X}_{ijkt}, \mu_{ik})\right]^{y_{ijkt}} \cdot \prod_{l=1}^{d_{\kappa_t} - y_{ijkt}} \left[\exp(-\sum_k \varphi_{jk}(l, t_i, \mathbf{X}_{ijkt}, \mu_{ik}))\right]^{1-y_{ijkt}}$$
$$\textit{for}\ \kappa_t = 0,1,2,\ i = 1,2,\ldots,N$$

Here y_{ijkt} is the censoring indicator, which takes value 1 if transition from *j* to *k* is realised, 0 if the spell is censored.

The likelihood for a complete spell is thus

$$L_i = \sum_w p_w \cdot \prod_{\kappa_t} L_{i\kappa_t}{}^{Z_{\kappa_t}}$$

and finally the total likelihood function for the whole sample can be easily acquired as

$$(5)\quad L = \prod_{i=1}^{N} L_i = \prod_{i=1}^{N} \sum_w p_w \cdot \prod_{\kappa_t} L_{i\kappa_t}{}^{Z_{\kappa_t}}$$

The randomness of treatment assignment incorporated in the hazard rate model also implies that any deterministic mechanism of assignment cannot be revealed to the intended treated *prior to* treatment. But in reality, it might happen that the individual has certain expectations regarding the probability of being treated and accordingly adjust his optimal strategy either to increase the probability of receiving treatment, or to avoid the treatment. For example, the Norwegian social security system in principal requires a quarantine period when the first benefit period (18-20 months) is exhausted. In order to maintain economic support after this period, participation in some labour market programmes might be required by authorities. In this case, the unemployed might intensify his search activity prior to the benefit cut-off time to avoid possible impending programmes participation. Equally possible, knowing that programme participation is highly probable, the unemployed might reduce his effort in job search accordingly to await forthcoming programmes. In either case, ignoring this anticipation effect of treatment would result in biased estimate on treatment effects, since treatment also affects the behaviour of non-participants. In practice, it is very difficult to find suitable proxies for such anticipating effect of treatment, but anticipation effects that are systematically related to spell duration will be captured by duration baseline hazard rates.

The totally non-parametric specification of our model is very ambitious to estimate. We have adopted an "implicit dummy" approach to effectively reduce the computational cost on multiplications of large amount of dummy variables; see Gaure and Røed (2003). We apply a maximum likelihood approach in estimation, starting by no unobserved heterogeneity and add one point of support to the vector of unobserved heterogeneity at each iteration, until the overall likelihood cannot be improved further. The maximization routine is hard-coded in Fortran 90 with MPI implementation for parallel processing[3].

As Zhang's (2003) Monte Carlo results suggest, the optimal number of points found for the unobserved heterogeneity distribution is sensitive with respect to maximising routine and search directions, and it is advisable to adopt some information criteria to penalise the excessive points found for the discrete mixing distribution when the sample size is small. However, the maximum penalised likelihood estimators converge to pure maximum likelihood estimators when the sample size is sufficiently large. We also adopt methods in Zhang (2003) on maximum penalised likelihood to check if our results are sensitive with respect to number of points found. In our analysis, we have at our disposal about 120,000 individuals, and our results appear to be robust with respect to the selection of maximum likelihood and maximum penalised likelihood stopping rules.

4. Results

Due to non-parametric specifications, there are totally over 1,000 model parameters. To outline our main findings, we organise the presentations of results as following: we first report the duration baselines for transitions from open unemployment to ordinary employment and labour market programmes by plotting estimated baseline hazard rates. We then look in to the deterministic factors of selections into each transition by examining the estimated coefficients for covariates. Secondly, we report estimated treatment effects on the transition probability to employment, both time-varying effects and heterogeneous treatment effects with respect to individual characteristics. Thirdly, we present stylised figures to further illustrate effects of labour market programmes over unemployment spells. We also offer a measure for the total effects of active labour market programmes through simulation.

[3] We are fortunate to have Senior Analyst Simen Gaure at the University Information Technology Centre at University of Oslo to help us programme the estimation routine. All estimations are done on HP Superdome at High Performance Computing Centre, University of Oslo.

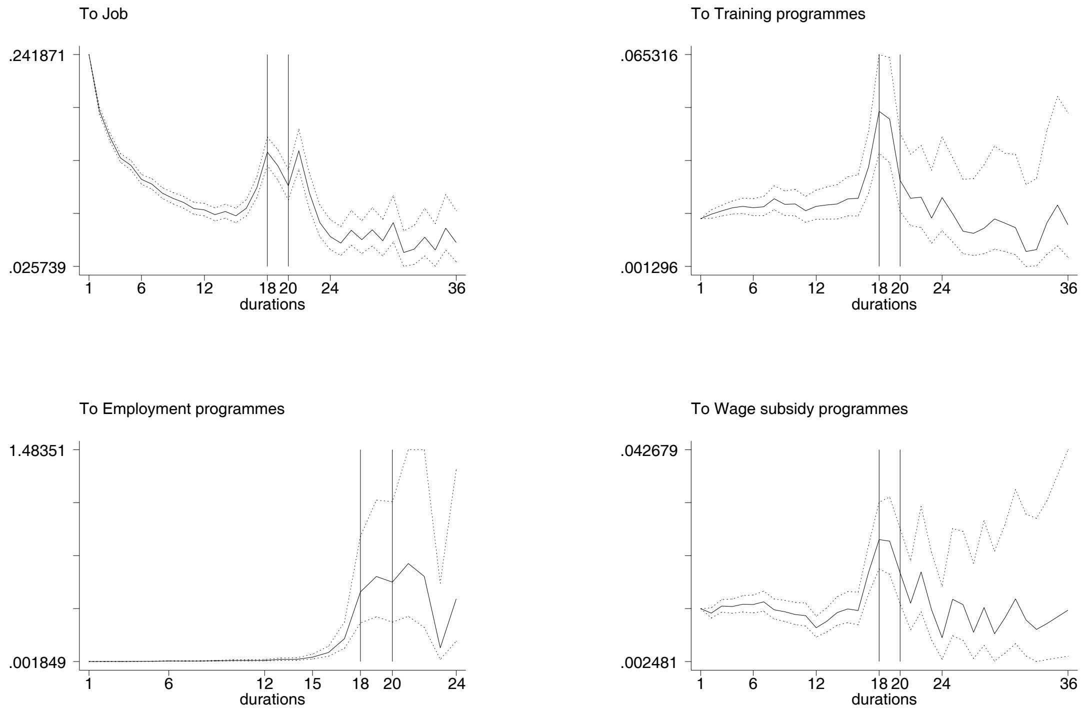
Selection into programmes

We plot estimates of the baseline hazard rates for transition to job and transitions to labour market programmes in Figure 2, together with 95% confidence intervals. The plotted curves are exponential of estimated coefficients and are normalised to the observed empirical hazard rates for the first month of spells. Note that they are estimates to the baseline hazard rates λ_{jkd} and do not have a direct interpretation of transition probabilities. For the baseline hazard rate to job, we find significant negative duration dependence even after controlling for unobserved heterogeneity. The hazard rate drops by half just after about 5 months. This suggests strong discouraged-worker effects and stigmatisation effect on transition to work. This agrees with several earlier studies on Norwegian labour market dynamics, see e.g. Røed and Zhang (2000), that even after control for unobserved heterogeneity, there is still strong negative duration dependence for the baseline hazard to job.

An interesting finding in the baseline for transition to job is that, at approximately 18 months of spell length, the hazard rate rises sharply from 0.11 up to 0.15 and remains this level until it drops down to 0.10 again after 21 months. The 18 months corresponds to about 80 weeks of first unemployment benefit entitlement period according to the Norwegian regulation, after which the benefit may be cut-off and there is a quarantine period before a possible renewal can take place. This seems to have a significant impact on the hazard rate out of the unemployment, as Røed and Zhang (2003) pointed out. Here the sharp rise of the hazard rate can to some extent be interpreted as an anticipation effect of impending labour market programmes. Given the knowledge of possible benefit sanction, the "threat" of participation in programmes seems to have considerably increased the hazard rate to employment.

The baseline hazard rates for transitions to training programmes and wage subsidy programmes seem to have no particular duration dependence at the beginning of spells. However, it is also interesting to observe the sharp rise of the hazard rates around 18 months for transitions to labour market programmes. Before the 18 months cut-off point, the baseline is almost flat. Around the benefit exhaustion time, the hazard rate estimates to both training programmes and wage subsidy programmes rise sharply by almost 100%

Figure 2: Duration baseline hazard rates with 95% confidence intervals.

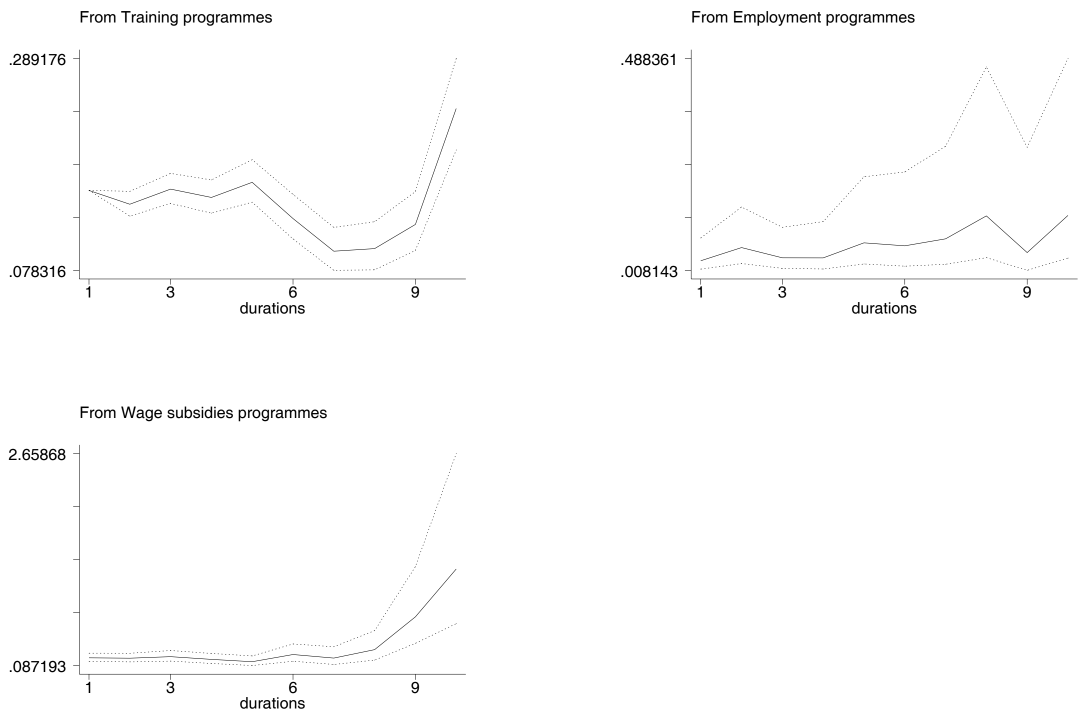


Note: Baseline hazard rates are normalised to the observed empirical hazard rates at the first month of spell. Duration for employment programmes is censored after 24 months due to lack of observations.

(from 0.05 to 0.08 for training programme, and from 0.002 to 0.005 for wage subsidy programme). This implies strong evidence of selection into programmes driven by the benefit exhaustion, which can be both self-selection (economic incentive of acquiring programmes allowances when benefits are exhausted), and administrative selection (priority of admission is given to those with exhausted benefits). The hazard rate approach here thus is able to take account of such self-selection into programmes via duration baselines.

The baseline hazard rate for transition to employment programmes is very low at the beginning of spell (around 0.0017) and quite flat until 15 months, where it rises sharply. This is possible evidence that employment programmes is designed for long-term unemployed and admission to programmes only occurs after certain length of duration. Due to lack of observations for longer spells for this transition, the baseline is censored after 24 months.

Figure 3: Duration baseline hazard rates for transitions back to open unemployment from participation in programmes, with 95% confidence intervals.



Note: all the baseline hazard rates are normalised to the observed empirical hazard rate of the first month participating in training programmes.

We also plot the baseline hazard rates for the transitions back to open unemployment while participating labour market programmes in Figure 3. We do not find significant evidence that the time spent in participation affects the hazard rate back to open unemployment. However, some positive duration dependence can be observed, especially for the wage subsidy programme. Explanation can be that the longer an individual stays in the programme participation, the higher the probability for back to open unemployment is, and it seems that the participation in programmes has a somewhat delayed effect which does not guarantee an immediate success.

Table 2 reports some of the important covariates estimations from the competing risks model. We restrict our attention to individual characteristics and their influences on hazard rates. The first column is the estimations of covariates for transitions from open unemployment to job. The second to fourth columns are estimations of transitions from open unemployment to labour market programmes. The last column is the estimations on the transition from programmes back to open unemployment (all three programmes combined). As to the determinants of transition to employment, female has a slightly better chance for job comparing to male unemployed (about 5.56%[4]); married adults seem to be more eager in finding employment, may be due to family responsibility; having younger dependents may reduce the probability of transitions to employment, possibly because taking care of youngsters reduces search intensity. Immigrants from non-OECD countries have difficulty in finding jobs comparing to natives, but once immigrants have acquired citizenship, the chance for an employment would increase by 7.32%. This is probably due to the fact that citizenship requires certain length of years staying in the country. Adaptation to language and culture, and basic knowledge of society would certainly contribute to success in the labour market. We find that younger people have better job prospects than elderly jobseekers. An individual's qualification measured in years of educational attainment plays an important role in employment opportunity. Compared to high school educated, with only primary school education would reduce the job probability by 15.1%. Also having relevant job training and experience helps to find employment quickly. All these findings are in concord with earlier studies on labour market dynamics, such as in Røed and Zhang (2000, 2003).

[4] The percentage changes are simply calculated by $\frac{e_1 - e_0}{e_0}$, where $e_1 = \exp(\hat{e})$, $e_0 = \exp(\hat{e}_0)$. $\hat{e}$ is the estimator, $\hat{e}_0$ is the reference.

Table 2: Estimated coefficients for competing risks hazard rate model.

	To job		To training programmes		To employment programmes		To wage subsidy programmes		Back to open unemployment	
	Est.	**Std.**	**Est.**	**Std.**	**Est.**	**Std.**	**Est.**	**Std.**	**Est.**	**Std.**
Gender (1=male)	-0.0581	0.0082	-0.0570	0.0254	-0.3683	0.0776	0.5038	0.0290	-0.0940	0.0322
Married (1=yes)	0.1965	0.0081	0.0250	0.0250	-0.0028	0.0730	0.1876	0.0288	-0.0898	0.0309
Having children under 18 years (1=yes)	-0.2050	0.0080	-0.0630	0.0248	-0.1318	0.0719	-0.0308	0.0285	0.0649	0.0304
Non-OECD immigrants (1=yes)	-0.5531	0.0255	0.1750	0.0643	-1.0815	0.2324	-1.1733	0.1126	0.0107	0.0901
Immigrants with Norwegian citizenship (1=yes)	0.0706	0.0333	-0.0647	0.0824	-0.4136	0.3280	0.4137	0.1386	0.0466	0.1143
Having relevant experience for intended job (1=yes)	0.1568	0.0144	-0.2753	0.0409	-0.2830	0.1236	0.0605	0.0506	-0.1077	0.0535
Having relevant training for intended job (1=yes)	0.0963	0.0095	0.1635	0.0291	-0.1723	0.0792	0.0772	0.0329	0.0293	0.0366
Age (ref: 36-40)										
25-30	0.1126	0.0109	-0.1006	0.0335	0.0907	0.0942	-0.0343	0.0388	-0.1127	0.0436
31-35	0.0199	0.0112	-0.0560	0.0342	0.0172	0.1005	-0.0852	0.0397	-0.0058	0.0443
41-45	-0.0493	0.0124	0.0303	0.0371	-0.0593	0.1091	-0.0561	0.0430	0.0289	0.0470
46-50	-0.1808	0.0139	-0.0886	0.0405	-0.2626	0.1214	-0.1512	0.0461	0.1804	0.0499
Educational Attainment (ref: 11-12 years)										
up to 9 years	-0.1637	0.0166	0.4057	0.0610	0.6613	0.2059	0.0969	0.0635	0.2795	0.0881
10 years	-0.0293	0.0173	0.3030	0.0635	0.4181	0.2125	0.2219	0.0659	0.0881	0.0917
13-16 years	0.2249	0.2480	*	*	*	*	-0.2779	0.9478	*	*
17 or more years	0.1577	0.2491	0.3014	0.9539	*	*	-0.6862	0.9896	*	*
County of residence (ref: Oslo)										
Akershus, Hedmark, Oppland, Buskerud	0.1522	0.0112	0.2742	0.0341	0.6406	0.1080	0.3755	0.0400	0.1370	0.0427
Vestfold, Telemark, Aust-Agder, Vest-Agder	0.1767	0.0130	0.2305	0.0395	0.8152	0.1260	0.4783	0.0447	0.0053	0.0513
Rogaland, Hordaland	0.1184	0.0120	0.3106	0.0368	0.3194	0.1207	0.0119	0.0453	0.0309	0.0466
Sogn og Fjoldane, Møre og Romsdal, Sør-Trondlag, Nord-Trondlag	0.2855	0.0126	0.1019	0.0419	1.6872	0.1182	0.2142	0.0473	0.1056	0.0535
Nordland, Troms, Finnmark.	0.3428	0.0142	0.1763	0.0477	2.0421	0.1262	0.5260	0.0492	-0.2057	0.0631
Occupational background (ref: Unspecified)										
Technical, physical science, humanistic and artistic	-0.0741	0.0400	-0.2500	0.1278	-0.4106	0.3526	0.2377	0.1706	-0.3279	0.1877
Administrative executive work, clerical work and sales	-0.2941	0.0400	-0.0936	0.1272	-0.9358	0.3523	0.3388	0.1698	-0.1664	0.1866
Agriculture, forestry, fishing and related work	0.0177	0.0477	-0.3798	0.1564	0.1892	0.3926	0.1040	0.1954	-0.1347	0.2233
Manufacturing, mining, quarrying, building, construction	-0.1360	0.0401	-0.1105	0.1272	-0.4538	0.3508	0.1082	0.1703	-0.0443	0.1868
Service work, transport and communication	-0.1320	0.0402	-0.3080	0.1282	-0.8773	0.3544	0.0700	0.1712	-0.0422	0.1875

Note: * indicates that this variable is omitted in estimation due to the fact that there is no observation for this variable in this particular transition.

As to the determinants of transition to labour market programmes, we find that participation in particular type of programmes is highly selective with respect to individual characteristics. For employment programmes, people with low qualification and low job market competitiveness have a large probability to participate. Compared with high school graduates, those with only primary educational attainment have 93.7% larger chance for participation in employment programmes. Females seem to have a large tendency to participate. Also there is strong regional variation in participating in the employment programme. The northern counties are over represented (in terms of probability of participation).

Participations in the training programmes and the wage subsidy programmes do not seem to have the same strong pattern of selection as observed for employment programmes. Men seem to have better chance to participate in the wage subsidy programmes, as well as married adults. Immigrants that have acquired Norwegian citizenship seem to have a larger chance to participate than non-OECD immigrants without citizenship. For training programme, those with lower education than senior high school (11-12 years) have strong tendency to participate. There are strong regional variations in terms of participation probabilities as well.

Noticeably from Table 2, estimated coefficients for the covariates associated with transition back to unemployment after participating in labour market programmes seem in general to have negative signs comparing to estimates from the job transition. This implies that those return to open unemployment after participation on average have lower job prospects. It is plausible that a sorting mechanism “selects” unemployed individuals out of the unemployment pool according to qualification and employability. Those with highest qualification get job first and leave unemployment quickest; those who need assistance in job search leave after participation in labour market programmes; those with lower qualification would eventually return to unemployment even after participation. Hence, it is evident that evaluation of labour market programmes on these different groups must take into account that those treated are in general a selected group. This aspect can be uncovered by duration model framework as demonstrated here, but usual static evaluation methods do not have the mechanism to explore this.

Our maximisation routine returns 5 points of support for the unobserved heterogeneity distribution for all transitions. Table 3 provides the calculated first and second order moments (in exponential form) of the unknown mixing distributions for the unobserved heterogeneity. We are hesitant to give an interpretation of estimated mass points, such as “ability” or “motivation”, as some authors suggest. Zhang (2003) has showed, it is often not possible to retrieve exact number of points for unobserved heterogeneity distribution, even when the true distribution is discrete with known number of support points. Rather, we suggest that emphasis should lie on the correct control for the unobserved heterogeneity such that the other model parameters of interest can be consistently estimated, see Zhang (2003) for a detailed discussion of this aspect. We find that estimators for model’s structure parameters do not have any significant numerical differences after finding of 4 points, neither do the estimated moments for mixing distribution.

Table 3 also reports the estimated correlations coefficients for the unobserved heterogeneities across diverse transitions. The correlations coefficients could have an interpretation of selections on the unobservables between different transitions (according to Abbring and Van den Berg(2003b)). Loosely put, a positive correaltion between two transitions means those with higher probability for transition to one state would also have a somewhat higher probability taking another transition; and vice versa. We find that there is a slight positive selection between job and training transition, also a somewhat positive selection has been found between job and wage subsidy programme. It seems also that different programmes are substitutes as all correlations coefficients between programmes are negative. Not surprising is the strong negative selection between job and back to open unemployment when the individual is participating in the programmes. This implies a negative selection between job transition and transition back to unemployment. Those with preferable employment prospects would leave unemployment earlier, possibly with the assistance of programme participation. Since we do not have the uncertainty measures for these estimators of correlations coefficients (they are not directly estimated but calculated from the estimated mass points distribution), we hesitate to draw any firm conclusion with respect to this and apply great caution on the interpretation.

Table 3: Estimations on the moments of the unobserved heterogeneity distributions and correlations coefficients for the unobserved heterogeneity between transitions.

	Expectation	Variance
Transition to job	0.2505	4.72E-03
Transition to training programmes	0.0270	9.56E-04
Transition to employment programmes	0.0010	4.08E-06
Transition to wage subsidy programmes	0.0021	4.16E-06
Back to open unemployment	0.1293	8.20E-03

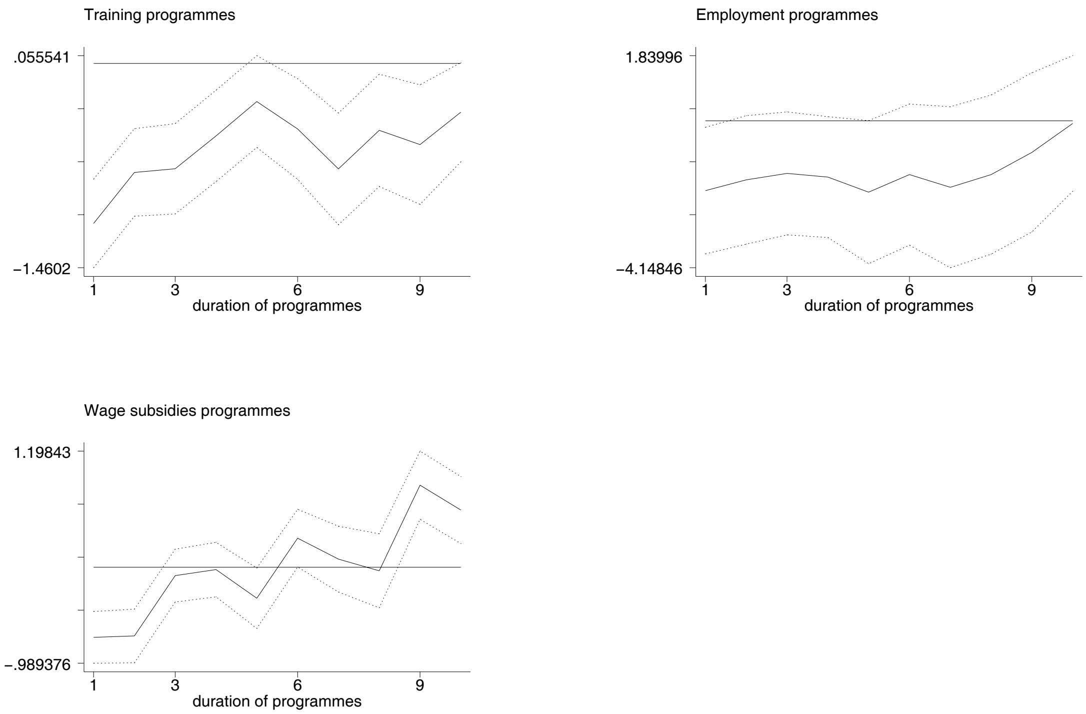
	Correlations coefficients of unobserved heterogeneities between transitions
before transitions to programmes	
job and training programmes	0.0648
job and employment programmes	0.0455
job and wage subsidy programmes	0.1136
training programmes and employment programmes	-0.2370
training programmes and wage subsidy programmes	-0.5925
employment programmes and wage subsidy programmes	-0.3532
after transitions to programmes	
job and back to open unemployment	-0.8019

Note: 1. maximisation returns 5 mass points of support for unobserved heterogeneity. 2. expectations and variances are calculated with exponential transformations. 3. correlations coefficients for unobserved heterogeneities are calculated based on the estimates for the mass points distributions.

Treatment effects

To assess the dynamics of treatment effects over time, we estimate the while-treatment effects and after-treatment effects of participation in each of labour market programmes with two step-functions ($\mathbf{D}_{0kt}$ and $\mathbf{D}_{1kt}$ in equation (3)). To facilitate the interpretations of the positive and negative sides of the effects, we plot directly the estimated coefficients for while-treatment effects and after-treatment effects over time in Figure 4 and 5, together with 95% confidence intervals. These coefficients of effects are estimated relative to that of a female middle-aged non-participant, under average labour market conditions and all other covariates taking mean values, which is indicated by the solid horizontal line with value zero in each figure. The formal comparisons of these effects on transition probabilities should be calculated by inputting these coefficients into the competing risks hazard rate formulations as showed in (3). Here we for the expository purpose report the effects of these estimates on the integrated monthly hazard rates $\varphi_{jk}(d,t,\mathbf{X}_{jkt},\mu_k)$.

Figure 4: While-treatment effects for transitions to employment.



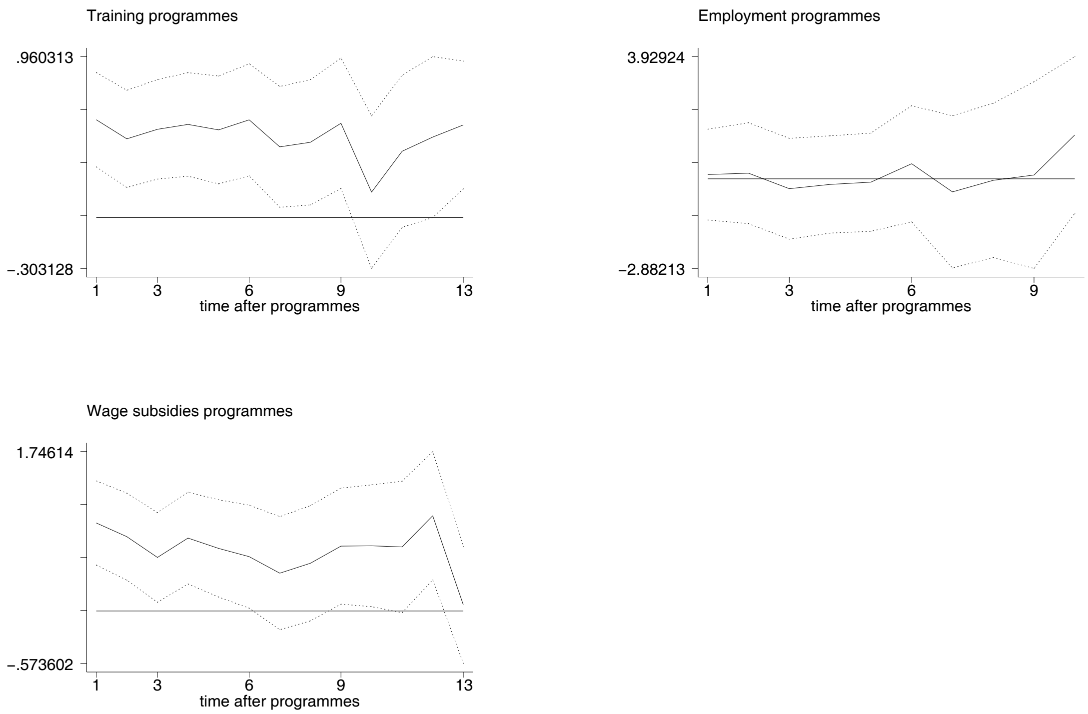
Note: 1. effects are measured relative to a middle-aged female non-participant with medium education, under average labour market conditions. 2. horizontal lines indicate zero effects (reference).

It is remarkable that while the treatment is undergoing, i.e. while participating in labour market programmes, we find a strong negative effect for the training programme relative to the reference, on average about 45.6%[5] reduction on the hazard rate to employment while participating in the training programmes. The negative effect is even stronger for employment programme (76.8%), while the wage subsidies programmes seem not have a significant impact on hazard rate to job on average (0.7%). We also observe that although the while-treatment effects are mostly negative, they increase over time. This holds for all types of labour market programmes. The increase is strongest for the wage subsidy programmes, just after 6 months of participation in the programmes, the effect on the hazard rate to employment is already positive, and remains growing. Equally increasing effect can be found with the training programmes as well. Even though the effect is negative during the entire training period, the

[5] Average effects are calculated based on estimators of time-varying treatment effects, relative to a middle-aged female non-participant with medium education, under average labour market conditions. Full set of estimators is available upon request.

estimated coefficients have increased sharply from -1.144 to -0.518 within 4 months. Somewhat increasing effect for the employment programmes can be observed as well.

Figure 5: After-treatment effects for transitions to employment.



Note: 1. effects are measured relative to a middle-aged female non-participant with medium education, under average labour market conditions. 2. horizontal lines indicate zero effects (reference).

The after-treatment effects are more encouraging. Positive effects are observed both for the training programmes and the wage subsidy programmes. Those that have been to the training programmes have achieved a 59.6% average increase of the hazard rate to employment. For wage subsidy group, the effect is even higher at 86.9%[6]. All these effects are significant (viewed from confidence intervals in Figure 5). The positive effects are not temporary, but lasting for a long post treatment period. However, the after-treatment effects do decline gradually with time. The effects are strongest immediately after completion of programme, and decline gradually as individual still remain unemployed. For participants in employment programmes, the average after-treatment effect is 19.2%, but not significantly different from zero (Figure 5).

[6] See footnote 5.

A possible explanation for the negative effects of the training programmes while the programmes are undergoing, is that participation in such programmes possibly reduces search intensity. It might be the case that participants wish to take advantage of the training opportunity to enhance their qualifications and human capitals. Such enhancement needs certain amount of time to accumulate. Once the programmes are completed, the job probability is increased significantly and the ex post effects of the training programmes are significantly positive. This is in accordance with the findings of Raaum et al. (2002).

The negative while-treatment effects of the employment programmes can be thought of as lock-in effects. Since the employment programmes are targeted at long-term unemployed to prevent them from dropping out of the labour force, they do not have the immediate goal to systematically improve the qualifications of low-skilled jobseekers. Instead, they have a kind of safety net feature by providing temporary employment with pay. Therefore the participants might as well lack of motivation in search for normal employment.

Contrary to the employment programmes participants, the wage subsidy programmes participants are generally more qualified and ready for employment. The programmes have already positive effects on the transition probability even when the programmes are undergoing. Immediately after the completion of the wage subsidy programmes, a significant increase on the hazard rate to ordinary employment can be observed.

Table 4 reports the estimated heterogeneous while-treatment and after-treatment effects with respect to selected individual characteristics as well as with business cycle conditions. For the while-treatment effects, our first observation is that there is not much difference across individual characteristics. However some of the after-treatment effects vary across individual characteristics. For the training programmes, women seem to benefit more from participation with a 15.2% higher effect than men. Similar findings have also been observed in Raaum et al. (2002). It holds for the wage subsidy programmes as well, where females have an even higher advantage to males with an increase of hazard rate to job as much as 21.2%. For the employment programmes, men seem to have a stronger effect than women, but this difference is not significant. Younger jobseekers benefit strongest from employment programme. Perhaps the most significant observation is that low education seems to have a negative impact on the effects of the employment programmes. As for the wage subsidy programmes, the impact of participation is stronger for women than for men. For the while-treatment effects, the training programmes display a significant pro-cyclical pattern. This implies that the effect of participating in a training programme is larger if the labour market condition is favourable. A similar pattern is observed for the after-treatment effects for the training programmes with some significance. In Raaum et al. (2002), they also find the pro-cyclical patterns of labour market training programmes. The intuition behind this finding can be thought of as follows: when the job market is unfavourable, job vacancies are scarce. Therefore it might be of little importance whether one has participated in the labour market programmes or not, since there are not many jobs to fill in anyway. When the labour market condition is good, those who have participated in labour market programmes might signal more positive qualifications than those who have not. Thus, the participation in the programmes has stronger impact on the employment probability when at the boom time.

Stylised analysis

To illustrate the dynamic effects of participation in labour market programmes on the transition probabilities to ordinary employment, we conduct a highly stylised analysis that resembles the matching study. The idea is that by keeping all other covariates that affect hazard rate fixed, we are able to isolate the causal effects of participation in labour market programmes by comparing the predicted hazard rates with and without the presence of programme participation.

We construct a representative unemployed jobseeker with all individual characteristics taking mean values of the estimation sample. We also fix calendar months and business cycle indicators to sample references. By using estimators for job transition, we predict hazard rates over a 36-months period using equation (3) for non-participants.

Table 4: Heterogeneous treatment effects.

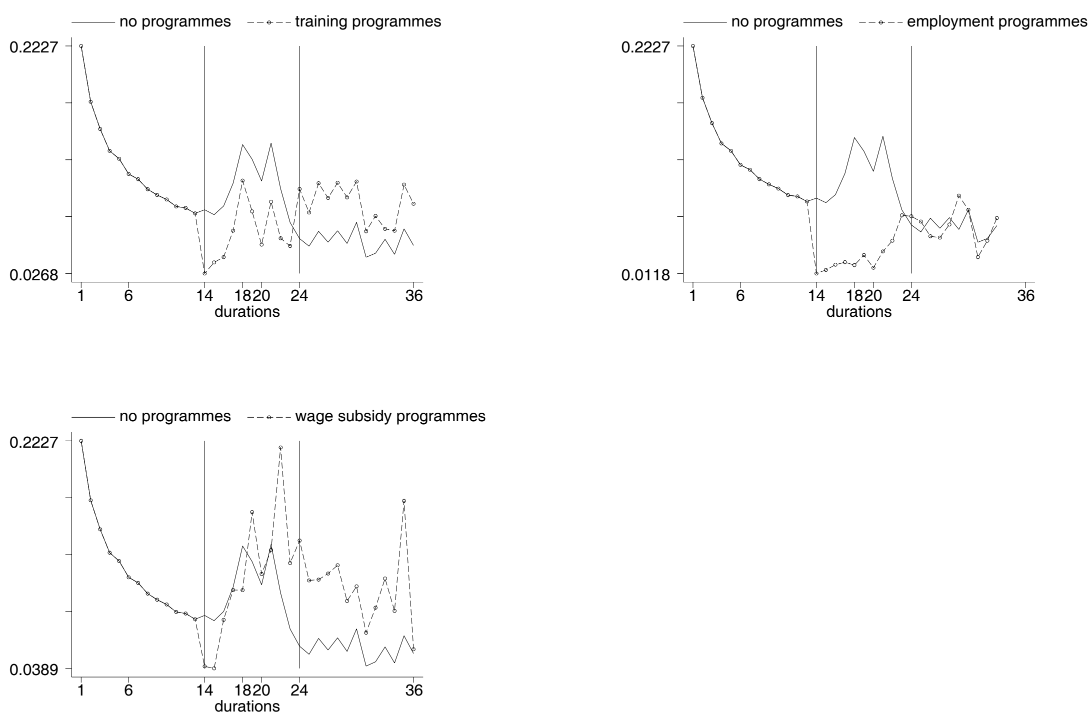
While-treatment effects	**Est.**	**Std.**
Training programmes		
× business cycle indicator	0.6693	0.1572
× low education (up to 9 years)	-0.0515	0.0672
× high education (more than 12 years)	1.3085	0.8386
× male	0.0321	0.0535
× younger jobseeker (age $\leq$ 30)	0.0288	0.0577
× elder jobseeker (age $>$ 45)	0.0687	0.0805
Public employment programmes		
× business cycle indicator	-0.2382	0.9980
× low education (up to 9 years)	-0.0951	0.3479
× male	0.3122	0.2309
× younger jobseeker (age $\leq$ 30)	0.1499	0.2420
× elder jobseeker (age $>$ 45)	-0.0950	0.4064
Wage subsidy programmes		
× business cycle indicator	-0.1466	0.1515
× low education (up to 9 years)	0.2870	0.0591
× male	-0.0318	0.0508
× younger jobseeker (age $\leq$ 30)	0.0097	0.0578
× elder jobseeker (age $>$ 45)	-0.0403	0.0722

After-treatment effects	**Est.**	**Std.**
Training programmes		
× business cycle indicator	0.2760	0.1286
× low education (up to 9 years)	0.1056	0.0644
× male	-0.1621	0.0455
× younger jobseeker (age $\leq$ 30)	0.0704	0.0532
× elder jobseeker (age $>$ 45)	-0.1260	0.0638
Public employment programmes		
× business cycle indicator	-1.9588	1.7547
× low education (up to 9 years)	-1.2637	0.6912
× male	0.4156	0.4134
× younger jobseeker (age $\leq$ 30)	0.9581	0.4551
× elder jobseeker (age $>$ 45)	0.6820	0.5027
Wage subsidy programmes		
× business cycle indicator	0.0688	0.2559
× low education (up to 9 years)	-0.1627	0.1037
× male	-0.2309	0.0859
× younger jobseeker (age $\leq$ 30)	-0.0328	0.1081
× elder jobseeker (age $>$ 45)	-0.0957	0.1108

Note: the reference is middle-aged female (31-45 years) with above 9 years educational attainment under the average labour market conditions.

Assume that at the start of 14th month[7], the “artificial jobseeker” participates in a labour market programme that takes 10 months to finish. We add while-treatment effect estimators to the hazard rate formulation and predict the “while-treatment hazard rate”. After completing of programme, we follow the spell further until 13 months and calculate “after-treatment hazard rate” by including after-treatment effect estimators into hazard rate formulation. We predict such representative hazard rates for all three groups of labour market programmes that we evaluate.

Figure 6: Predicted treatment effects on transition probabilities to employment.



Note: vertical lines indicate the start and the end of programmes.

Figure 6 depict the stylised figures on how participation in labour market programmes affects the hazard rate to employment. We observe that immediately after starting a programme, the hazard rate drops significantly. While participating in a training programme, the hazard rate is lower than that of non-participation, but gradually catches up over the duration of participation. After the completion of the training programme,

[7] Because the total length of spell in estimation sample is 36 month, and we have 10 estimators for the programme duration and 13 estimators for the post-programme duration, therefore the pre-programme spell duration is set to 13 month.

the hazard rate for after-treatment period rises sharply above that of non-participation, though it again decreases gradually as the spell lengthens. For the wage subsidy programme, the effect of increasing the hazard rate comes much earlier. After only 3 months of participation, the hazard rate due to participation is already higher than that of non-participation. The hazard rate remains higher as well and lies above that of non-participation after the participation is finished. For the employment programme, we observe the decrease of the hazard rate during the participation, but the after-treatment hazard rate is almost the same as that of non-participation.

The above figures give some visual illustration of the impacts of active labour market programmes on the hazard rates to job. Since the treatment effects are mostly negative during the participation, and positive after the participation, it is desirable to derive a measure for the total impact of the active labour market programmes on the spell length. However, the prediction of expected spell duration with programme participations cannot be solved analytically, since we do not have the knowledge of future development of labour market conditions, as well as the covariate processes that have influences on the hazard rates. We provide here an approach based on simulation to offer an assessable measure of the total impact of the treatment effects.

The idea here is to first simulate a counterfactual situation that no programmes have any effects on the hazard rate to job[8]. Based on the estimation sample, we predict the expected spell durations in our competing risks model. We take one individual and record his/her observed characteristics at the first month of the unemployment spell, as well as at the calendar time at which the spell starts. Then by utilising the complete estimates for the transition to job and labour market programmes (coefficients of covariates, baseline hazard rates, estimates for the calendar time effects and the averages for the unobserved heterogeneity), we predict the progression of each spell. For the sake of simplicity, we fix the individual characteristics throughout the spell. The previous censoring scheme is applied here as well such that the spell is censored after 36 months, or if the spell has exceeded the observation window (from Jan. 1990 to Dec. 2000). The dynamic processes depicted in Figure 1 are followed in the simulation.

[8] There are however the possible anticipation effects of programmes remaining. We have found that the existence of programmes could possibly affect the behaviour of individuals even for non-participants. Because we do not have any estimators for such anticipation effects, we cannot predict the spell durations excluding such anticipations. Since the anticipation effects are (in part) captured by the baseline hazard rates, the predicted spell durations based on those baseline hazard rate estimates are compatible to those in the real data.

Repeating this process for all spells, we get a sample for the unemployment within the counterfactual state of no programmes effects. The total amount of unemployment months is then measured.

We next consider the situation where only one of the programmes has effects corresponding to our point-estimates, while the others have zero effects[9]. Interaction terms of treatment effects with individual characteristics and business cycle indicators are also added to the hazard rates. After simulation of the spells for this single programme effects situation, the total amount of unemployment months, compared with that from no programme effects, gives us a measure of marginal impact from one particular programme. We conduct this simulation separately for all three active labour market programmes.

Last, in the similar manner we predict the complete competing risks model, including all three programmes' effects evaluated earlier. Again, individual characteristics are fixed. By incorporating the time-varying while-treatment effects and after-treatment effects to the hazard rates, we predict a sample of unemployment spells when there are three types of active labour market programmes that have effects on the hazard rates. This simulation provides a sample that bears the satisfactory similarity to that of the estimation sample in terms of distribution of spell lengths. The total amount of unemployment months are then measured and used to compare with that from the counterfactual situation of no programme effects to assess the total impact of active labour market programmes in terms of the changes in the total amount of unemployment.

We conduct the above simulation routines 100 times to get the average total impact of active labour market programmes with uncertainty measures. Table 5 reports the results from this highly stylised exercise.

[9] In the simulation, we censor the programme duration after 10 months, and post programme duration after 13 months, respectively, to resemble the same censoring practice in the estimation earlier.

Table 5: Total impacts of the active labour market programmes.

	Total amount of unemployment months of all spells	
	mean	**std**
No programme effects	819533.00	2206.44
With effects from the training programmes	791289.32	2422.91
Changes due to the training programmes	**-28243.68**	**3277.02**
Causal effects of the training programmes	-3.45 %	
With effects from the employment programmes	824070.26	2404.52
Changes due to the employment programmes	4537.26	3263.45
Causal effects of the employment programmes	0.55 %	
With effects from the wage subsidy programmes	790612.94	2352.19
Changes due to the wage subsidy programmes	**-28920.06**	**3225.08**
Causal effects of the wage subsidy programmes	-3.53 %	
With effects from all three programmes	766933.90	2208.92
Changes due to all three programmes	**-52599.10**	**3122.13**
Causal effects of all three programmes	-6.42 %	

Note: 1. bald-faced fonts indicate significant estimators. 2. mean and standard errors are calculated across 100 simulation trials.

The means and standard errors are calculated across 100 simulations. The impacts of programmes are measured as reduced total amount of unemployment months, and the percentage changes could have the interpretation as the causal effects of the programmes. We see that both training programmes and wage subsidy programmes have positive effects in terms of reduced total unemployment. The causal effect of the training programmes alone is about 3.45%, while for the wage subsidy programmes is about 3.53%. The employment programmes do not seem to have significant effect on reducing the total unemployment. When viewing all three programmes together, the total impact of active labour market programmes is about 6.42% reduction of total unemployment and the effect is significant[10].

5. Conclusions

By estimating treatment effects of Norwegian labour market programmes on transition probabilities to employment, we evaluate causal effects of participation in the active labour market programmes for Norwegian prime-aged unemployed workers. The estimation is carried out by applying non-parametric competing risks hazard rate model.

We find significant impacts of participations in active labour market programmes on the transition probabilities to ordinary employment. Both training programmes and wage subsidy programmes have significant positive effects on employment probabilities *after* the completion of programmes. There is some evidence that these two groups of active labour market programmes have their intended effects on enhancing job opportunities and function as effective tools in combating the unemployment. However, *during* the participation of programmes, the transition probabilities are low comparing to non-participants. This can be due to the nature of programmes participation (reduced search intensity during participation). The employment programmes on the other hand do not display strong causal effects on the transition probabilities after the programmes have finished. During the programmes period, the transition probabilities are significantly lower than that of non-participants. There is limited evidence on the heterogeneous treatment effects with respect to the individual characteristics. Women seem to benefit more after participating in the training programmes and the wage subsidy programmes. The younger jobseekers benefit more from the employment programmes.

There is some evidence of selection into different programmes with respect to individual characteristics. This may be due to that the different programmes are targeted

[10] Recall that in the estimation data, we also censor the spell once a transition from one programme to another programme has occurred. Also if there are repeated participations in the same or different programmes, the spell is censored as well. Ideally, we should also include such options as possible transitions and censor the spells accordingly in the simulation. But since we do not have the estimates for cross-programme transitions and repeated participations, in our simulation, such cross-programmes or repeated participations are not modelled. Although in estimation such censoring does not impose bias on the estimators, this innocuous practice in simulation might have the consequences on the predicted spell durations. Thus the total effects of programmes in terms of reduced amount of unemployment might be overestimated.

on the different population of participants. The employment programmes are targeted on long-term unemployed to prevent them from dropping out of labour force, while the wage subsidy programmes offer qualified jobseekers a final assistance in finding employment. The evaluation of effects across different programmes must take account for the differences of the intended treated.

The effects of labour market programmes change over time and business cycle conditions. Effects of both training programmes and wage subsidy programmes have a pro-cyclical pattern, which means the effects are stronger the better the labour market conditions are. Also we find that the treatment effects change over time spent during participation and time spent after participation. During the programmes participation, the effects of programmes grow with elapsed the programme duration. There is evidence that treatment effects need time to build up. The after-treatment effects are significantly positive both for training programmes and wage subsidy programmes. The effects are strongest when participants have just finished the programmes, and persistent over the spell length for participants remaining unemployed.

The total impacts of all three active labour market programmes are measured in terms of reduced total unemployment volumes by simulations. We find a significant effect of 6.42% reduction of the total amount of unemployment months due to the active labour market programmes. However, we interpret these results with caution, because the simulation method used here might not be suitable (see footnote 39). The case of evaluation of treatment effects due to cross-programme transitions and multiple participations is remaining for future research.

By studying various types of programmes over time within the duration model framework, we hope to provide some insights on the causal effects of Norwegian active labour market programmes and the dynamics of these effects. Nevertheless, the social gains of the active labour market programmes must be evaluated in the conjunction with the costs of programmes, both in terms of individuals' opportunity cost during the participation, and the administrative cost of providing these programmes. A cost-benefit analysis might be a nature continuation of this study. The policy implications of this study should be focused on the dynamic side of programmes effects. Given the evidence of heterogeneity of treatment effects both over intended treated and over unemployment duration and business cycle, it is of importance for policy makers to design active labour market programmes tailored to the different needs across the different unemployment population, and to adjust the scope and volume accordingly at different stages of business cycles.

References

Aakvik, Arild, James J. Heckman and Edward J. Vytlacil (2000), “Treatment effects for discrete outcomes when responses to treatment vary among observationally identical persons: an application to Norwegian vocational rehabilitation programs.” *NBER Technical Working Paper No 262.* Cambridge, MA.

Abbring, Jaap H. and Gerard J. van den Berg (2003a) “The Identifiability of the Mixed Proportional Hazards Competing Risks Model” Forthcoming in *J. Royal Statistical Society: Series B*.

Abbring, Jaap H. and Gerard J. van den Berg (2003b) “The Non-Parametric Identification of Treatment Effects in Duration Models” *Forthcoming in Econometrica.*

Ackum Agell, Susanne and Martin Lundin (2001), “Erfarenheter av svensk arbetsmarknadspolitikk.” *Ekonomisk debatt,* 29, pp 239-250.

Baker, Michael and Angelo Melino (2000), “Duration Dependence and Nonparametric Heterogeneity: A Monte Carlo Study” *Journal of Econometrics* 96, 357-393.

Brinch, Christian (2000) “Identification of Structural Duration Dependence and Unobserved Heterogeneity with Time-varying Covariates” Memorandum No. 20, 2000, Department of Economics, University of Oslo.

Calmfors, Lars, Anders Forslund and Maria Hemström (2001), *Does active labour market policy work? Lessons from the Swedish experiences*. Working paper. Uppsala: IFAU – office of labour market policy evaluation.

Fay, Robert G. (1996): "Enhancing the Effectiveness of Active Labour Market Policies: Evidence from Programme Evaluations in OECD countries", *Labour Market and Social Policy Occasional Papers*, #18, OECD.

Fertig, Michael, Christoph M. Schmidt, and Hilmar Schneider (2002) “Active Labor Market Policy in Germany - Is There a Successful Policy Strategy?” *IZA Discussion Papers* 576, Institute for the Study of Labor (IZA).

Gaure, Simen and Knut Røed (2003), " How Tight is the Labour Market? A Micro-Based Macro Indicator" *Memoranda,* Department of Economics, University of Oslo, Norway 09/2003.

Gerfin, Michael and Michael Lechner, (2002), "Microeconometric Evaluation of the Active Labour Market Policy in Switzerland", *The Economic Journal*, 112 (482), 854-893.

Heckman, James. J. (1979), "Sample Selection Bias as a Specification Error (with an Application to the Estimation of Labor Supply Functions)", *Econometrica* 47(1) 153-161.

Heckman, James and Burton Singer (1984), "A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data" *Econometrica*, Vol. 52, 271-320.

Heckman, James and Burton Singer (1985), "Social science duration analysis" in Heckman and Singer (ed.) *Longitudinal analysis of labor market data*, Cambridge University Press, 39-110.

Heckman, James and Bo Honoré (1989) "The Identifiability of the Competing Risks Model" *Biometrika* Vol. 76, No. 2. pp. 325-330.

Heckman, James J., Hidehiko Ichimura and Petra Todd (1997), "Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme." *Review of Economic Studies,* 64, pp. 605-654.

Heckman, James J., Robert J. Lalonde and Jeffrey Smith (1999), "The economics and econometrics of active labor market programs." In O. Ashenfelter and D. Card (Eds.) *Handbook of Labor Economics*, Vol. 3a, North-Holland.

Holland, P.W. (1986), "Statistics and Causal Inference", *Journal of the American Statistical Association*, vol 81, issue 396, 945-960.

Honoré, Bo (1993), "Identification Results for Duration Models with Multiple Spells" *The Review of Economic Studies*, Vol. 60, No. 1. (Jan., 1993), pp. 241-246.

Lalive, Rafael, Jan C. van Ours and Josef Zweimueller (2001) "The Impact of Active Labor Market Programs on the Duration of Unemployment, *IEW Working Paper No. 51*, University of Zurich.

LaLonde, Robert J. (1986) "Evaluating the Econometric Evaluations of Training Programs with Experimental Data", *The American Economic Review*, Vol. 76, No. 4., pp. 604-620.

McCall, Brian P. (1994), "Identifying State Dependence in Durations Models," *American Statistical Association 1994, Proceedings of the Business and Economics Section*, 14-17.

McCall, Brian P. (1996), "The Identifiability of the Mixed Proportional Hazards Model with Time-Varying Coefficients," *Econometric Theory*, 12, 733-738.

McCall, Brian P. (1997), "The Non-Parametric Identifiability of a Competing Risks Model with Regressors" mimeo, University of Minnesota.

Raaum, Oddbjørn, Hege Torp and Tao Zhang (2002), "Business cycles and the impact of labour market programmes", Memoranda, 14/2002, University of Oslo.

Richardson, Katarina and Gerard J. van den Berg (2002) "The effect of vocational employment training on the individual transition rate from unemployment to work" *IFAU working paper*, 2002:8.

Rubin, D.B. (1974), "Estimating Causal Effects of Treatments in Randomised and Nonrandomised Studies," *Journal of Educational Psychology*, 66, 688-701.

Røed, Knut and Tao Zhang (2000), "Labour Market Transitions and Economic Incentives." *Memoranda,* Department of Economics, University of Oslo, Norway 15/2000.

Røed, Knut and Oddbjørn Raaum (2003) "The Effect of Program Participation on the Transition Rate from Unemployment to Employment." *Memoranda,* Department of Economics, University of Oslo, Norway 13/2003.

Røed, Knut and Tao Zhang (2003), "Does Unemployment Compensation Affect Unemployment Duration?" *Economic Journal*, Vol. 113, issue 484, 190-206.

Torp, Hege (1995), "Labour market Institutions and Development. Norway Baseline Study." Oslo: Institute for Social Research, Report 1995:11.

van den Berg, Gerard J. (2001), Duration Models: Specification, Identification, and Multiple Durations. *Handbook of Econometrics*, Vol. 5, Chapter 55, Elsevier.

Zhang, Tao (2003) "A Monte Carlo Study on Non-parametric Estimation of Duration Model with Unobserved Heterogeneity" Working paper.