The Effects of Job Creation Schemes on the Unemployment Duration in Eastern Germany*

*Reinhard Hujer and Christopher Zeiss***

Job creation schemes (JCS) have been one of the most important programmes of active labour market policy in Germany throughout the 1990s and into the first decade of the new century. A number of studies have analysed the effects of job creation schemes in Germany, presenting an overall disappointing picture. JCS seem to perform poorly in improving the employability or the chances of leaving unemployment for the participating individuals. The study extends the existing literature by an evaluation of JCS with the timing-of-events methodology in the duration context using administrative data for eastern Germany. The analysis is based on a multivariate mixed proportional hazard rate model that accounts for observable and unobservable characteristics. The results show that JCS increase the individual unemployment duration of the participants. The negative effect results from a locking-in effect and a strong negative effect after the programme has finished. Therefore, the results suggest that JCS do not improve the employment prospects for the participants.

* This paper was released for publication in November 2007.
** The authors thank two anonymous referees for valuable comments. We thank Steffen Kaimer and Melanie Stamm for their help in the preparation of the data. Financial support from the Institute for Employment Research (IAB) within the project 'Effects of Job Creation and Structural Adjustment Schemes' is gratefully acknowledged.

Contents

1 Introduction

Germany's active labour market policy (ALMP) programmes urgently require critical reassessment, given the high and persistent unemployment rates in eastern and western Germany (20.1 and 9.4 percent in 2004), tight government budgets and massive amounts spent on these programmes (19.5 bn Euros in 2003). One of the most important programmes during the 1990s and early 2000s were job creation schemes *(Arbeitsbeschaffungsmaßnahmen,* JCS). Designed as a kind of subsidised work for unemployed persons facing barriers to employment, JCS aim at stabilising the economic situation of unemployed people and qualifying them for later re-integration into regular jobs. Although the efforts of the Federal Employment Agency (FEA) have been immense and these programmes were the second most important in terms of fiscal spending and the number of individuals receiving support (about 1.7 million between 1997 and 2004, with expenditures amounting to over 24 billion Euros), doubt has been raised about the effectiveness of the programme in terms of improving people's employment chances. The main criticism concerns the lack of components that improve human capital and the presence of negative incentives to seek work actively, like excessively high wages and long programme durations of about 12 months. The effects of JCS in Germany have been analysed in a number of studies, revealing an overall disappointing picture: JCS seem to perform poorly in improving the employability or chances of leaving unemployment for those participating.

The purpose of this paper is to supplement the existing literature by an evaluation of JCS with the timing-of-events methodology, as suggested by Abbring and van den Berg (2003). Recent programme evaluation literature (see Abbring and van den Berg (2003) and Fredriksson and Johansson (2004)) has emphasised the importance of the information on the timing of the treatment event. First Abbring and van den Berg (2003) showed that the timing of the treatment event conveys additional useful information for the identification of the treatment effect. Second, as emphasised by Fredriksson and Johansson (2004), the dynamic assignment of treatments has serious implications for the validity of the conditional independence assumptions usually invoked to estimate treatment effects. Furthermore, the following approach considers the individual unemployment duration as the outcome of interest. If the purpose of JCS is achieved, i. e. a participation in a JCS programme increases the probability of a re-integration into employment, we would observe a reduction of the individual unemployment duration. For analysing the impact of JCS on the individual unemployment duration we use highly informative administrative data of the FEA for eastern Germany only. In comparison, existing evaluations of JCS based on administrative data typically consider the impact on employment rates. A recent example is Hujer and Thomsen (2006), who estimate the impact of JCS on the employment rate with a propensity score matching which, similar to the following analysis, takes into account the timing of the treatment event.

The econometric model is based on a multivariate mixed proportional hazard model that accounts for observed and unobserved factors. The consideration of the unobserved factors enables the identification of the treatment effect in the presence of selectivity conditional on unobservable factors. Most evaluation studies solve the selectivity problem via conditional independence assumptions, which require that all selectivity is captured by observable characteristics. In contrast, the analysis in the mixed proportional hazard framework also allows us to account for possible unobserved determinants. The possibility to account for unobserved heterogeneity, however, comes at the cost of several assumptions with respect to the functional form in the empirical model. Recently, similar approaches have been applied in studies on other countries, like Bonnal, Fougere, and Serandon (1997) for France, Richardson and van den Berg (2001) for Sweden, Lalive, van Ours, and Zweimüller (2002) for Switzerland and van Ours (2004) for Slovakia. A comprehensive survey of the methodology can be found in van den Berg (2001).

The paper is organised as follows. Section 2 presents the institutional set-up for JCS in Germany and a brief overview of the existing studies in Germany. Section 3 presents the empirical model utilised to estimate the effect of JCS on the transition into regular employment. Section 4 presents a description of the data used. The results of the empirical analysis are discussed in Section 5. Section 6 concludes.

2 Job Creation Schemes in Germany

JCS were introduced in 1969. For many years they were the second most important measure of German ALMP after vocational training programmes. The legal basis is defined in §§ 260 to 271 and 416 of the Social Code III *(Sozialgesetzbuch III,* SGB III) enacted in 1998, replacing the Employment Promotion Act *(Arbeitsförderungsgesetz,* AFG) from 1969. JCS provide jobs for unemployed persons facing barriers to employment and aim at stabilising the economic situation of participants and qualify them for later (re-)integration into regular (non-subsidised) work. The jobs are in different economic sectors, e. g., agriculture, construction and social services. Financial support takes the form of wage subsidies (in general 30 to 75 percent of the worker's salary) or loans to the institutions carrying out the programme, i. e. service providers or employers. The ordinary duration of support for JCS is twelve months, but exceptions can be made extending the duration to 24 or even 36 months if participation will be followed by a permanent job. To prevent deadweight losses and substitution effects the programme is intended to support only those activities that are additional in nature, of value to society and carried out by persons in need of assistance. Additional in nature means that the activities would not be accomplished without the subsidies. They are of value to society if their outcome is for the collective good. Due to these requirements, the majority of JCS are low-skill jobs.

Eligible individuals are assigned to these programmes by caseworkers. Eligibility is generally granted to those who have been long-term unemployed (more than one year) or unemployed for at least six of the twelve months prior to programme start. They also have to fulfil the eligibility criteria for receipt of unemployment benefit or assistance, for vocational training programmes, or for vocational integration of the disabled. Independently of these requirements, the local employment agencies (LEAs) are allowed to place younger unemployed people (aged 25 or younger) without completed vocational training, severely disabled people, tutors and up to five percent of the participants who do not meet the general eligibility criteria. When the unemployed person has registered at the LEA, the case is assigned to a caseworker who meets the unemployed person at regular intervals to evaluate the individual's efforts at finding a job and to develop a plan together with the unemployed person for integration into employment. This procedure grants the caseworker a large degree of discretion in allocating these programmes to unemployed individuals. The caseworker offers only the unemployed person a job in a JCS when the individual is deemed needy of assistance because he/she cannot be integrated into regular employment and does not fulfil the conditions for other ALMP programmes. The caseworker chooses the job in consultation with the unemployed person and according to the individual's qualifications and interests. Priority is given to projects that explicitly aim at improving the foundations for permanent employment, provide occupations for unemployed people facing special barriers to employment, or improve the social and environmental infrastructure.[1] Once assigned by a caseworker, the programme is compulsory for the individual and rejection is sanctioned by stopping benefits for up to twelve weeks. In repeated cases, the unemployed individual may lose his/her unemployment benefit entitlement permanently. Since placement depends on the places available in programmes, it may sometimes it may be impossible to accommodate some unemployed persons in these programmes.

JCS in Germany have been analysed in a number of studies, see e. g. Huebler (1997), Kraus, Puhani, and Steiner (2000), Eichler and Lechner (2002), Caliendo, Hujer, and Thomsen (2004, 2005, 2007) and Hujer and Thomsen (2006). Whereas the earlier studies were based on survey data, the more recent studies (since 2003) are based on the administrative data of the FEA like the data used in our analysis. Most studies were not able to establish positive effects in terms of the different outcome variables analysed (e. g. employment, unemployment) with some exceptions (see Eichler and Lechner (2002) and some subgroups in Caliendo, Hujer, and Thomsen (2004, 2005, 2006, 2007)). These disadvantageous results of JCS were also found in restricted estimations for eastern Germany. For this reason the overall picture presented by the existing studies suggests that JCS are not able to support the re-integration into regular employment.

3 Econometric Model

We evaluate the impact of JCS on the transitions from unemployment into regular employment using a bivariate duration model as suggested by Abbring and van den Berg (2003). Normalising the point in time when an individual enters unemployment to zero, we measure the duration until the individual enters a regular job, T_e, and the duration until the individual enters a job creation scheme, T_p. T_e and T_p are assumed to be non-negative and continuous random variables with realisations denoted as t_e and t_p. The durations T_e and T_p are assumed to vary with time-invariant observable characteristics x and unobservable characteristics v. The observable characteristics x are the same for both distributions, i. e. no exclusion restrictions on x are imposed. For the unobserved characteristics, we assume $v_e(v_p)$ to capture the unobserved determinants of $T_e(T_p)$.

The empirical analysis is based on the assumption that participation in a job creation scheme affects the distribution of T_e if the treatment occurs before the individual leaves unemployment. Following Ab-

[1] Unemployed persons with special barriers to employment are defined as long-term unemployed, severely disabled persons, older unemployed persons with placement restrictions, as well as applicants for vocational rehabilitation programmes.

bring and van den Berg (2003), we assume that the realisation t_p affects the distribution of T_e in a deterministic way from t_p onwards. For the specification of the joint distributions $T_e, T_p | x, v_e, v_p$, we focus on the conditional hazard rates $\theta_e(t | t_p, x, v_e)$ and $\theta_p(t | x, v_p)$.

We use mixed proportional hazards (MPH) specifications, where duration dependence, observable and unobservable covariates enter the hazard rate multiplicatively. The hazard rate for the transition into employment at time t is given by

$$\theta_e(t | t_p, x, v_e) = \lambda_e(t) \exp[x'\beta_e + \mu(t - t_p, x) I(t > t_p) + v_e], \quad (1)$$

where $\lambda_e(t)$ is the baseline hazard that captures the duration dependence. The individual level of the hazard rate conditional on the observable characteristics is determined by the systematic part $\exp(x'\beta)$ and the term $\exp(v_e)$, which represents the influence on the individual level due to the unobserved characteristics. The treatment effect $\exp[\mu(t - t_p, x) I(t > t_p)]$ is specified as the causal effect of t_p on the hazard rate $\theta_e(t | t_p, x, v_e)$, where $I(t > t_p)$ is an indicator function taking the value 1 if $t > t_p$. The treatment effect can be interpreted as a shift of the hazard rate by $\exp[\mu(t - t_p, x)]$, which is directly associated with the expected remaining unemployment duration, i. e. a positive treatment effect will shorten the expected remaining unemployment duration. In this general specification, the treatment effect is allowed to depend on the time since the treatment has started $t - t_p$ and on the observable characteristics x. In our empirical analysis, we utilise three specifications for the treatment effect. First, we estimate a time-invariant treatment effect $\exp[\mu I(t > t_p)]$ that shifts the hazard rate permanently by $\exp(\mu)$ if the individual starts a job creation scheme. Second, we specify a piecewise constant treatment effect with two intervals $\exp[\mu_1 I(t_p < t \leq t_p + c) + \mu_2 I(t > t_p + c)]$, where c is an exogenous given constant. With this specification, the hazard rate shifts by $\exp(\mu_1)$ at the moment the individual enters the programme and after a duration c, the hazard is shifted by $\exp(\mu_2)$. This model enables us to test whether the treatment effect is constant over time. Finally, we estimate the treatment effect as a time-invariant treatment effect that is allowed to vary over individual characteristics $\exp[\mu(x)]$.

The transition rate from unemployment into JCS is analogously specified as

$$\theta_p(t | x, v_p) = \lambda_p(t) \exp[x'\beta_p + v_p], \quad (2)$$

with the baseline hazard $\lambda_p(t)$, the systematic part $\exp(x'\beta_p)$ and the unobserved heterogeneity term $\exp(v_p)$. In the empirical model we not only consider the binary information if the individual has received a treatment, but also utilise the information on the timing of the treatment within the unemployment spell for the identification of the treatment effect. Abbring and van den Berg (2003) have shown that this conveys additional useful information for the identification of the treatment effect in the presence of selectivity. Selectivity means that those individuals who are seen to receive a treatment at t_p are a non-random subset with respect to t_e. In the following, we assume that all selectivity is related to observable and unobservable characteristics. Therefore, conditional on the observable variables x selectivity appears as a dependence between the unobserved heterogeneity terms v_e and v_p. Conditional on the set of observable variables x and the unobservable heterogeneity v_e und v_p the durations T_e and T_p are only dependent in $\exp[\mu(t - t_p, x) I(t > t_p)]$. Thus, this factor can be given a causal interpretation as the treatment effect (Abbring and van den Berg, 2003). In comparison with the usual matching estimation technique that solves the selectivity problem by means of a conditional independence assumption with respect to observable characteristics, the model (1)–(2) imposes an extended conditional independence assumption that accounts for observable and unobservable characteristics. Therefore the model (1)–(2) can identify the treatment effect even in the case where the available observable characteristics are not sufficient to describe the selection process. Note that with regard to the observable characteristics the model (1)–(2) imposes a proportionality assumption that is not imposed by usual matching techniques.

The timing of the treatment is a useful piece of information since it allows us to distinguish between a time-invariant selection effect embodied by a dependence between v_e and v_p and a causal treatment effect that becomes effective at the moment the treatment starts. If we consider the timing of a treatment, a positive causal treatment effect leads to a pattern where a transition into employment is typically realised very quickly after a transition into treatment, no matter how long the elapsed duration of unemployment is. In contrast, in the case of a selection effect, we would observe a correlation between the points in time of the transitions into employment and programme (Abbring and van den Berg 2003). In the case of a positive selection effect, we would typically observe a pattern where a quick transition into a programme is followed by a quick transition into employment, i. e. both transitions occur very rapidly after the start of the unemployment spell. Thus, the main difference between a treatment and a selectivity effect is that the former affects the transition rate into employment only after a treatment has been realised, whereas the latter affects the transition rate everywhere. Including the timing of events as identifying information has the further advantage that no exclusion restrictions have to be imposed on the observable variables, as is the case in selection models. Such exclusion restrictions on x are often hard to justify from a theoretical point of view, since the information available to the researcher is usually also available to the individual under consideration.

Identification of the treatment effect requires that individuals do not anticipate future treatments. Anticipatory effects are present if, for example, individuals who are informed about their future participation in a job creation scheme reduce their search activity in order to wait for the programme. In this case, the hazard rate at t of an individual who anticipates a future treatment at time t_p, will be different from the hazard rate of an individual who obtains an alternative treatment at time t_p^* for $t \leq \min\{t_p, t_p^*\}$. Due to the anticipatory effect, the information on the timing of the event would not be sufficient for identification since a causal change in the hazard occurs at the moment the information shock of the treatment arrives. Information on the moment when individuals are informed about a future treatment is not available for the empirical analysis and we rule out anticipatory effects of JCS. In this context, it has to be noted that the assumption of no anticipatory effects does not rule out that the individuals act on the determinants of T_p. That is, individuals are allowed to adjust their optimal behavior to the determinants of the treatment process, but not to the realisations of t_p.

To account for the possible dependence in the unobserved heterogeneity terms, we allow v_e and v_p to follow an arbitrary joint distribution function $G(v_e, v_p)$. Abbring and van den Berg (2003) show that, with assumptions similar to those made in standard univariate MPH models, the bivariate model (1)–(2) and the treatment effect in particular are identified. Furthermore, since no parametric assumptions with respect to the baseline hazard and the unobserved heterogeneity distribution are required, identification of the treatment effect is nonparametric. In order to estimate the model by maximum likelihood[2], we specify a flexible duration dependence as a piecewise constant baseline hazard rate.

In order to build the likelihood function for the estimation of the model, we have to account for censored observations. If we define the censoring indicators δ_e and δ_p, with $\delta_e = 1$ ($\delta_p = 1$) if $T_e(T_p)$ is right-censored, the individual likelihood contributions are given by:

$$\ell_e(t|t_p, x, v_e) = f_e(t|t_p, x, v_e)^{\delta_e} \exp[-\int_0^t \theta_e(u|t_p, x, v_e)\, du]^{1-\delta_e}, \qquad (3)$$

$$\ell_p(t|x, v_p) = f_p(t|x, v_p)^{\delta_p} \exp[-\int_0^t \theta_p(u|x, v_p)\, du]^{1-\delta_p}. \qquad (4)$$

With the assumption that $T_e|t_p, x, v_e$ is independent from $T_p|x, v_p$ we can write (see van den Berg (2001)):

$$\ell_{e,p}(t|x) = \int_0^\infty \int_0^\infty \ell_e(t|t_p, x, v_e)\, \ell_p(t|x, v_p)\, dG(v_e, v_p). \qquad (5)$$

Following Heckman and Singer (1984), the arbitrary distribution function $G(v_e, v_p)$ can be approximated by a discrete distribution with a finite number of support points. For the unobserved heterogeneity distribution, we assume that v_e and v_p can take on two possible values, such that four combinations with an associated probability are possible. This specification is rather flexible and computationally feasible (Richardson and van den Berg 2001). The estimates were done by maximum likelihood, where the joint unobserved heterogeneity distribution adds seven unknown parameters to the model. For the estimation by maximum likelihood, it is helpful to utilise a logistic specification for the probability, where the four probabilities are specified as

$$\pi_{j,k} = \frac{q_{j,k}}{\sum_{m=1}^{2} \sum_{n=1}^{2} q_{m,n}} \qquad (6)$$

and $q_{j,k}$ are parameters to be estimated.

4 Data

Our empirical analysis is based on an inflow-sample of individuals who entered unemployment in the months June, August and October 2000. The infor-

[2] We repeated all estimations from different starting values in order to find the global maximum. Alternatively, the model could be estimated by an EM algorithm as suggested by Heckman and Singer (1984). However, the convergence speed is extremely slow.

mation is merged from several administrative sources of the FEA. These sources are the job-seeker database (*Bewerberangebotsdatei*), the employment statistics register (*Beschäftigtenstatistik*) and the programme participants master data set (*Maßnahme-Teilnehmer-Grunddatei*). The job-seeker database contains information on socio-demographic characteristics, qualification and placement restraints, a short labour market history and the date of entry into unemployment. From these data, we obtain the observable covariates and the entry date into unemployment.

Our outcome of interest, the transition into employment, is derived from the employment statistics register, which includes information on all persons registered in the social security system. These are all individuals in regular employment and participants in several ALMP programmes, but no self-employed persons or pensioners. It is the basis for individual pension claims, and contains information on all episodes of dependent employment. In addition, we use data from the programme participants master data set to identify episodes of participation in ALMP programmes and especially JCS. For the observation period from June 2000 to December 2003 the merged data allows us to identify whether the individuals were registered as employed or as participants in an ALMP programme. For the registered employment periods, we observe the associated record dates (usually at the end of the month) and for the programme participation periods, the exact entry and exit dates. From this information and the entry date into unemployment, we are able to calculate the duration of unemployment until the first transition into registered employment T_e and the duration of unemployment until the first transition into a JCS T_p with the day as the time unit. It should be noted that with the exception of the entry date into unemployment, we are not able to observe whether the individuals are registered as unemployed. Therefore, the time from the entry into unemployment until the first record of registered employment serves as an approximation of the unemployment duration. In particular, labour force movements and unregistered employment cannot be considered with this data. This might be especially of importance for women, who leave the labour force more often compared to men.

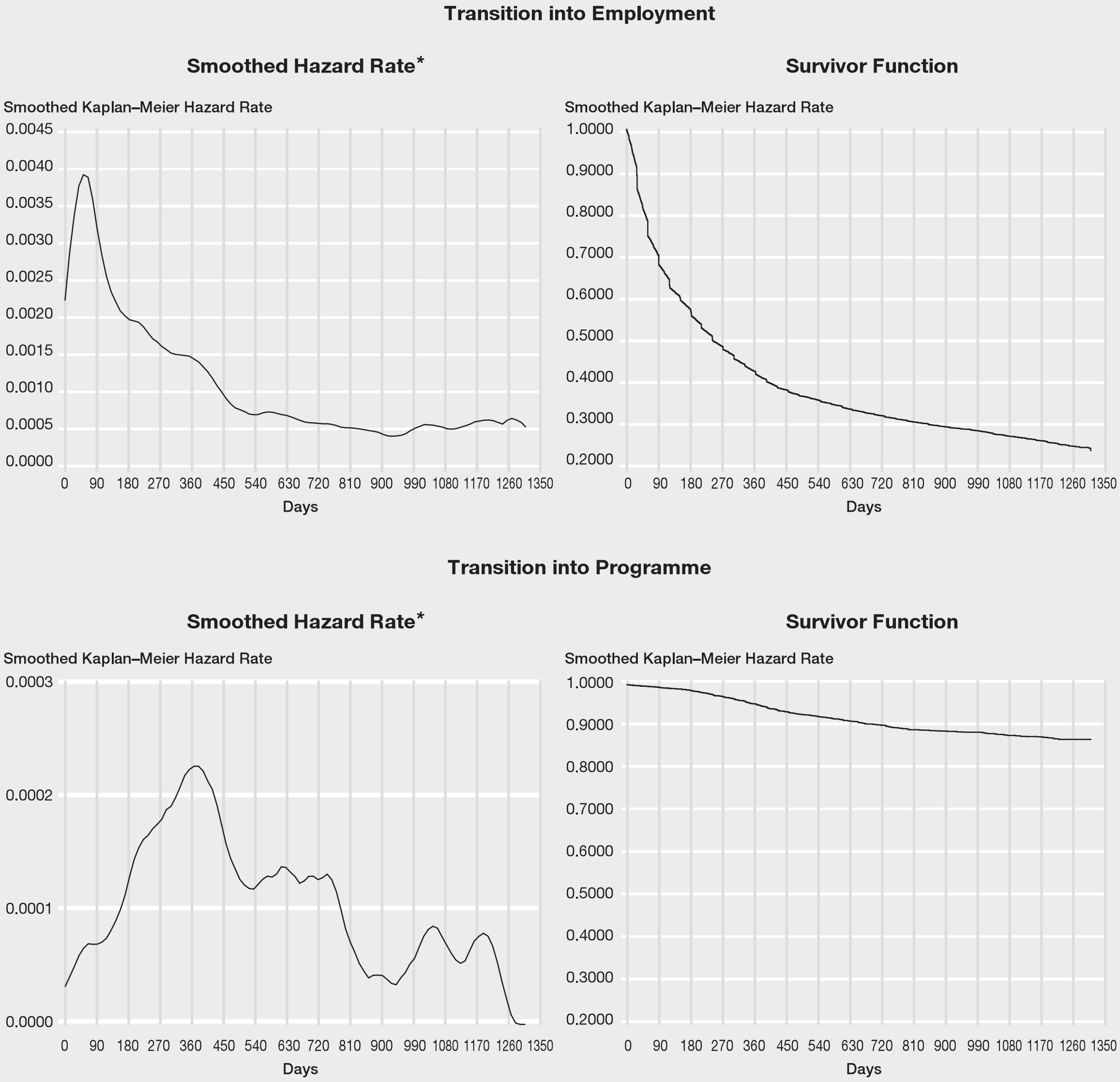
From the programme participants master data set we also observe whether individuals enter alternative ALMP programmes such as vocational training measures. If an individual enters an alternative ALMP programme before he/she enters a registered job we consider the unemployment spell as censored at the point in time when the transition into the alternative programme occurs. Hence, a participation in a JCS after a participation in an alternative programme is not considered, nor are any transitions into employment after a participation in an alternative programme. As a consequence the estimated treatment effect refers only to the impact of a single JCS participation within the unemployment spell that is not accompanied by an alternative treatment. Furthermore, we observe censored spells in cases where no transition within the observation window can be found.

The initial sample consists of 42,969 individuals in eastern Germany, with 13,295 individuals who entered unemployment in June 2000, 17,081 individuals who entered unemployment in August 2000 and 12,593 individuals who entered unemployment in October 2000. The differences in the size of the samples is mainly due to seasonal fluctuations. From this sample, we excluded 4,381 individuals who either participated in ALMP programmes in the period from January 2000 up to their unemployment entry or exhibited errors in the data. Furthermore, we restricted the sample for homogeneity reasons to 17,475 individuals who are domestic, not affected by health restrains, not disabled and between 25 and 55 years of age. Regarding the number of participants, i.e. those individuals who entered a job creation scheme within their unemployment spell, we observe 628 (3.6 %) participants in the sample.

JCS have an ordinary programme duration of 12 months. Therefore, it is reasonable to assume that within this period participants withdraw at least partly from active job-search, especially if participation entails a full-time job. In the presence of this locking-in effect, our model ignores the fact that the transition rate into employment would be extremely low during the participation period. In order to avoid a misspecification of the model Richardson and van den Berg (2001) suggested that the period when individuals are placed in the programme should not be included. So, as our baseline assumption, the time spent in a JCS does not contribute to the unemployment duration. In this case, the treatment effect corresponds only to the after-programme period, and the variable of interest is the duration of regular unemployment. Note that if we include the length of the participation period, the treatment effect would correspond to the in- and after-programme period and the variable of interest would be the duration without a regular job. We address this issue explicitly in a sensitivity analysis in the following section.

Figure 1 presents non-parametric Kaplan-Meier estimates of the hazard rate and the survivor function

Figure 1
Non-Parametric Estimates



** The bandwidth used in the kernel smooth to plot the estimated hazard function was set to 30.*

for our sample (see Kalbfleisch and Prentice (2002)). For the hazard rate into employment, the figure shows a sharp increase immediately after the unemployment spell has started. After an unemployment duration of approximately three months the hazard rate starts to decline. The associated estimated survivor function shows that the probability to still being unemployed after one year is around 40 % and around 30 % after two years. Apparently discouraged worker and stigmatisation effects play a significant role here.

Considering the hazard rate into JCS, we find that the probability of being assigned to a programme increases within the first year of unemployment. The maximum hazard is achieved shortly after one year of unemployment. In the subsequent period up to one and a half years, the hazard decreases to a lower level, which remains throughout the second year of unemployment. After the second year, the hazard rate decreases further, and finally increases again shortly before the third year of unemployment is completed. In line with the hazard rate, the estimated survivor function barely shows a decrease especially for the first six months. A 10 % probability to enter a JCS is achieved after two years of unemployment. Generally, the figures show that the probability to be placed in a JCS increases as the prob-

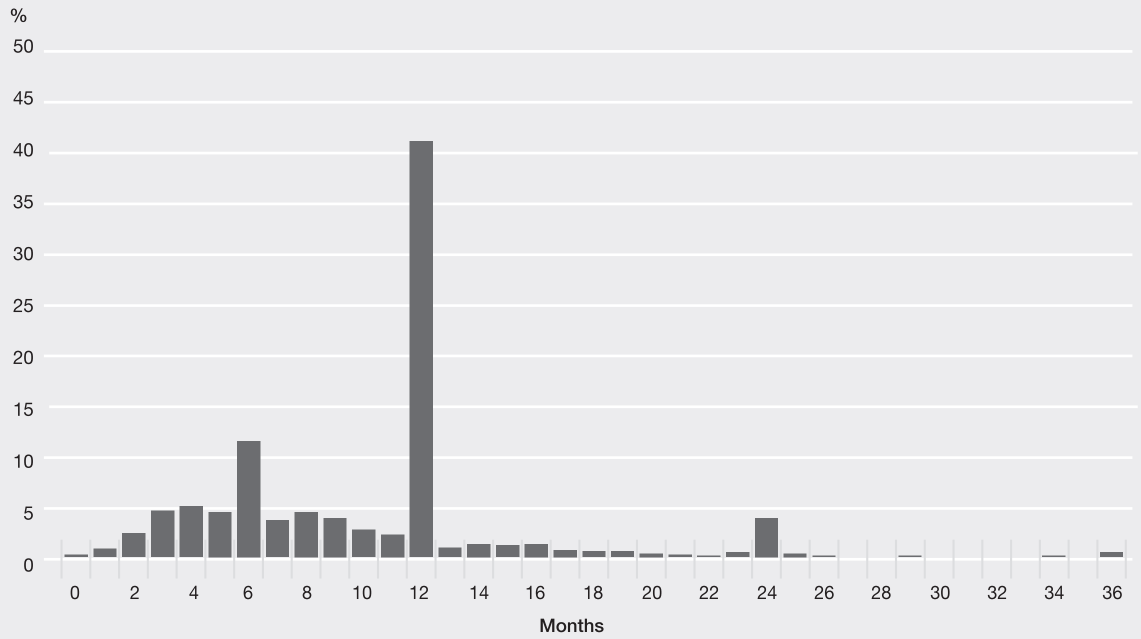
Table 1
Descriptive Statistics for the Covariates

	Tota	Participants	Non Participants
Observations	17,475	628	16,847
Frequencies (in %)			
Women	43.38	46.18	43.28
Applicant for Full-Time Job	91.18	92.36	91.14
Occupational Experience (Yes)	92.63	92.20	92.65
Vocational Education			
In-Firm Training	70.96	69.59	71.01
Off-the-Job Training	1.01	0.64	1.03
Vocational School	0.86	0.64	0.87
Technical School	4.60	6.21	4.53
University	5.03	3.18	5.10
Advanced Technical College	1.73	0.64	1.77
Level of Qualification			
University Level	5.28	3.34	5.35
Advanced Technical College Level	2.47	2.71	2.46
Technical School Level	2.56	3.03	2.54
Skilled Employee	58.55	53.98	58.72
Schooling			
Lower Secondary School Leaving Certificate	23.85	32.96	23.51
Intermediate Secondary School Leaving Certificate	56.25	50.96	56.44
Certificate of Aptitude for Advanced Technical College	2.49	1.27	2.54
Upper Secondary School Leaving Certificate	10.78	6.85	10.92
Family Status			
Single Parent	7.06	6.69	7.08
Married	51.31	57.32	51.09
Desired Occupational Group			
Manufacturing Industry	41.69	46.34	41.52
Technical Occupation	4.88	3.98	4.91
Service	49.10	41.72	49.37
Means			
Age	38.20	41.68	38.07
No. of Children	0.67	0.71	0.67

ability to enter employment decreases. This shows that JCS are mainly aimed at the long term unemployed.

Table 1 presents descriptive results for the observable covariates separated for the total sample, the treatment group and the non-treatment group respectively. The covariates cover several variables to characterise the individual heterogeneity. All of the variables are measured at the point in time when the individuals enter the unemployment spell and are therefore constant over the observed time period. They include sociodemographic variables like age, sex (women), family status and number of children. Individual qualifications are represented by the type of vocational education, schooling and the caseworker's assessment of occupational qualifications (Level of Qualification). Further information includes vocational experience and the type of work the individuals are looking for (Applicant for Full-

Figure 2
Programme Durations



time Job, Desired Occupational Group). The sets of dummy variables refer to the following reference categories: those for vocational education to individuals with no vocational education, those for the level of qualifications to individuals with or without technical knowledge, those for schooling to individuals with no secondary school qualifications, those for family status to single and unmarried individuals, and the dummy variables for the desired occupational group refer to individuals who want to work in the agriculture and fishery industry, the mining industry and miscellaneous occupations.

For our sample we find that the majority of individuals are applicants for full-time jobs and have occupational experience. Furthermore, we find that most individuals obtained their vocational education by means of in-firm training and have a low level of qualifications and schooling. Regarding the desired occupational group, we find that most individuals want to work in service occupations and in the manufacturing industry.

Considering the descriptives for the participant and non-participant groups separately, we find several differences. The participant group consists of older individuals and features a larger share of women and married individuals. With respect to education the descriptive results show that participants generally have a lower level of vocational and school eduction. This shows that JCS are targeted towards disadvantaged persons in the labour market. This also confirms the results the qualification level, where a larger share of participants with the lowest level of qualifications can be found. Regarding the desired occupational group, we find for the participant group a larger share of individuals who want to work in the manufacturing industry, whereas in the non-treatment group, jobs in service occupations are preferred.

Although the available data provides a relatively extensive set of observable characteristics some possible important determinants for both transition rates are not available. For example, information on former unemployment or employment periods as well as information on the motivation of the individuals is not considered. However, in the empirical analysis these unconsidered determinants are captured by the unobserved heterogeneity term.

Finally, Figure 2 presents the distribution of the programme durations in our sample, measured in months. The figure shows that participation in a JCS usually last for a period of one year. Further peaks can be found for programme durations of six months and two years. The relatively high share of programmes with a duration of 12 months shows that locking-in effects are an important issue when evaluating JCS.

5 Estimation Results

Table 2 shows the estimation results for the basic model where the treatment effect is specified as a constant and permanent shift of the hazard rate. The main parameter of interest is the treatment effect μ which represents the causal impact of participation in a job creation scheme on the hazard rate into employment. This effect is, with $\exp(-0.22) = 0.8$, negative and significantly different from zero. Since in this specification, the length of the participation period is excluded from T_e, the treatment effect corresponds to the after-programme period, i. e. there is no locking-in effect at work here. Implicitly, this effect compares a participant in the period after having completed the programme with a non-participant in the period after the programme has started. The effect states that at the point in time when an individual has finished a job creation scheme, the hazard rate is reduced by 20 %.

From the estimated effect on the hazard rate, we are able to derive the effect on the expected unemployment duration conditional on the programme entry. For a programme entry after six months of unemployment, we find that a participant has a 27 % higher expected unemployment duration than an individual who is not treated at all. If the programme entry occurs after a year, the treatment effect implies an extension of the expected unemployment duration of only 21 % and if programme entry is after one and a half years, the expected unemployment duration is reduced by 17 %. Thus, the model implies that treatment at an earlier stage of unemployment has a stronger effect on the expected unemployment duration.

Turning to the covariate effects, we find that the transition rate into employment is higher for women, married people and individuals who are seeking a job in the manufacturing industry or in service occupations. Furthermore, we detect a positive impact of in-firm training and a negative impact of age. Regarding the transition rate into JCS, we find that the hazard increases with age and the number of children, and we find a higher hazard for women. With respect to education, we observe a positive impact of education at technical schools and of qualifications at the advanced technical college level.

Considering the unobserved heterogeneity distribution, the estimates in Table 2 imply a constant term of $v_{e1} = -9.64$ and $v_{e2} = -4.36$ for the transition rate into employment and a constant term of $v_{p1} = -11.38$ and $v_{p2} = -11.21$ for the transition rate into JCS. The associated probabilities are $P(v_{e1}, v_{p1}) = 0\,\%$, $P(v_{e1}, v_{p2}) = 56\,\%$, $P(v_{e2}, v_{p1}) = 44\,\%$ and $P(v_{e2}, v_{p2}) = 0\,\%$. With two points of support for each unobserved heterogeneity term, v_{e1} and v_{p1} represent a relatively low propensity, and v_{e2} and v_{p2} a relatively high propensity to leave unemployment and enter employment or programme participation. The estimated distribution of the unobserved heterogeneity terms only supports the mass points $(v_{e,1}, v_{p,2})$ and $(v_{e,2}, v_{p,1})$. Thus, only individuals with a high propensity to enter employment and a low propensity to enter a programme and individuals with a low propensity to enter employment and a high propensity to enter a programme are supported. However, for the transition rate into a programme, the unobserved heterogeneity term is relatively small and not significantly different from zero. Furthermore, the standard errors for the estimated probability of the unobserved heterogeneity distribution are very large. Thus, we cannot find an impact of unobserved determinants on the hazard into programme participation and the results with respect to the unobserved heterogeneity distribution are not very robust. This suggest that the set of observable variables available in the administrative data are sufficient to describe the selection process into JCS.

To test the robustness of the estimates with respect to the unobserved heterogeneity, Table 3 presents the estimation results for the basic model where unobserved heterogeneity is ignored. For this model, only one point of support for the constant term is imposed. Considering the treatment effect we also find a negative significant treatment effect of $\exp(-0.30) = 0.73$. Thus, if we ignore the unobserved heterogeneity, we obtain a stronger treatment effect. With respect to the covariates we observe that the inclusion of unobserved heterogeneity reduces the significance of most of the estimated parameters.

A big difference between the models with and without unobserved heterogeneity can be found for the estimated piecewise constant duration dependence. For the model without unobserved heterogeneity, we observe – with the exception of the last interval – a negative duration dependence. In contrast, the model that accounts for unobserved heterogeneity shows a positive duration dependence up to the third interval, and for the remaining periods a negative duration dependence which is similar to the model without unobserved heterogeneity. This points to a dynamic sorting process which is captured by the unobserved heterogeneity. Note that a stronger negative duration dependence is typical if unobserved heterogeneity is ignored (see e. g., Lan-

Table 2

Estimation Results

Variable	Transition Rate into Employment		Transition Rate into JCS	
	Coeff	t Value	Coeff	t Value
Baseline Hazard				
$90 \geq T_e < 180; 180 \geq T_p < 540$	0.6126	21.49	0.8605	7.99
$180 \geq T_e < 360; 540 \geq T_p < 900$	3.2499	26.97	0.3574	2.65
$360 \geq T_e < 540; \quad T_p \geq 900$	2.8887	22.89	–0.2168	–1.20
$540 \geq T_e < 720$	2.3824	18.12		
$720 \geq T_e < 900$	2.1869	16.06		
$900 \geq T_e < 1080$	1.9350	13.50		
$1080 \geq T_e$	2.0217	13.59		
Unobserved Heterogeneity (ν_e, ν_p)	5.2868	44.11	0.1760	0.81
Constant	–9.6468	–61.43	–11.3862	–28.02
Age	–0.0068	–4.60	0.0432	7.85
Women	0.0466	1.72	0.2283	2.37
Applicant for Full-Time Job	–0.0490	–1.28	0.2419	1.55
Occupational Experience (Yes)	–0.0012	–0.03	–0.0915	–0.61
No. of Children	–0.0067	–0.51	0.0789	1.78
Vocational Education				
In-Firm Training	0.0828	2.21	0.1054	0.82
Off-the-Job Training	–0.0615	–0.56	–0.2171	–0.42
Vocational School	–0.0240	–0.20	–0.3005	–0.58
Technical School	0.0581	0.81	0.5767	2.34
University	–0.0111	–0.12	0.0713	0.18
Advanced Technical College	0.1219	1.02	–0.5491	–0.89
Level of Qualification				
University Level	–0.0283	–0.35	0.0221	0.06
Advanced Technical College Level	0.0437	0.45	0.5991	1.79
Technical School Level	–0.0695	–0.84	0.1881	0.67
Skilled Employee	–0.0257	–0.92	–0.0297	–0.30
Schooling				
Lower Secondary School Leaving Certificate	–0.0099	–0.20	0.2319	1.37
Intermediate Secondary School Leaving Certificate	0.0235	0.46	0.1499	0.84
Certificate of Aptitude for Advanced Technical College	–0.0439	–0.45	–0.4736	–1.09
Upper Secondary School Leaving Certificate	–0.0027	–0.04	–0.2745	–0.98
Family Status				
Single Parent	–0.0382	–0.77	–0.0571	–0.31
Married	0.0994	3.65	0.1645	1.68
Desired Occupational Group				
Manufacturing Industry	0.1415	2.58	–0.2482	–1.58
Technical Occupation	0.0149	0.19	–0.5651	–2.11
Service Professions	0.1028	1.91	–0.6821	–4.33
Entry into the Sample				
Entry in August	0.0582	2.28	–0.1034	–1.13
Entry in October	0.0642	2.27	–0.4125	–3.88
Treatment Effect	–0.2168	–2.51		
q_1	7.3007	0.6095		
q_2	7.0652	0.5903		
q_3	–4.7169	–0.0918		
π_1	0.0004			
π_2	0.5584			
π_3	0.4412			
π_4	0.0000			
Log-Likelihood	–83072.47			

Table 3

Estimation Results without Unobserved Heterogeneity

Variab e	Transition Rate into Emp oyment		Transition Rate into JCS	
	Coeff	t Va ue	Coeff	t Va ue
Baseline Hazard				
$90 \geq T_e < 180; 180 \geq T_p < 540$	–0.5334	–20.30	0.8990	9.16
$180 \geq T_e < 360; 540 \geq T_p < 900$	–0.8069	–30.69	0.3957	3.11
$360 \geq T_e < 540; T_p \geq 900$	–1.2656	–33.52	–0.1784	–1.02
$540 \geq T_e < 720$	–1.7658	–33.25		
$720 \geq T_e < 900$	–1.9581	–30.66		
$900 \geq T_e < 1080$	–2.2137	–28.36		
$1080 \geq T_e$	–2.1414	–24.62		
Constant	–5.4534	–61.41	–11.2499	–30.5430
Age	–0.0131	–10.06	0.0433	7.8740
Women	–0.0190	–0.79	0.2290	2.3790
Applicant for Full-Time Job	–0.0208	–0.60	0.2415	1.5540
Occupational Experience (Yes)	0.0878	2.35	–0.0933	–0.6200
No. of Children	–0.0459	–3.88	0.0795	1.7940
Vocational Education				
In-Firm Training	0.1693	5.06	0.1042	0.8020
Off-the-Job Training	0.0489	0.48	–0.2182	–0.4220
Vocational School	–0.0131	–0.12	–0.2994	–0.5760
Technical School	0.1650	2.62	0.5762	2.3260
University	0.0439	0.53	0.0709	0.1770
Advanced Technical College	0.2488	2.34	–0.5521	–0.8930
Level of Qualification				
University Level	0.0635	0.86	0.0201	0.0570
Advanced Technical College Level	0.1139	1.30	0.5986	1.7910
Technical School Level	0.0398	0.55	0.1863	0.6640
Skilled Employee	0.0787	3.18	–0.0310	–0.3050
Schooling				
Lower Secondary School Leaving Certificate	0.0279	0.63	0.2314	1.3680
Intermediate Secondary School Leaving Certificate	0.0878	1.95	0.1488	0.8380
Certificate of Aptitude for Advanced Technical College	–0.0092	–0.11	–0.4735	–1.0900
Upper Secondary School Leaving Certificate	0.0854	1.40	–0.2753	–0.9820
Family Status				
Single Parent	–0.0397	–0.90	–0.0570	–0.3120
Married	0.2188	9.11	0.1624	1.6580
Desired Occupational Group				
Manufacturing Industry	0.0909	1.86	–0.2473	–1.5770
Technical Occupation	–0.0156	–0.22	–0.5637	–2.1060
Service Professions	0.0964	2.01	–0.6815	–4.3310
Entry into the Sample				
Entry in August	–0.0117	–0.51	–0.1026	–1.1200
Entry in October	–0.0460	–1.87	–0.4108	–3.8700
Treatment Effect	–0.3094	–3.79		
Log-Likelihood	–83247.05			

caster (1990)). For the transition rate into a programme, we do not observe a substantial difference between the models with and without unobserved heterogeneity. This is in line with the insignificant unobserved heterogeneity parameter v_p.

A further sensitivity analysis deals with the assumption that the time spent in JCS does not contribute to the unemployment duration. Therefore, we estimated the basic model where the length of the participation period in JCS is included in T_e. With this specification, the estimated treatment effect can be interpreted as an average effect that consists of an in-programme effect and an after-programme effect (Richardson and van den Berg 2001). Table 4 contains the estimation results for the basic model where the time spent in programmes is excluded from T_e. For the estimation we use the specification of the basic model with respect to the baseline hazard, the covariates and the unobserved heterogeneity. The results for the baseline hazard and the covariates are similar to the results from Table 2. For the treatment effect we obtain a more negative effect of $\exp(-0.28) = 0.75$ compared to the effect in Table 2. The stronger effect when the participation period is included suggests that the in-programme effect is negative, i. e. JCS are associated with a locking-in effect. However, the difference is not extremely large. One explanation might be that JCS are targeted at long-term unemployed people and that locking-in effects are of minor importance for these individuals.

The treatment effect estimated so far is specified as a permanent and constant shift of the hazard rate that occurs at the moment when the individual enters a JCS programme. However, it is reasonable to expect that a treatment effect is not constant over time. For example, the effect of a participation in a job creation scheme may take some time to develop or the effect may diminish after a certain amount of time. In order to analyse the dynamic development of the treatment effect, we estimate an extended model where the treatment effect is allowed to vary over time. As presented in Section 3, the treatment effect is specified as a piecewise constant function of $t - s$, with μ_1 as the treatment effect for the period $[s, s + c)$ and μ_2 as the treatment effect for the period $[s + c, \infty)$. The extended model is estimated with the same specification for the baseline hazard, the systematic part and the unobserved heterogeneity. Furthermore, to compare the results with the basic model in Table 2, the length of the participation period is excluded from T_e. Therefore, the point in time t_p corresponds to both the start and the end of participation in the JCS. We estimated three models where the exogenous given threshold c was set to 90, 180 and 360 days respectively. The estimated parameters are given in Table 5. The estimates for the baseline hazard, the covariates and the unobserved heterogeneity are basically the same compared to the basic model. For reasons of brevity these coefficients are not reported.

The model with $c = 90$ shows a strong and significant negative effect of $\exp(-1.36) = 0.25$ for the first three months after the programme has finished and an insignificant effect for the remaining period. Thus, in the period up to three months after completion of the programme, we find a hazard rate that is reduced by 75 %. For the model where the treatment effect is allowed to shift after 180 days, we again find a negative significant effect of $\exp(-1.09) = 0.33$ for the period up to six months, but a positive significant effect of $\exp(0.22) = 1.25$ for the remaining periods. The model implies that in the period up to six months after programme completion the hazard rate is reduced to 33 %, and after six months it increases to 125 % of the baseline hazard. Finally, the model with $c = 360$ again shows a negative significant effect for the period up to one year, which is smaller than the effect for the model with $c = 180$, and a positive but insignificant effect for the remaining period. Calculating the associated impact on the expected unemployment duration under the assumption that the participant enters a JCS after one year, we find an increase by 14 % for the model with $c = 90$, an increase by 12.6 % for the model with $c = 180$ and for the model with $c = 360$ an increase by 9.8 %.

The results suggest that the negative effect of JCS on the hazard rate is especially strong in the period immediately after the programme ends. Obviously, if participants leave the programme they need some time to recommence active job search. Interestingly, we find a slightly positive effect, which is located approximately in the period between six months and twelve months after the programme. However, as the basic model in Table 2 shows, this positive effect is not strong enough to induce a positive total effect. Furthermore, note that these results do not include the locking-in effect which generally leads to a more negative picture of JCS.

A final question we want to answer is whether the treatment effect is heterogenous with respect to the observable characteristics. Therefore, we estimated a second extended model where the treatment effect is specified as a permanent and constant shift of the hazard rate, but where it is allowed to vary with the observable characteristics. In addition to a main treatment effect, we estimate a difference parameter for females, for individuals without occupational ex-

Table 4

Estimation Results when Time in Job Creation Schemes is included

Variable	Transition Rate into Employment		Transition Rate into JCS	
	Coeff	t-Value	Coeff	t-Value
Baseline Hazard				
$90 \geq T_e < 180$; $180 \geq T_p < 540$	0.6140	21.51	0.6401	6.49
$180 \geq T_e < 360$; $540 \geq T_p < 900$	3.2484	26.51	0.1383	1.09
$360 \geq T_e < 540$; $T_p \geq 900$	2.8612	22.28	–0.4358	–2.51
$540 \geq T_e < 720$	2.3856	17.88		
$720 \geq T_e < 900$	2.1324	15.38		
$900 \geq T_e < 1080$	2.0673	14.60		
$1080 \geq T_e$	2.2082	15.29		
Unobserved Heterogeneity (ν_e, ν_p)	5.3062	43.57	3.7454	2.27
Constant	–9.6569	–60.98	–14.7254	–8.64
Age	–0.0071	–4.81	0.0425	7.74
Women	0.0442	1.64	0.2236	2.32
Applicant for Full-Time Job	–0.0477	–1.25	0.2442	1.57
Occupational Experience (Yes)	0.0028	0.07	–0.0801	–0.53
No. of Children	–0.0069	–0.53	0.0748	1.68
Vocational Education				
In-Firm Training	0.0819	2.18	0.1129	0.88
Off-the-Job Training	–0.0630	–0.58	–0.2097	–0.41
Vocational School	–0.0164	–0.14	–0.3091	–0.60
Technical School	0.0554	0.78	0.5790	2.34
University	–0.0159	–0.17	0.0747	0.19
Advanced Technical College	0.1280	1.07	–0.5303	–0.86
Level of Qualification				
University Level	–0.0276	–0.34	0.0330	0.09
Advanced Technical College Level	0.0286	0.29	0.6033	1.80
Technical School Level	–0.0825	–1.00	0.2019	0.72
Skilled Employee	–0.0266	–0.96	–0.0205	–0.22
Schooling				
Lower Secondary School Leaving Certificate	–0.0123	–0.25	0.2354	1.39
Intermediate Secondary School Leaving Certificate	0.0250	0.49	0.1571	0.88
Certificate of Aptitude for Advanced Technical College	–0.0461	–0.47	–0.4739	–1.09
Upper Secondary School Leaving Certificate	–0.0042	–0.06	–0.2691	–0.96
Family Status				
Single Parent	–0.0369	–0.74	–0.0581	–0.32
Married	0.1014	3.73	0.1777	1.81
Desired Occupational Group				
Manufacturing Industry	0.1392	2.55	–0.2535	–1.62
Technical Occupation	0.0218	0.28	–0.5735	–2.14
Service Professions	0.1045	1.94	–0.6859	–4.37
Entry into the Sample				
Entry in August	0.0576	2.26	–0.1084	–1.18
Entry in October	0.0657	2.32	–0.4232	–3.99
Treatment Effect	–0.2822	–3.92		
q_1	5.9862	0.1203		
q_2	5.7459	0.1158		
q_3	–3.0568	–0.4150		
π_1	0.0014			
π_2	0.5590			
π_3	0.4396			
π_4	0.0001			
Log-Likelihood	–83261.27			

Table 5
Time Varying Treatment Effect

Effect	$c = 90$		$c = 180$		$c = 360$	
	Coeff.	t-Value	Coeff.	t-Value	Coeff.	t-Value
μ_1	–1.3628	–4.87	–1.0979	–6.47	–0.3969	–3.63
μ_2	0.0300	0.32	0.2202	2.24	0.2275	1.52
Log-Likelihood	–83054.12		–83047.09		–83066.63	

Table 6
Effect Heterogeneity

Effect	Coeff.	t-Value
Main Effect	–0.2167	–1.69
Women	0.0078	0.04
High Qualification	0.0674	0.19
Without Occupational Experience	–0.3131	–0.70
Log-Likelihood	–83072.05	

perience and for individuals with a high qualification level. This latter group comprises individuals with a university or advanced technical college degree. The model extended with respect to the effect heterogeneity is estimated with the same specification for the baseline hazard, the systematic part and the unobserved heterogeneity, and the length of the participation period is excluded from T_e. The results for the treatment effect are presented in Table 6, where again the estimates for the baseline hazard, the covariates and the unobserved heterogeneity are not reported for the sake of brevity.

The main effect, which corresponds to the group of men with low qualifications and with occupational experience, is with $\exp(-0.21) = 0.81$, nearly identical to the effect estimated by the basic model. For none of the groups, we do find any significant difference for the treatment effect. Thus the estimated effect is relatively constant with respect to the considered observable characteristics.

6 Conclusion

JCS have been an important ALMP programme in Germany in terms of the number of individuals receiving support and the amount spent. Although their importance has decreased in recent years, they are still used in particular on a large scale in eastern Germany. Our empirical analysis aims to extend the existing literature on the effects of JCS to incorporate the timing-of-events approach of Abbring and van den Berg (2003). Our analysis investigates whether JCS are able to reduce the unemployment duration of participants. In the empirical model the timing of treatment within the unemployment spell affects the distribution of the unemployment duration. The econometric analysis is based on a bivariate mixed proportional hazard model, where the transition rates into employment and into programmes are specified simultaneously. Selectivity problems with respect to programme participation are solved by allowing the transition rates to depend on observable and unobservable characteristics.

The empirical analysis is based on an inflow-sample of individuals who entered unemployment in the months June, August and October 2000. The information is merged from several administrative sources of the FEA. The estimates for a basic model where the treatment effect is specified as a time-invariant shift of the hazard rate shows a significant negative effect of JCS on the transition rate into employment. However, if we take the time spent within JCS into account as well, the effect becomes more negative, i. e. JCS are apparently associated with a locking-in effect. The analysis of an extended model that allows for a time-varying treatment effect shows that participation in a JCS is associated with a strong negative effect, which appears immediately after the programme has finished. Subsequent to this period, we find a slight positive effect, which is located approximately in the period from six up to twelve months after the programme has finished. However, this effect is not strong enough to result in a positive total effect. A further extended model allows the treatment effect to vary over several observable characteristics. However, the estimates do not suggest a heterogenous treatment effect with respect to the selected observable characteristics.

Summarising the results, we find that JCS in eastern Germany increase the individual unemployment duration of the participants. This results from a locking-in effect and a strong negative effect on the transition rate into employment which is especially observable for the period directly after the programme is completed, and when the participants re-enter unemployment. Despite this clear negative finding, we cannot make any statements about the impact of JCS on subsequent unemployment spells or on the stability of employment periods.

References

Abbring, J. H./van den Berg, G. J. (2003): The Nonparametric Identification of Treatment Effects in Duration Models, Econometrica, 71 (5), 1491–1517.

Bonnal, L./Fougere, D./Serandon, A. (1997): Evaluating the Impact of French Employment Policies on Individual Labour Market Histories, Review of Economic Studies, pp. 683–713.

Caliendo, M./Hujer, R./Thomsen, S. L. (2004): Evaluation der Eingliederungseffekte von Arbeitsbeschaffungsmaßnahmen in reguläre Beschäftigung für Teilnehmer in Deutschland, Zeitschrift für Arbeitsmarktforschung – Journal for Labour Market Research, 3, 211–237.

Caliendo, M./Hujer, R./Thomsen, S. L. (2005): The Employment Effects of Job Creation Schemes in Germany – A Microeconometric Evaluation, Discussion Paper No. 1512, IZA.

Caliendo, M./Hujer, R./Thomsen, S. L. (2006): Sectoral Heterogeneity in the Employment Effects of Job Creation Schemes in Germany, Jahrbücher für Nationalökonomie und Statistik, 226/2, 139–179.

Caliendo, M./Hujer, R./Thomsen, S. L. (2007): Identifying Effect Heterogeneity to Improve the Efficiency of Job Creation Schemes in Germany, Applied Economics, forthcoming.

Eichler, M./Lechner, M. (2002): An Evaluation of Public Employment Programmes in the East German State of Sachsen-Anhalt, Labour Economics, 9, 143–186.

Fredriksson, P./Johansson, P. (2004): Dynamic Treatment Assignment – The Consequences for Evaluations Using Observational Data, Discussion Paper No. 1062, IZA.

Heckman, J. J./Singer, B. (1984): A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data, Econometrica, 52 (2), 271–320.

Huebler, O. (1997): Evaluation beschäftigungspolitischer Maßnahmen in Ostdeutschland, Jahrbücher für Nationalökonomie und Statistik, 216, 21–44.

Hujer, R./Thomsen, S. L. (2006): How Do Employment Effects of Job Creation Schemes Differ with Respect to the Foregoing Unemployment Duration?, Discussion Paper No. 06–047, ZEW.

Kalbfleisch, J. D./Prentice, R. L. (2002): The Statistical Analysis of Failure Time Data. John Wiley and Sons, New York. Chichester. Brisbane. Toronto. Singapore, 2 edn.

Kraus, F./Puhani, P. A./Steiner, V. (2000): Do Public Works Programs Work? Some Unpleasant Results from the East German Experience, in: Research in Labour Economics, ed. by S. Polachek. JAI Press.

Lalive, R./van Ours, J. C./Zweimuller, J. (2002): The Impact of Active Labor Market Programs and Benefit Entitlement Rules on the Duration of Unemployment, Working Paper, Institute for Empirical Research in Economics, University of Zurich.

Lancaster, T. (1990): The Econometric Analysis of Transition Data. Cambridge University Press, Cambridge, New York, Oakleigh.

Richardson, K./van den Berg, G. J. (2001): The Effect of Vocational Employment Training on the Individual Transition Rate from Unemployment to Work, Swedish Economic Policy Review, 8 (2), 175–213.

Van den Berg, G. J. (2001): Duration Models: Specification, Identification, and Multiple Durations, in: Handbook of Econometrics, ed. by J. J. Heckman, and E. Leamer, vol. 5, chap. 55, pp. 3381–3462. North-Holland, Amsterdam.

Van Ours, J. C. (2004): The Locking-In Effect of Subsidized Jobs, Journal of Comparative Economics, 32 (1), 37–52.