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The Motivation Effect of Active Labor Market Policy on Wages

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Abstract:

This paper analyzes the motivation effect of activation programs on wages and employment. We utilize a reform of the Danish UI system in 1998 that reduced the period of unconditional benefits and thereby created exogenous variation in the probability of people entering a mandatory activation program. Wages are measured by their position in the overall wage distribution, and we estimate how this position reacts to an increased probability of an individual being enrolled in activation. The wage effect is estimated using a competing risk duration model with exit states to employment at a higher wage or a lower wage. Overall, we find an increased hazard of exit to employment and of exit to higher-paying jobs as the probability of activation increases, and no change in the exit rate to lower-paying jobs. These results do not hold for individuals with higher education, for whom we find no employment or wage effects of a higher probability of activation.

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1 Introduction

In this paper we investigate the motivation effect of activation on wages; what does the existence of mandatory activation do to unemployed workers' re-employment wages? Workers who are made redundant will on average experience a wage reduction (Jacobsen et al. (1993)) and the question is whether activation enhances this process or hinders it. The main focus of our study is the wage effect for those unemployed workers who leave unemployment prior to activation.

Even disregarding rehabilitation and other active social policy programs, Denmark still uses around one percent of its GDP on its active labor market policy (ALMP): a level of spending which is bigger than that of our neighboring countries and almost three times as great as the spending in the average OECD country. The employment effect of this enormous effort has been studied intensively over the years, and it has been found that there are positive effects for many of the individuals who participate in the activation programs or who are motivated to find employment quickly in order to avoid participation. Moreover, there also seems to be a positive affect at the aggregate level, in the sense that local unemployment is reduced in municipalities with intensive activation schemes; however, the marginal effect seems to be very small for most types of programs, although there are exceptions (DØR (2012) and Gautier et al. (2012)).

The official purpose of the labor market programs is to qualify the unemployed for jobs in order to facilitate their quicker reemployment. In reality, the programs also-and sometimes only-work as a test of the unemployed individual's availability for a job. The flip-side of this coin is the motivation effect, or threat effect. If participation in a mandatory activation program is less attractive than receiving benefits without sacrificing leisure time, the prospect of full-time activation might mean that unemployment becomes less attractive than employment for individuals for whom this would not have been the case without mandatory activation. Thus, as the time before the start of compulsory activation shrinks, such individuals are increasingly encouraged to find a job. This motivation effect of activation has been carefully studied, and a positive effect on employment is (almost) always found; see, for example Geerdsen (2006); Geerdsen and Holm (2006); Rosholm and Svarer (2008); Black et al. (2003); DØR (2007); Graversen and Ours (2008).

While the various employment effects have been studied intensively, the wage consequences of ALMP have only been considered in a few Danish studies. Jespersen et al. (2008)

studied employment and wage effects after program participation and found negative wage effects for programs that prolong the unemployment spell. In studying the wage effects of a program that intensifies job search assistance, Andersen (2013) found negative short run effects, but no medium term effects on average; while Sørensen (2012) also found mainly negative short run effects on wages, but positive and negative effects respectively of approximately the same size for men and women in the longer run. The motivation effect of approaching mandatory activation on re-employment wages has not been given much attention, however. Bennmaker et al. (2012) studied a Swedish policy change for older workers and found a positive wage effect as a reaction to turning parts of the passive UI period in to mandatory activation.

The results reported in Van den Berg et al. (2008) indicate that unemployed individuals lower their reservation wages and increase their search intensity prior to the expected commencement of participation in an activation program. This suggests that individuals try to prevent program participation by accepting lower paid jobs than they would otherwise have done. The data used are cross-sectional survey data, and no duration and wage outcomes are recorded. Nevertheless, the study by Van den Berg et al. suggests that the observed results for wages are the net effects of two forces. One would expect that the unemployed individuals would reduce their reservation wage. That could result in exit to lower-paying jobs on average for fixed search effort. However, the unemployed workers might also increase their search intensity, with the result that they find jobs more quickly and possibly also to higher wages on average. Even if the reservation wage is adjusted downwards as unemployment persists, earlier exit from unemployment could mean exit to a higher paid job compared to what would have been the case without the motivation from the approaching activation. If the search effort is increased enough and job offers are collected, exit to higher paying jobs could occur even for fixed unemployment duration. In a study using the Danish Labor Force Survey, Amilon (2010) shows that search activity does indeed increase as mandatory activation approaches.

Selection in and out of activation programs implies that we need an instrument in order to study this motivation effect, and here we use the shortening of the so-called "passive period" that was enacted by Parliament in Denmark in the late 1990s. The passive period is the initial period of unemployment before mandatory activation, during which benefits are paid unconditionally. Specifically, we use the exogenous variation that was introduced by the reform to identify a causal effect on wages of the probability of being enrolled in activation. The wage effect is measured as a change in the position of the treated worker's wage in the over all wage distribution. Thereby, we capture the net wage effect as the difference between the wages of workers who are affected by higher probability of activation and all workers. A higher probability of activation will potentially influence the wages of all workers. Thus, the reform might not only have increased the probability of activation for the treated workers, it could also have altered the overall wage distribution by affecting the bargaining position of both unemployed and employed workers. By measuring wages, not in deflated real terms, but as relative wages measured by their position in the overall wage distribution, this approach captures some but not all general equilibrium effects initiated by the reform, as well as controlling for general changes in the wage structure during the investigated period that begins one year before the first part of the activation reform is implemented and ends one year after the entire reform has been enacted.

In order to check our data and model, we also estimate the employment effects so that we can compare our model with others described in the literature. Like other authors, we find an increased hazard of exit to employment as the probability of activation increases. Moreover, we also find an increased exit rate to higher-paying jobs and no change in the exit rate to lower-paying jobs. As the wage change up and down on are average of the same magnitude, this suggests that the wage drop that is generally the result of a period of unemployment will be reduced as the probability of activation increases. These results do not hold for individuals with a higher education (college degree and above), for whom we find no employment or wage effects.

The paper is structured as follows. In Section 2 we describe the data. In Section 3 we discuss the Unemployment Insurance (UI) reform which is used for identification. In Section 4 we present our empirical strategy, and Section 5 presents the motivation effects for employment. In Section 7 we examine the results for subgroups defined by educational level, and in Section 8 we summarize and discuss our findings. Finally, we conclude in Section 9.

2 The Data

In this section we introduce the data and the different variables used in the analysis. All the basic data are drawn from one of the following four full population registers held at Statistics Denmark: the population register, the DREAM data base, the tax authority´s income register, and the education register. The registers are briefly introduced below. From these registers we construct a panel data set of unemployment spells commencing between 1998 and 2001, with weekly information on the wages of individuals before unemployment, numbers of unemployment spells, participation in activation programs, transition to employment, and individuals´ wages in their new jobs.

From the population register we create a 25 percent random sample of males aged 25 to 49 between 1998 and 2001. We include information on age, gender, municipality of residence, unemployment rate of the municipality of residence, identity of cohabiting partner, and number of children in the household. Males and females seem to react very differently to the prospect of participating in activation programs. In fact, there is hardly any reaction in terms of faster exit to employment to be found for females (see Rosholm and Svarer (2008, 2011)) whereas a strong motivation effect is generally found for men. Consequently, we concentrate on studying the effects for men and perform robustness tests with mixed samples. We also remove individuals from the sample who are not full-time insured against unemployment. This information is gathered from the the Central Register of Labor Markets Statistics (CRAM). Finally, we restrict our sample to unemployed men under the age of 49 and over 24, since other UI rules apply in Denmark for individuals outside this age range.

Information on individuals´ unemployment histories is taken from the DREAM database. The DREAM data-base is an event data base based on data from the Ministry of Employment, Welfare and Education, the Ministry of Social Affairs and Integration, the Danish Central Business register (CVR) register and the Danish Tax Authority. The data-set consists of all individuals who have received some kind of public benefit during the study period. The benefit type and payment are recorded weekly.

Benefit payments are mutually exclusive, and an individual cannot have two different DREAM payments in the same week. If an individual has two kinds of benefit payment, or one payment and one activation program participation record in the same week, the dominant activity in terms of number of days is recorded. Since only one weekly code is registered, there exists an order of priority within the DREAM codes. This means that the unemployment codes have a higher rank than social assistance benefit codes, sickness benefit payment codes have a higher priority than unemployment benefit codes and activation program codes have higher rank than unemployment codes. This means that it is possible to identify all periods of unemployment with benefit payments. To be categorized as being unemployed in a specific week we require that an individual has received UI benefits for the full week, and weeks of unemployment and weeks of participation in activation programs are treated as belonging to the same unemployment spell. If an individual has three weeks or less without benefit payments between two unemployment spells, the two spells are treated as one spell.

In order for us to consider an unemployment spell to have ended, an individual must have four consecutive weeks out of unemployment (with activation program participation counting as unemployment) and with no other benefit payments. If the individual receives other benefit payments, the spell is right-censored. The spell is also right-censored when the individual reaches the age of 50 years.

We construct an indicator variable, Emp, that indicates an exit to employment or self-support, which we will simply call "Employment". The fraction of individuals who exit unemployment to Emp and who do not earn a wage is small and only amounts to 3 %. The variable $Prev\,UI$ is constructed as the sum of weeks in unemployment over the previous 36, 33, 27 and 24 months for spells beginning in 1998, 1999, 2000 and 2001 respectively. Individuals have to earn the right to UI benefits within these time frames. The requirement is 52 weeks of regular and unsubsidized employment during the previous 36, 33, 27 or 24 months, depending on the year in which the spells started.

Information on gross income and wage income is taken from the tax register. Wage income is all earned income received from an employer during the fiscal year, and gross income is the sum of all income reported to the tax authorities, including the wage income.

The education register provided information on the highest-level completed course of education as of 1st January each year. Educational levels are grouped into the following categories: $Unskilled$ covering primary school, lower and upper secondary school, and missing information; $Skilled$, non-academic vocational training related to a specific trade or occupation; and $Short$, *Medium-length*, and *Long courses of higher (academic tertiary level) education* covering three-year, four-year or five-year (or more) university-level courses respectively. We use the category $Unskilled$ as the reference category.

Based on the information from the tax register and the DREAM database we construct our wage variable, the weekly wage, which is the yearly earned income divided by the number of weeks with no public transfer payments. The main analysis is concerned with relative wages, so instead of the nominal weekly wage we use as our wage variable the corresponding percentile in the wage distribution for all male wage earners in Denmark aged 25-49. Thus, individuals´ wages in the analysis are integers between 1 and 100. Finally, we construct indicator variables, $High$, Low, and $None$ that indicate exit to employment with a higher wage, a lower wage, or with missing wage information. Exit to the same wage percentile as before unemployment is categorized as exit to a higher wage; however, this seldom occurs. The wage indicator variables are based on the wage income one year before exit and one year after. If there is no information on the wage in one of these years we use the wage two or three years before and/or after an exit. An exit in 1999 will therefore be categorized as an exit to a higher, lower or no wage by comparing the wage in 2000 to the wage in 1998.

Each person can have multiple spells of unemployment, and each unemployment spell is censored after the first period of activation program participation. The reason for this censoring is to avoid confusing the post program effect with the threat effect.

2.1 Sample statistics

The panel we arrive at consists of 45,849 individuals with 88,200 unemployment spells; 48,393 spells have information on wages before unemployment and 58,561 have information on wages after unemployment; 22,716 spells are right-censored due to either the age requirement or the restrictions imposed by the sampling period; and 14,385 spells include some form of activation program participation.

Table 2.1 shows the summary statistics for the estimation sample.

Table 2.1: Summary Statistics

Variable	Mean	SD	Min	Max
Age	36.3	7.2	25	49
Cohabiting spouse	0.58	0.49	0	1
Child living at home	0.40	0.49	0	1
Vocational training	0.45	0.49	0	1
Short higher edu.	0.04	0.19	0	1
Medium-length higher edu	0.06	0.24	0	1
Long higher edu	0.06	0.23	0	1
Mean numbers of spells	4.04	2.8	1	27
Spell length (weeks)	17.8	22.2	1	238
Prev. unemployment (weeks)	11.48	33.2	0	152
Wage before unemp. (percentile)	58.2	24.2	1	100
Wage after unemp. (percentile)	56.1	23.4	1	100

The mean age is 36 years (SD 7.2). 58% of the individuals in the sample have cohabiting spouse and 40% have a child living at home. Most of the unemployed are either unskilled or have vocational training (84%);, only 6% have a higher education. The average unemployed individual in the sample had just over 4 spells of unemployment. The average duration of each spell was 17.8, and on average each unemployed person had 11.48 weeks of previous unemployment before the current spell. The wage percentile is higher before unemployment than after unemployment, as expected.

Some exits from unemployment are not associated with a positive post-unemployment wage, which creates a potential selection problem when estimating the exits to either a higher or lower wage. However, the "zero wage" state does not indicate a missing value. The individual is listed in the tax register, but he or she is registered as having zero wage income. Zero wage, and no registered public transfers, is likely to indicate an exit to self-support (either by relatives, as self-employed, or from own savings), and should not count as an exit to a lower wage. Therefore we classify "zero wage" as a state. This gives the following distribution of the main exit statistics: 40 percent exit to a higher wage, 51 exit to a lower wage, and 6 percent exit to zero wage.

3 The Probability of Activation and the 1998 Unemployment Insurance Reform

We estimate the wage effect of activation for workers with unemployment insurance. In 2002 more than 80 percent of the members of the Danish workforce were insured against unemployment, which is a public but voluntary insurance scheme (see Parsons et al. (2003)). The benefit period, which is very long by international standards, begins with a so-called "passive period" and continues after a period of unsuccessful job search into the "active period", during which benefits are paid conditionally on participation in activation programs. When UI benefits are exhausted it is possible to receive means tested social assistance from the local municipality. An unemployed worker can voluntarily choose activation during the passive period and thus we have to take into account the fact that program participation can take place at any time during unemployment.

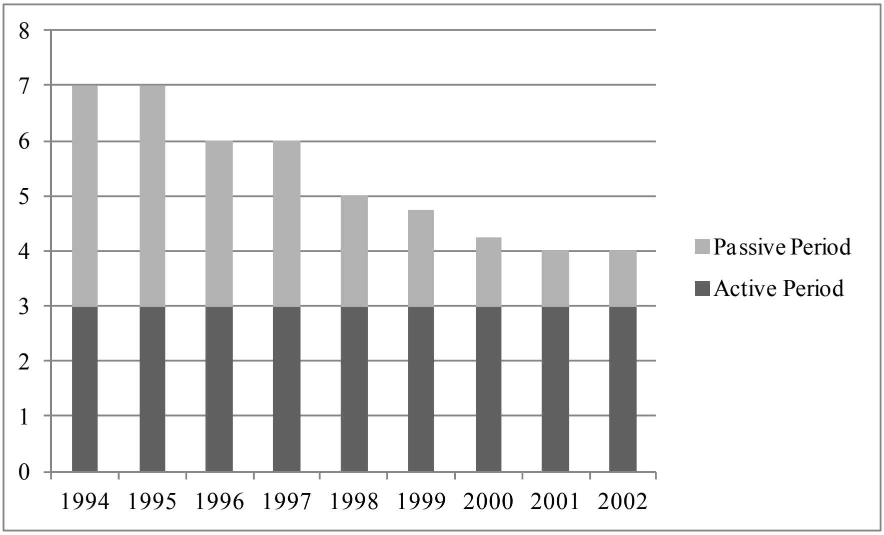
Significant changes were made to Danish labor market policy during the 1990s. The search requirements for the unemployed were raised and the passive period shortened. Below we describe the developments in and the reforms of the Danish UI system during the years 1994 to 2002.

The reforms had an administrative element and an element concerned with expanding the active labor market policy and integrating these activation elements system.[1]. We will only consider the way the active and the passive elements of the UI scheme changed, which they did several times during the 1990s. Figure 3.1 shows the shortening of the passive period from 1994 to 2002, which took place in three stages. It was the last reform of 1998, which shortened the passive period from two years to one, that we will be using for identification.

According to the 1998 reform, unemployed individuals had to participate in activation programs after only one year of unemployment. To smooth the transition to the shorter

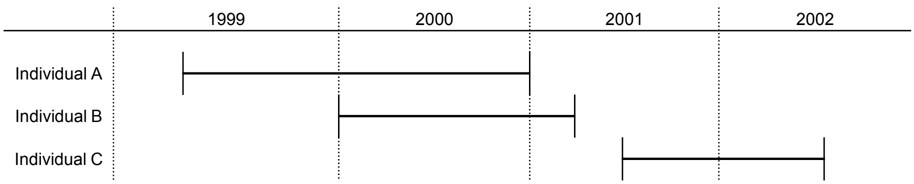
[1] The administrative element was implemented on 1 January 1993 and the activation element was implemented on 1 January 1994

Figure 3.1: Reduction of the passive period during the 1990s



passive period, the reduction was implemented gradually. Figure 3.2 shows the implementation of the reform.

Figure 3.2: Implementation the new passive period between 1999 and 2002



Individuals who entered unemployment between 1 January 1999 and 31 December 1999 had a passive period of 1 year and 9 months, while those who entered between 1 January 2000 and 31 December 2000 had the right to a passive period of 1 year and 3 months. The reform was not fully implemented until 1 January 2001, where the passive period was reduced to 1 year. The passive period was implemented in form of as a voucher and after a certain amount of time in unsubsidized employment this voucher was restored to its initial value. The time in employment required to regain the passive period voucher was 3 years in 1998, 2 years and 9 months in 1999, 2 years and 3 months in 2000 and 2 years in 2001. Stricter rules applied for people under 25 years of age (Act 592, §52.a).

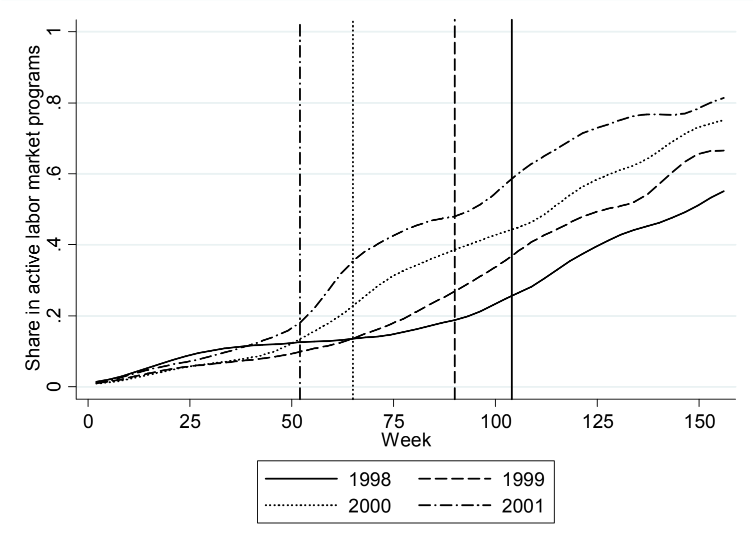
The changes in the length of the passive period over time provide us with an exogenous variation in the unemployed individuals' time until mandatory activation. This enables us to make causal interpretations of the effects change in the length of time until activation program participation on the probability of finding a job and on the probability of subsequently ending up with either a higher or a lower wage.

3.1 The probability of activation

With the final data available it is possible to investigate the effects of the legislative changes in the length of the passive period from 1998 until 2001. We calculate how much of the allotted time each person has spent in the passive period, and note whether they participated in activation programs or not. Spells beginning in 1998 had a passive period of 104 weeks, while spells beginning in 1999, 2000 and 2001 had passive periods of 92, 65 and 52 weeks respectively. We would expect to see a sharp rise in activation program participation around these points in time, in accordance with the legislation. Figure 3.3 shows the fraction of individuals in active labor market programs for spells beginning in each year, with markers for the points in time for activation programs in accordance with the legislation. Note that it is only in 2001 that we see a marked increase in the fraction of individuals in activation programs around the legislated time for participation. This is in line with the findings of Geerdsen and Holm (2006). As Figure 3.3 shows, the take-up rate is fairly smooth, and therefore it is not the best approach to base the model on legislative changes alone. That would bias the measure of time to activation significantly. A better alternative is to model the time until activation as the probability of participation conditional on year of spell start. A crucial thing to note here is that the fraction of unemployed individuals in activation increases each year, although the fraction of those ones entering unemployment in 1998 tends be high in the first 52 weeks and then only lower than the fraction in 1999 by the 65-week mark. Although the legislative changes in the length of the passive period were not strictly implemented, they did increase the share of individuals participating in ALMPs. This increase is our means of identification as described in the next section.

As Figure 3.3 shows there are significant differences in activation program participation between the various years. This confirms the strength of our instrument. The largest jump after expiry of the passive period seems to be in 2001. This could indicate stronger enforcement by case officers in this year. Almost all individuals entering unemployment in 2001 and still unemployed after 150 weeks have been activated (at some point in time). Note, however, that even eight months after the expiry of the passive period, only 60% of individuals were participating in activation programs. Furthermore, there is a positive take-up rate before the passive period runs out. At the time of as the exhaustion of passive benefits around 25% of individuals were already enrolled in activation programs for unemployment entry years 1998, 1999 and 2000. For 2001 it was around 20%. This is

Figure 3.3: Fraction of unemployed individuals in activation programs from 1998 to 2001



voluntary participation, and it indicates that some individuals expect a positive outcome from participation.

If the timetable of the reform itself is used, every individual would have a zero percent probability of activation before the passive period expired, and a 100 percent probability afterwards. Figure 3.4 shows that this was certainly not the case in reality and the estimation results would be biased if individuals´ expectations were correct.

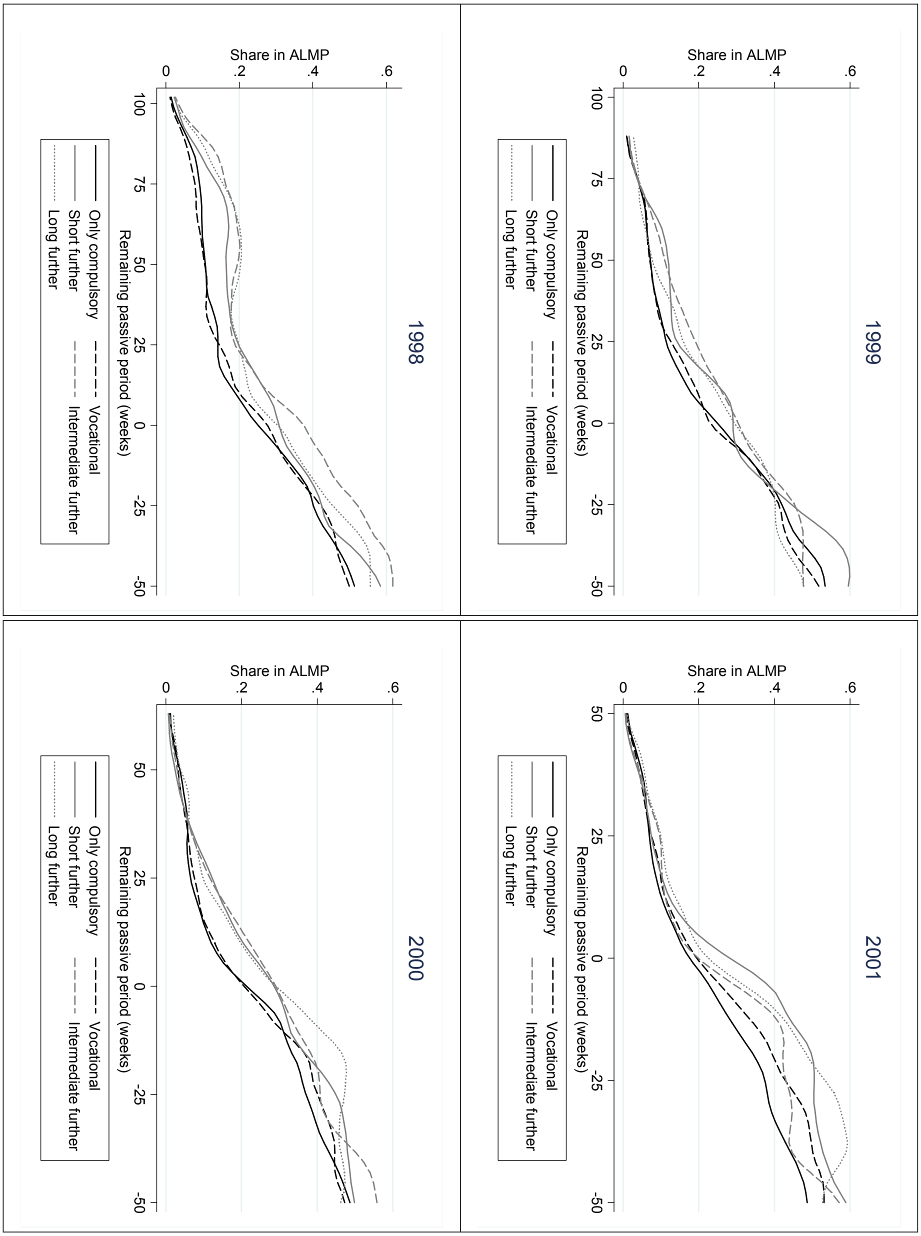
3.1.1 Individual differences in activation

Geerdsen and Holm (2006) found that individuals with different characteristics are treated differently in the unemployment insurance system. We check whether this is also the case with our data by looking at activation take-up rates for different educational groups. The take-up rates are shown for a 30-year-old male when he commences his unemployment spell.

Figure 3.4 shows that individuals indeed face different levels of risk of program participation. The individuals with short and long higher education are more likely to participate in activation. We cannot say if this is voluntary or driven by more strict enforcement for these groups by the case officers. The share of participants rises rapidly as the remaining passive period expires for all educational groups, although the increase seems to begin earlier for the unemployed with a long further higher education.

There could be various explanations for the differences in the probability of activation. The unemployed are supposed to follow individual "action plans" that are drafted together with a case worker, and these case workers differ in their attitudes. The various programs are available in differing numbers in different municipalities; these municipalities have different policy regimes that may also change over time, thus introducing variation into the level of spending and the composition of the activation menu locally. Altogether, this suggests that predicting the probability of activation is an appropriate approach.

Figure 3.4: Activation program take-up rate for different educational groups



4 Empirical Framework

In this section we set up the empirical model. The econometric method we use is survival analysis, following Jenkins (2005). Specifically, we set up a duration model that follows the unemployed individuals week by week, and we observe whether they leave unemployment or not as time until activation decreases. We furthermore divide these exits into different wage categories to establish whether individuals receive a higher wage or a lower wage as a consequence of an increased perceived threat of activation. In the following, we construct two models: one with exit to employment, and a competing risk model with exit to different wage states.

According to the Danish UI scheme, activation occurs at a fixed point in time, after a certain period of unemployment. In reality, however, activation does not happen at a fixed point in time, as we have seen previously. Estimation using legislative rules alone is thus not optimal. Instead, if one wishes to estimate the motivation effect of activation, the model should be based on the unemployed individual's perceived threat of activation. Technically, we want to estimate the probability of activation conditional on certain characteristics and then use this probability to estimate the probability of leaving unemployment. In doing this we assume that the unemployed individuals are able to observe what we as researchers observe. The unemployed person may not have information about the entire distribution of the probability of participation, but he certainly has a lot of relevant information concerning himself. In any case, if the unemployed individual does not react to the approaching activation program, we cannot determine whether this is due to incorrect expectations or becausehe is attracted by the programs.

4.1 The models

We present two models: a single-exit to employment model, and a three-exit wage model. Both models depend on the likelihood of participating in activation. We suppress individual and time denotation to simplify the notation. Following Lillard (1993), we want the exit hazard(s) in both the employment model and the wage model to depend on a second hazard, namely the hazard of exit into activation. This method of using multiple clocks is also used by Rosholm and Svarer (2008) and Geerdsen and Holm (2006). To obtain the probability of participation we simply model the transition to activation simultaneously with the hazard of exit to employment and of exit to the various wage states respectively.

4.1.1 The employment model

The model for employment has a single hazard of exit to employment which is modeled simultaneously with the hazard of ALMP activation program participation. Both the hazard into employment and the hazard into activation program participation are modeled using a logistic function. The employment model can thus be stated as two simultaneous equations:

$$P\left(Emp_{ij}|T \geq j\right) = \frac{exp\left(\beta'_{EMP}X_{ij}\right)}{1 + exp\left(\beta'_{EMP}X_{ij}\right)}\ ,\ Pr\left(ALMP_t\right) = \frac{exp\left(\beta'_{ALMP}X_A\right)}{1 + exp\left(\beta'_{ALMP}X_A\right)}$$

where the parametrization for the activation equation is:

$$\begin{aligned}\beta'_{ALMP}X_A \quad = \quad & \alpha^{ALMP} + \sum_{t=1}^{t=7}\delta_t Di_t + \sum_{t=1}^{t=7}\sum_{r=1998}^{r=2001}\gamma_{rt}D_r Di_t + \eta_1 PREVUI_t \\ & +\eta_2 D1999 + \eta_3 D2000 + \eta_4 D2001 + \eta_5 X_t\end{aligned}$$

and the parametrization for the employment equation is:

$$\beta'_{Emp}X = \alpha + \sum_{t=1}^{t=7}\tau_t Di_t + \lambda_1 P\left(ALMP_t = 1\right)\left(1 - ALMP\right) + \lambda_2 ALMP_t + \lambda_3 PREVUI_t + \lambda_4 X_t$$

where $\sum_{t=1}^{t=7}\delta_t Di_t$ are duration dummies with cut-off points at 13 weeks, 26 weeks and so on, and where the last dummy captures all durations above 102 weeks. Durations under 13 weeks are the baseline. $PREVUI$ is the number of weeks spent in unemployment during the previous 36, 33, 27 and 24 months for spells commencing in 1998, 1999, 2000 and 2001 respectively. The value of this variable is formed at spell start and is constant over the entire spell. The dummy variables $D1999$, $D2000$ and $D2001$ indicate the calendar year of spell start-1998 is the reference year. $ALMP$ is an indicator variable for active labor market program participation. X_t is a time-varying vector of socioeconomic variables including a dummy for cohabitation, a dummy indicating whether there are children at home, age and age squared, the unemployment rate of the municipality of residence and dummies for educational level. The educational dummies are *Vocational*, *Short higher*, *Medium-length higher* and *Long higher* with no education as the reference. The cohabitation, children, age and education variables are at the yearly level, while the unemployment rate is at the monthly level.

The functional form of the hazards results in the overall likelihood function for a single spell with length, j:

$$\mathcal{L} = \mathcal{L}_{Emp} \times \mathcal{L}_{ALMP}$$

The likelihood contribution from the employment hazard is:.

$$\mathcal{L}_{Emp} = \left(\frac{exp\left(\beta'_{EMP}X\right)}{1+exp\left(\beta'_{EMP}X\right)}\right)^{EMP}\left(\frac{1}{1+exp\left(\beta'_{EMP}X\right)}\right)^{1-EMP}\prod_{k=1}^{j-1}\left(\frac{1}{1+exp\left(\beta'_{EMP}X\right)}\right)$$

where EMP is an indicator variable for exit to employment. The likelihood contribution from the activation hazard is:

$$\begin{aligned}\mathcal{L}_{ALMP} &= \left[\frac{exp\left(\beta'_{ALMP}X_A\right)}{1+exp\left(\beta'_{ALMP}X_A\right)}\right]^{\delta^{ALMP}}\left[\frac{1}{1+exp\left(\beta'_{ALMP}X_A\right)}\right]^{1-\delta^{ALMP}} \\ &\prod_{k=1}^{j-1}\left[\frac{1}{1+exp\left(\beta'_{ALMP}X_A\right)}\right]\end{aligned}$$

where δ^{ALMP} is an indicator variabe for exit to activation.

This is the likelihood function arising from assuming a logistic hazard function, which is the same as that for the standard logistic regression applied to person-period data with an indicator variable as the dependent variable.

4.1.2 The wage model

For the wage model we partition the employment exits into three mutually exclusive states: exit to a higher or equal wage, exit to a lower wage and exit to an unknown wage. The functional form of the individual wage hazards is chosen as a multinomial logistic function, following Allison (1982). The final wage model can thus be written as these four simultaneous equations:

$$P\left(H_{ij}|T \geq j\right) = \frac{exp\left(\beta'_H X_{ij}\right)}{1+exp\left(\beta'_H X\right)+exp\left(\beta'_L X\right)+exp\left(\beta'_N X\right)}$$

$$P\left(L_{ij}|T \geq j\right) = \frac{exp\left(\beta'_{L}X_{ij}\right)}{1 + exp\left(\beta'_{H}X\right) + exp\left(\beta'_{L}X\right) + exp\left(\beta'_{N}X\right)}$$

$$P\left(N_{ij}|T \geq j\right) = \frac{exp\left(\beta'_{N}X_{ij}\right)}{1 + exp\left(\beta'_{H}X\right) + exp\left(\beta'_{L}X\right) + exp\left(\beta'_{N}X\right)}$$

$$Pr\left(ALMP_{t}\right) = \frac{exp\left(\beta'_{ALMP}X_{A}\right)}{1 + exp\left(\beta'_{H}X\right) + exp\left(\beta'_{L}X\right) + exp\left(\beta'_{N}X\right)}$$

where $d\epsilon\left\{H, L, N\right\}$. H, L and N represent exits to employment with a higher wage, lower wage or no wage information. .

The parametrization for the ALMP hazard is:

$$\begin{aligned} \beta'_{ALMP,}X_{A} &= \alpha^{ALMP} + \sum_{t=1}^{t=7}\delta_{t}^{ALMP}Di_{t} + \sum_{t=1}^{t=7}\sum_{r=1998}^{r=2001}\gamma_{rt}D_{r}Di_{t} + \eta_{1}PREVUI_{t} \\ &\quad + \eta_{2}D1999 + \eta_{3}D2000 + \eta_{4}D2001 + \eta_{5}X_{t} \end{aligned} \tag{4.1}$$

And the parametrization for any wage state is:

$$\beta'_{d}X = \alpha^{d} + \sum_{t=1}^{t=7}\tau_{t}^{d}Di_{t} + \lambda_{1}^{d}P\left(ALMP_{t} = 1\right)\left(1 - ALMP\right) + \lambda_{2}^{d}ALMP_{t} + \lambda_{3}PREVUI_{t} + \lambda_{4}^{d}X_{t} \tag{4.2}$$

where $d\epsilon\left\{H, L, N\right\}$. The choice of hazards results in the following likelihood for a single spell of length, j:

$$\mathcal{L} = \mathcal{L}_{Wage} \times \mathcal{L}_{ALMP}$$

where the likelihood contribution from the wage hazard is given by:

$$
\begin{aligned}
\mathcal{L}_{Wage} = & \left[\frac{exp\left(\beta'_H X\right)}{1+exp\left(\beta'_H X\right)+exp\left(\beta'_L X\right)+exp\left(\beta'_N X\right)}\right]^{\delta^H} \\
& \left[\frac{exp\left(\beta'_L X\right)}{1+exp\left(\beta'_H X\right)+exp\left(\beta'_L X\right)+exp\left(\beta'_N X\right)}\right]^{\delta^L} \\
& \left[\frac{exp\left(\beta'_N X\right)}{1+exp\left(\beta'_H X\right)+exp\left(\beta'_L X\right)+exp\left(\beta'_N X\right)}\right]^{\delta^N} \\
& \left[\frac{1}{1+exp\left(\beta'_H X\right)+exp\left(\beta'_L X\right)+exp\left(\beta'_N X\right)}\right]^{1-\delta^H-\delta^L-\delta^N} \\
& \prod_{k=1}^{j-1}\left[\frac{1}{1+exp\left(\beta'_H X\right)+exp\left(\beta'_L X\right)+exp\left(\beta'_N X\right)}\right]
\end{aligned}
$$

where δ^H, δ^L and δ^N are indicator variables for an exit to either a higher wage, a lower wage or no wage. The likelihood contribution from the activation program hazard is given by:

$$
\begin{aligned}
\mathcal{L}_{ALMP} = & \left[\frac{exp\left(\beta'_{ALMP} X_A\right)}{1+exp\left(\beta'_{ALMP} X_A\right)}\right]^{\delta^{ALMP}} \left[\frac{1}{1+exp\left(\beta'_{ALMP} X_A\right)}\right]^{1-\delta^{ALMP}} \\
& \prod_{k=1}^{j-1}\left[\frac{1}{1+exp\left(\beta'_{ALMP} X_A\right)}\right]
\end{aligned}
$$

which is the same as for the exit to employment model.

4.2 Identification

Activation in Denmark is eventually mandatory but it is not assigned randomly to individuals, and we must rely on the quasi-experiment provided by the legislative cuts in the passive period by the 1998 UI reform. In both the models above the motivation or threat effect is identified by the coefficient λ_1 in equation 4.2 while the program participation effect is identified by the coefficient λ_2 in equation 4.2. Identification in the model relies on the probability of participation being exogenous. We need some exclusion restrictions, some variables in the activation equation that are not included in the employment and the wage equations. We propose that the dummies $D1999$, $D2000$ and $D2001$ in equation 4.1 explain the probability of activation program participation and do not affect the hazard of exit to employment or to the various wage states given, the other controls applied.

As we saw in the section on the Danish UI system, the time before activation program ALMP participation was 24, 21, 15 and 12 months in the years 1998, 1999, 2000 and 2001 respectively. A person who became unemployed at the end of 1998 had a 24-month passive period, while a person who became unemployed at the beginning of 1999 only had 21 months until activation program participation. If the only difference between individuals over time is the length of the passive period, then identification is ensured. However, the dummies could explain some of the variation in the employment and wage equations because of the co linearity with the overall unemployment rate in the economy and, therefore, we include the unemployment rate in all equations to eliminate confounding variables. If no other time-varying variable can explain the hazard into employment, identification is ensured.

4.2.1 Entanglement of time until benefit exhaustion and time until activation program participation

When considering the shortening of the passive period, it should be noted that the time until benefit exhaustion is also shortened. The legislative changes from 1998 through 2001 shortened the passive period, but the length of the active period was not changed, thus shortening the entire period during which individuals could receive benefit payments. The effect of the shortening of the passive period and the effect of the shortening of the time until benefit exhaustion are thus entangled. As Geerdsen and Holm (2006) argue this problem is negligible because the effect of a shortening of the passive period is expected to dominate, because the time until benefit exhaustion is three years later than the time of compulsory activation program participation.

4.3 Unobserved heterogeneity

There is, however, a possible problem of self-selection over time in the sample: for instance, because stronger characters leave unemployment faster than weaker characters. To alleviate this problem we follow the approach suggested by Heckman and Singer (1984). Estimations results in duration models are very sensitive to the assumed distribution of the error term. Their approach does not need any assumptions regarding the distribution of the error term; it is only necessary to choose the number of support points for the discrete distribution. As the number of support points rises, the computational power required increases. Non-parametric estimation is only appropriate when dealing with large samples compared to the number of parameters estimated; we have over a million observations, so that is not of great concern.

Suppose that the vector of error terms μ has a discrete distribution with M points of support and these mass points are estimated together with the probabilities π_m for $m = 1, ...M$ of the different combinations of μ. Letting the likelihood contribution for each combination of mass points be given by $\mathcal{L}_m(\vartheta|\mu)$ where the regression parameters are represented by the vector ϑ, the overall likelihood contribution for each person is

$$\mathcal{L}* = \sum_{m=1}^{M} \pi_m \mathcal{L}_m(\vartheta|\mu)$$

where

$$\sum_{m=1}^{M} \pi_m = 1$$

.

We include an error term in the destination specific hazards, so the hazard of transition to a higher wage is rewritten as a function of $\beta'_H X + \mu_H$. Similarly the hazard of transition to a lower wage and to no wage are rewritten as $\beta'_L X + \mu_L$ and $\beta'_N X + \mu_N$ respectively. Similarly, $\beta'_{ALMP} X_A$ is rewritten as $\beta'_{ALMP} X_A + \mu_{ALMP}$. We choose $m = 2$ and normalize all error terms in the second likelihood function to zero. This leads to the final expression for the complete likelihood for the employment estimation:

$$\mathcal{L}* = \pi_{Emp} \mathcal{L}_1(\vartheta|\mu_{Emp}, \mu_{ALMP,Emp}) + (1 - \pi_{Emp}) \mathcal{L}_2(\vartheta)$$

where the fraction in each group is determined by the logistic expression:

$$\pi_{Emp} = \frac{exp(a_{Emp})}{1 + exp(a_{Emp})}$$

The final likelihood expression for the wage estimation is:

$$\mathcal{L}* = \pi_{Wage} \mathcal{L}_1(\vartheta|\mu_H, \mu_L, \mu_N, \mu_{ALMP,Emp}) + (1 - \pi_{Wage}) \mathcal{L}_2(\vartheta)$$

where the fraction is again determined by a logistic expression

$$\pi_{Wage} = \frac{exp(a_{Wage})}{1 + exp(a_{Wage})}$$

When normalizing the error terms for one group, the fraction $1-\pi$, will be the baseline and the estimated error terms can be used to determine the second groups characteristics compared to those of the baseline group. The unobservable characteristics for the employment regression are completely characterized by the parameter set $\{\mu_{Emp}, \mu_{ALMP,Emp}, a_{Emp}\}$ while the wage regression is described by the set $\{\mu_H, \mu_L, \mu_N, \mu_{ALMP,Emp}, a_{Wage}\}$. This way of specifying the unobserved heterogeneity assumes that the individual's unobserved heterogeneity is constant within and between spells. See **??** in the Appendix for a brief overview of the software used in the estimation.

4.4 Interpretation of the estimation results

The estimation results can be interpreted using odds ratios. We want to interpret the effect on the odds ratio when increasing one of the explanatory variables by the amount $\triangle$. An odds ratio is given by the ratio between the odds of the baseline scenario and the scenario with an increase in $\triangle$:

$$OR = \frac{\dfrac{h\left(\beta_1\left(x_1+\triangle\right)+...\right)}{1-h\left(\beta_1\left(x_1+\triangle\right)+...\right)}}{\dfrac{h\left(\beta_1 x_1+...\right)}{1-h\left(\beta_1 x_1+...\right)}} = \frac{exp\left(\beta_1\left(x_1+\triangle\right)+...\right)}{exp\left(\beta_1 x_1+...\right)} = exp\left(\beta_1\triangle\right)$$

In the case of small hazards, the odds ratio approximates the hazard ratio:

$$\lim_{h\to 0}\frac{\dfrac{h\left(\beta_1\left(x_1+\triangle\right)+...\right)}{1-h\left(\beta_1\left(x_1+\triangle\right)+...\right)}}{\dfrac{h\left(\beta_1 x_1+...\right)}{1-h\left(\beta_1 x_1+...\right)}} = \frac{\dfrac{h\left(\beta_1\left(x_1+\triangle\right)+...\right)}{1}}{\dfrac{h\left(\beta_1 x_1+...\right)}{1}} = \frac{h\left(\beta_1\left(x_1+\triangle\right)+...\right)}{h\left(\beta_1 x_1+...\right)}$$

In interpreting the results from the wage regression, it is possible to calculate both the odds of exit to one wage state vs. those of exit to another, and the odds of exit to one wage state vs the baseline as when interpreting the employment regression results. The odds of exit to a higher wage vs. exit to a lower wage are then

$$\begin{aligned} ODDS_{HL} &= \frac{h_H\left(\beta_H' X\right)}{h_L\left(\beta_L' X\right)} = \frac{\dfrac{exp\left(\beta_H' X\right)}{1+\sum_K exp\left(\beta_K X\right)}}{\dfrac{exp\left(\beta_L' X\right)}{1+\sum_K exp\left(\beta_K X\right)}} = \frac{exp\left(\beta_H' X\right)}{exp\left(\beta_L' X\right)} \\ &= exp\left(\left[\beta_H' - \beta_L'\right] X\right) \end{aligned}$$

We want to construct an odds ratio for a change in one of the variables. First, the odds are written in terms of the individual's explanatory variables:

$$ODDS_{HL} = exp\left(\left[\beta_{H1} - \beta_{L1}\right] x_1 + ...\right)$$

Next, one of the explanatory variables is increased by the amount $\triangle$:

$$ODDS_{HL,\triangle} = exp\left(\left[\beta_{H1} - \beta_{L1}\right] (x_1 + \Delta) + ...\right)$$

The odds ratio is the ratio between the odds of an increase in x_1 and the odds of no increase:

$$OR = \frac{exp\left(\left[\beta_{H1} - \beta_{L1}\right] (x_1 + \Delta) + ...\right)}{exp\left(\left[\beta_{H1} - \beta_{L1}\right] x_1 + ...\right)} = exp\left(\left[\beta_{H1} - \beta_{L1}\right] \triangle\right)$$

4.5 Relevance of the instrument

We test the relevance of the instrument by estimating the probability of activation as a random effects logit model with and without the yearly dummies and interactions. This is done using a standard random effects logit model. In Table 4.1 the regression results are listed both with and without the instrument dummies

We check for significance of the coefficients of the year dummies and perform an LR test of the two estimations. The null hypothesis of the LR test is that the nested models are identical and hence have the same log likelihood. If H_0 is rejected, the model with the year dummies does indeed explain more. The LR test statistic is calculated as $LR = -2\left(-53245.467 - (-51914.988)\right) = 2661$ and i χ^2 distributed with 25 degrees of freedom because the alternative model has 25 more parameters. The critical value of the χ^2 distribution at the 5% level is 37.65, and the alternative model is thus significantly different from the restricted model. This is almost to be expected with such a large sample.

Finally it is necessary to check whether the year dummies have any explanatory power in the activation equation. For every year we see an increase in the hazard from week 53 and onward, except in 1999 where the increase is first seen from week 66 and onward. The parameters σ_μ and ρ represent the mean the and variance of the distribution of the unobserved heterogeneity. We have now shown that the year dummies create significant variation in the probability for activation program participation. In the next section we will estimate the threat effect using the yearly variation caused by the reform.

Table 4.1: logit regression of P(ALMP) with and without year dummies

	Without instrument	With instrument
14-26 weeks	1.95***	2.19***
27-39 weeks	2.97***	3.31***
40-52 weeks	4.04***	4.41***
53-65 weeks	5.45***	4.87***
66-88 weeks	7.64***	5.89***
89-101 weeks	10.02***	8.15***
102+ weeks	12.39***	11.55***
D1999		-0.52***
D2000		-0.17*
D2001		0.65***
week 14-26 * D1999		-0.33***
week 27-39* D1999		-0.53***
week 40-52* D1999		-0.71***
week 53-65* D1999		-0.15
week 66-88* D1999		1.03***
week 89-101* D1999		1.48***
week 102+* D1999		-0.79*
week 14-26 * D2000		-0.43***
week 27-39* D2000		-0.35***
week 40-52* D2000		-0.09
week 53-65* D2000		1.67***
week 66-88* D2000		4.59***
week 89-101* D2000		5.49***
week 102+* D2000		4.18***
week 14-26 * D2001		-0.09
week 27-39 * D2001		-0.10
week 40-52 * D2001		-0.04
week 53-65 * D2001		1.80***
week 66-88 * D2001		3.78***
week 89-101 * D2001		4.05***
week 102+ * D2001		2.60***
Previous UI	0.02***	0.02***
Cohabitating	0.09	0.12*
Child at home	0.31***	0.26***
Vocational	-0.83***	-0.76***
Short higher edu.	0.55*	0.60*
Medium-length higher edu.	-0.33	-0.32
Long higher edu.	-0.06	-0.07
Age	-0.07	-0.16**
Age squared	0.003***	0.003***
Unemp. rate	-0.01	-0.02
Constant	-9.81***	-6.76***
σ_μ	4.62 (se: 0.03)	4.57 (se: 0.06)
ρ	0.87 (se: 0.003)	0.86 (se: 0.003)
Log likelihood	-53245.467	-51914.988
N	320125	

Significance levels: *** = 0.1%, ** = 1%, * = 5%, + = 10%

5 The Motivation Effect of Activation on Employment

In this section we present the results for the motivation effect of activation on employment. We begin by summarizing the four different types of unemployment spells in Table 5.1.

Table 5.1: Means and standard deviations associated with different unemployment histories

	No ALMP				ALMP			
	No exit		Exit		No exit		Exit	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Age	36.7	7.6	36.1	7.1	37.0	7.12	36.8	7.0
Child at home	0.36	0.48	0.42	0.49	0.34	0.47	0.38	0.48
Cohabiting	0.55	0.50	0.61	0.49	0.49	0.50	0.52	0.50
Vocational	0.44	0.50	0.47	0.50	0.34	0.48	0.36	0.48
Short higher	0.03	0.18	0.04	0.19	0.05	0.21	0.05	0.23
Medium-length higher	0.05	0.22	0.06	0.24	0.07	0.25	0.06	0.24
Long higher	0.06	0.23	0.05	0.23	0.08	0.27	0.08	0.27
Unemp. spell length (weeks)	16.0	20.3	12.9	14.8	40.5	33.8	40.4	31.9
Prev. unemp. spell length (weeks)	13.0	33.9	5.8	23.8	34.6	51.6	34.3	53.0
Numbers of spells	4.2	2.9	4.2	3.1	3.7	2.3	3.8	2.4

The unemployment spell length of individuals in activation programs is expected to be longer (40.5 and 40.4), because, an unemployed person has to have a substantial amount of unemployment before being required to participate in an activation program. This is also the explanation for the high level of previous unemployment for individuals in the activation program participation states. Note that the individuals who find employment before program participation are the ones with the lowest amounts of previous unemployment, 5.8 weeks during the preceding 2-3 years, and shortest current spell length, 12.9 weeks. This is not surprising, since many studies show a negative duration dependence of unemployment on the employment hazard. This will be confirmed in the estimation displayed later in this section. Table5.1 also shows that unemployed individuals with a long course of higher education are overrepresented among participants in activation programs (8%) compared to non-participants in activation (5-6%), i.e. there are relatively more highly-educated individuals who participate in activation programs than not. The opposite applies for individuals with vocational training, where relatively fewer individuals participate in programs than do not.

In Table 5.3 we list the estimation results for the hazard of activation program participation and the hazard of exit to employment. We find a significant positive motivation effect of activation programs. The motivation effect is implicit, since individuals react to the estimated probability of activation program participation (Geerdsen and Holm (2006)). The motivation effect increases the odds ratio of exit to employment by up to 55 percent [1]. This result is also robust to changes in the specification; excluding unemployment spells shorter than four weeks and excluding the spells for which there is no information on pre-unemployment wages changes neither the sizes of the figures nor the levels of significance

We obtain similar results to those from the many previous studies of the threat effects of activation, such as Geerdsen (2006), Geerdsen and Holm (2006), and Rosholm and Svarer (2008). There are variations in the results from these studies, but they can be explained by the different sampling periods and the differences in the samples with respect to age and gender. The size of the threat effect that we find is also consistent with the one found by Black et al. (2003).

Since we take account of unobserved heterogeneity in the regression, we calculate two mass points. In Table 5.2 we list the results of the discrete distribution of random effect. The distribution has two mass points: one at $(\mu_{ALMP}; \mu_{Employment}) = (0; 0)$ and one at $(\mu_{ALMP}; \mu_{Employment}) = (-4.07\,; 0.93)$. The share belonging to the latter mass point is given by

$$\pi = \frac{exp(1.54)}{1 + exp(1.54)} = 0.82$$

.

Table 5.2: Estimation result of unobserved heterogeneity

Parameter	Coef.	S.E.
a	1.54	0.010
μ_{ALMP}	-4.07	0.007
$\mu_{Employment}$	0.93	0.02

[1]If the hazard of activation program participation rises from 0 to 100 percent

Table 5.3: Motivation effect estimation results

Variable	P(ALMP)	P(EMP)
week 14-26	1.34***	-0.35***
week 27-39	1.93***	-0.70***
week 40-52	2.41***	-0.99***
week 53-65	2.73***	-1.16***
week 66-88	3.52***	-1.40***
week 89-101	4.53***	-1.53***
week 102+	5.49***	-1.72***
D1999	-0.03*	
D2000	-0.25***	
D2001	0.16***	
week 14-26 * D1999	-0.19***	
week 27-39* D1999	-0.34***	
week 40-52* D1999	-0.50***	
week 53-65* D1999	-0.20***	
week 66-88* D1999	0.61***	
week 89-101* D1999	0.85***	
week 102+* D1999	0.12***	
week 14-26 * D2000	-0.21***	
week 27-39* D2000	-0.15***	
week 40-52* D2000	0.02	
week 53-65* D2000	0.90***	
week 66-88* D2000	1.60***	
week 89-101* D2000	1.19***	
week 102+* D2000	-0.18***	
week 14-26 * D2001	0.02	
week 27-39 * D2001	0.16***	
week 40-52 * D2001	0.36***	
week 53-65 * D2001	1.37***	
week 66-88 * D2001	1.62***	
week 89-101 * D2001	0.63***	
week 102+ * D2001	-0.74***	
Previous unemployment	0.01***	-0.006***
Cohabiting	0.06***	0.17***
Child	0.10***	0.07***
Vocational training	0.06***	0.21***
Short higher edu.	0.24***	0.02
Medium-length higher edu.	0.03*	0.05***
Long higher edu.	0.03**	-0.17***
Age	0.14***	-0.02***
Age squared	0.002***	0.0002*
Unemp. rate	-0.06***	0.007***
ALMP		-0.08***
P(ALMP=1)(1-ALMP)		0.53***
Constant	1.3***	-3.36***
N	3,158,273	
Spells:		

Significance levels: *** = 0.1%, ** = 1%, * = 5%, + = 10%

6 The Motivation Effect of Activation on Wages

In this section we estimate the motivation effect of activation on wages. An unemployed individual can leave unemployment either for a higher or a lower wage compared to his or her pre-unemployment wage. Unlike the employment effect, the wage effect is not unambiguously predicted by theory.

Standard search theory predicts that an unemployed worker will reduce his reservation wage and increase his search intensity as he approaches the point in time at which benefits expire or where the benefits start to be given conditionally on some kind of effort being made by the recipients, as in activation and workfare schemes. The same is the case if the probability of activation or benefit exhaustion just increases progressively rather than kicking in at a fixed point in time. The way we study this is by estimating the change in exit behavior when the probability of activation increases, which in our case is the result of the shortening of the period with passive benefits (unconditional benefits). Such a shift is expected to increase search intensity and reduce the reservation wage; both are functions of the probability of activation (or benefit exhaustion), increasing and decreasing respectively. The reform we use as an instrument implies a positive shock to the probability of activation. This causes the search intensity function to shift upwards and the reservation-wage function to shift downwards, both implying earlier exit to employment and hence a shorter unemployment spell. The observed effect on the realized re-employment wage, however, will depend on the relative size of these two behavioral reactions. If the employment effect is driven mainly by a revision of the reservation wage we will see a negative effect on wages and if the employment effect is driven mainly by higher search intensity we might see a positive wage effect, i.e. more people will exit to a higher wage percentile as the probability of activation increases. This of course all depends on the way the reform affects the two schedules and on the elasticities of the reservation wage and the search intensity functions. The more elastic the reservation wage is (with respect to the spell length), the more likely it is that a given employment effect is associated with higher exit wages for given search intensity. And if the search intensity increases sufficiently and offers are remembered, then exit to higher wages could be associated even with the same unemployment spell duration.

Before showing the estimated wage effects we will briefly discuss some key descriptive statistics.

6.1 Descriptive statistics

To give an idea of the socioeconomic characteristics of the individuals who exit to different wage states, our sample is divided up according to the state at which exit occurs. This is shown in Table 6.1.

Table 6.1: Descriptive statistics for the wage states

	No wage		Higher wage		Lower wage	
Variable	Mean	S.D.	Mean	S.D.	Mean	S.D.
Age	36.4	6.9	36.1	7.0	36.9	7.1
Cohabitation spouse	0.55	0.50	0.61	0.49	0.61	0.49
Child home	0.40	0.49	0.43	0.50	0.43	0.50
Compulsory education	0.37	0.48	0.38	0.48	0.38	0.48
Vocational education	0.41	0.49	0.46	0.50	0.50	0.50
Short further edu.	0.05	0.21	0.04	0.19	0.04	0.19
Intermediate further edu.	0.07	0.25	0.06	0.24	0.05	0.21
Long further edu	0.11	0.31	0.06	0.23	0.04	0.20
Numbers of spells	4.0	2.8	4.8	3.23	4.6	3.4
Spell length	25.4	25.3	16.1	17.6	12.5	12.8
Previous unemployment	11.7	33.9	6.7	25.3	2.99	17.4
Wage before	54.1	28.2	46.9	23.8	67.6	20.2
Wage after	-	-	66.5	20.5	47.5	22.0
N	2,178		22,932		22,586	

As Table 6.1 shows, the individuals who leave unemployment for a job with a lower wage have on average shorter unemployment spells and less previous unemployment than the individuals who find higher-paying jobs. Wages are on average lower after unemployment than before unemployment.

The individuals who find higher-paid jobs are characterized by having longer unemployment spells than individuals who exit to lower-wage jobs. They also have more previous unemployment, are better educated, and tend to be a little younger than those who exit to a lower wage percentile.

The individuals who exit without wage information are also those with the longest spells of unemployment and the largest amount of previous unemployment.

6.2 Results

The results of the estimation of the wage effect are shown in Table 6.2. We estimate the effect of an increased probability of activation on the relative wage measured by the position of the individual's wage in the overall wage distribution, i.e. the wage percentile.

6.2.1 The probability of activation

Column 1 of Table 6.2 lists the estimates of the probability of ALMP participation. Note first that as expected, the unemployment duration dummies (week 14-27 - > week 102+) show a significantly higher probability of activation as the unemployment spell increases in length. Note also that the year dummies (D1999-D2001) show that there was no monotonous development in the probability of activation over the period from 1998, the reference year, to 2000.

Table 6.2 also shows that there is a significantly higher probability of activation for married individuals and for parents, and that the skilled and individuals with higher education have a higher probability of activation than the unskilled. Finally, we see that the probability of activation decreases as the individuals get older, and that after the age of 37, the probability of activation starts to increase again.

6.2.2 The wage effect

First, note that the unemployment duration dummies show a negative duration dependence for the hazard of exit to both higher and lower wage percentiles. A high level of previous unemployment also decreases the hazard of finding both higher-paid and lower-paid jobs, although the effects are small compared to the duration itself. A high level of unemployment in the past could well be a sign of difficulties in general with finding jobs.

The influence of age, however, is very different when it comes to exit to higher and lower wages. Age decreases the likelihood of exiting to a higher wage but increases the likelihood of exit to a lower wage (the coefficients for age squared are too small to offset this).

Individuals with a spouse have a higher exit hazard to both higher and lower wage levels, whereas children in the household are associated with higher exit rates to lower wages.

The motivation effect of activation on wages is captured by the coefficient to P(ALMP)(1-ALMP), which shows a significantly higher exit rate to higher wage percentiles, an insignificant effect on the exit rate to lower wages, but also a significantly higher exit rate to the state with no wage information. Thus, as the wage change up and down are of the same magnitude, a higher probability of activation causes a higher average re-employment

Table 6.2: Estimation results for wages

Variable	P(ALMP)	P(Higher wage)	P(Lower wage)	P(No wage)
week 14-26	1.48***	-0.22***	-0.28***	0.25***
week 27-39	2.10***	-0.44***	-0.51***	0.35***
week 40-52	2.47***	-0.59***	-0.67***	0.49***
week 53-65	2.80***	-0.71***	-0.65***	0.63***
week 66-88	3.80***	-0.99***	-0.84***	0.86***
week 89-101	5.31***	-1.11***	-0.84***	0.85***
week 102+	6.66***	-1.43***	-1.03***	0.78***
D1999	0.08**			
D2000	-0.09**			
D2001	0.22***			
week 14-26 * D1999	-0.26***			
week 27-39 * D1999	-0.38***			
week 40-52 * D1999	-0.41***			
week 53-65 * D1999	-0.40***			
week 66-88 * D1999	0.32***			
week 89-101 * D1999	0.33**			
week 102+ * D1999	-0.46***			
week 14-26 * D2000	-0.39***			
week 27-39 * D2000	-0.39***			
week 40-52 * D2000	-0.27***			
week 53-65 * D2000	0.55***			
week 66-88 * D2000	1.41***			
week 89-101 * D2000	0.56***			
week 102+ * D2000	-0.94***			
week 14-26 * D2001	-0.08*			
week 27-39 * D2001	0.10*			
week 40-52 * D2001	0.42***			
week 53-65 * D2001	2.16***			
week 66-88 * D2001	2.42***			
week 89-101 * D2001	0.74***			
week 102+ * D2001	-1.15***			
Previous unemployment	0.012***	-0.005***	-0.002***	0.0034***
Cohabiting	0.04*	0.12***	0.15***	-0.17***
Child at home	0.04*	0.02	0.09***	0.03
Vocational training	0.26***	0.12***	0.19***	-0.006
Short higher	0.66***	-0.10***	-0.04+	0.05
Medium-length higher	0.28***	-0.03	0.02	0.02
Long higher	0.00	-0.22***	-0.24***	0.30***
Age	-0.30***	-0.07***	0.02*	-0.06**
Age squared	0.004***	0.001***	-0.0002*	0.001*
Unemployment rate	-0.06***	0.00	-0.008***	-0.05***
P(ALMP)(1-ALMP)		0.50***	0.15	1.02***
ALMP		0.79***	0.81***	1.23***
Constant	4.04***	-2.73***	-4.52	-5.47***
N	1,762,185			
Log likelihood	-705,449.37			

Significance levels: *** = 0.1%, ** = 1%, * = 5%, + = 10%

wage. It seems that workers faced with a higher probability of activation increase their search intensity sufficiently not only to exit unemployment earlier but also to do so with a higher re-employment wage, even though the reservation wage function might have been shifted downward.

Recall that we found a significant lock-in effect of activation when we estimated the exit to employment; participation in activation reduces the rate of exit to employment. However, for the unemployed for whom we have information on wage before unemployment, who do exit, exit more quickly to both higher and lower wages. Finally, the coefficients of the education variables show that individuals with vocational training are more likely to exit to both higher and lower wages than unskilled workers. This is opposite of the case for individuals with both (short and long) higher education, who have a significantly lower probability of exit to both lower and higher wage percentiles than the unskilled.

6.2.3 Unobserved heterogeneity

The results from modeling unobserved heterogeneity are presented in Table 6.3. The Heckman-Singer correction results in a discrete distribution with two mass points: one at $(\mu_{ALMP}; \mu_H; \mu_L; \mu_N) = (0\,;\,0\,;\,0\,;\,0)$ and one at $(\mu_{ALMP}; \mu_H; \mu_L; \mu_N) = (-5.98\,;\,0.89\,;\,0.97\,;\,1.02)$ The share belonging to the latter mass point is given by

$$\pi = \frac{exp(2.75)}{1 + exp(2.75)} = 0.94$$

.

Table 6.3: Unobserved heterogeneity

Parameter	Coef.	S.E.
a	2.75	0.017
μ_{ALMP}	-5.98	0.021
μ_H	0.89	0.04
μ_L	0.97	0.04
μ_N	1.02	0.21

6.3 Robustness analysis

In this section we will test the robustness of our results. We will perform the same test of robustness as in Section 5 and we will also estimate the model on a 12.5% random sample including both men and women; Table 6.4 shows the results. Column 2 shows the results when we exclude short spells[1].

[1] Hence excluding potentially temporary unemployment.

Table 6.4: Robustness analysis of the wage effects of the threat of Active Labor Market Programs

	Original (men)	No short spells	Both men and women
Threat to higher wage	0.50***	0.64***	0.60**
Threat to lower wage	0.15	0.18	-0.04
Threat to no wage	1.02***	1.19***	0.85**
Log likelihood	-705,449.37	-556,289.24	-352,229.97
N	1,762,185	1,666,453	938,218

Significance levels: *** = 0.1%, ** = 1%, * = 5%, + = 10%

Table 6.4 shows that the results reported above are robust to the exclusion of temporary unemployment and inclusion of women in the sample; the estimated wage effects do not differ qualitatively between columns 2, 3 and 4.

6.4 Discussion

In Table 6.2 we show the estimation results for the motivation effect of active labor market programs on wages. We found an increase in the hazard of exit to higher-paying jobs, but not to lower-paying jobs. These effects are consistent with a situation where, due to an increasing probability of program participation, individuals increase their search intensity and possibly even reduce their reservation wage. The higher search intensity dominates, however, and the employment effect is associated with a higher average re-employment wage for the unemployed who exit before activation.

To the best of our knowledge, this is the first study of the motivation effects of active labor market programs on wages for the average worker. Bennmaker et al. (2012) studied a Swedish reform targeting older workers and found a positive wage effect as a reaction to turning parts of the passive UI period into mandatory activation.

Van den Berg et al. (2008) used a rich survey data set to identify labor market program effects on the development of individuals' reservation wage as expected program participation time approaches. They found a significant positive threat effect which results in a reduction in the reservation wage. Unfortunately, we have no information about the reservation wage. We do, however, have information on actual pre- and post-unemployment wages, and thus we can study the realized rather than the expected situation.

Black et al. (2003) studied the threat effect of the reemployment service on employment and earnings. They studied experimental data from Kentucky, where a random sample of new UI benefit claimants were treated during their first quarter of their unemployment spell. They found significantly higher average earnings for the treatment group compared to the control group during the first two quarters of the unemployment spells. This most probably reflects the fact that a larger fraction of the treatment group became employed during that period, basically because they went back into employment faster. After the second quarter the control group had caught up, and employment and earnings were the same across the two groups. We cannot compare our results directly with the results of Black et al. (2003), because we estimate the wage effect contingent on employment. Nevertheless, it is possible to state that their results are fairly compatible with our results; they find an increased hazard of exit to employment, and no indication that the treatment group got into employment more quickly by taking lower paid jobs.

Jespersen et al. (2008) studied Danish data and found that participation in active labor market programs significantly decreases the re-employment wage after program participation. They found a 5 % decrease in the re-employment wage after individuals had participated in an active labor market program. We do not study the program effect of activation on wages, but we consider what happens to wages when unemployed individuals exit to employment during a program. Individuals who participate in activation have an increased hazard of exit to employment both with lower and with higher wages (relative wage position) compared to their pre-unemployment wages, as shown in Table 6.2.

In the next section, we estimate the motivation effect of activation on employment and wages for different educational groups.

7 The Motivation Effect and the Level of Education

In this section we look at the motivation effects of activation on employment and wages for individuals with different levels of education. We estimate the model used before separately for each of the following educational groups: unskilled, skilled and with higher education (college degree and above).

A priori, we would expect different results for these three groups. Both the consumption and the investment values of participating in an activation program are likely to vary among individuals with different levels of education. The marginal value of extra training will most probably differ, although it is not obvious in what way. On the one hand, the marginal value of extra training should fall, the more education the individual already had to begin with. On the other hand, the value of re-investing in keeping educational qualifications up to date might be greater in occupations that require a high level of education to begin with. Another source of difference in the valuation of activation is that the more highly educated unemployed individuals might be better at influencing the type of activation that they are to be enrolled in, thereby increasing the consumption value of participation. If the ability to get something valuable out of activation, even though activation is ultimately mandatory, increases with the level of education, then the motivation effect of activation on exit to employment should decrease with longer education. With regard to the effects on wages, it is even more uncertain what to expect of the effect across different levels of education. However, if a strong employment effect is mainly driven by higher search intensity, this would be consistent with a weak wage effect and possibly even a positive effect on wages.

Below we look first at the motivation effect of activation on the exit rate to employment.

7.1 Motivation effect on employment and the level of education

Table 7.1 shows the employment effect of motivation of activation programs for the unskilled, the skilled and individuals with higher education. As expected, the motivation effect and the participation effects differ significantly across the educational groups. The full regression output is shown in the Appendix.

Table 7.1: Employment effect of the threat effect of activation on sub-samples.

Variable	Unskilled	Skilled	Higher edu
P(ALMP)(1-ALMP)	0.98***	0.64***	0.09
ALMP	0.13	-0.10**	-0.22***
Log likelihood	-52,986.004	-476,296.77	-223,544.6
N	138,960	1,237,627	592,107

Significance levels: *** = 0.1%, ** = 1%, * = 5%, + = 10%.

Table 7.1 shows a clear picture with respect to the difference across education levels. The lower the level of education, the stronger the motivation effect and the weaker the lock-in effect, which suggests that the ability to get something of value out of participating in activation increases with the level of education, and hence that the threat of activation decreases and the lock-in effect becomes stronger with a higher level of education.

The difference in the magnitude of the effects is considerable. If the hazard of program participation increases for unskilled and skilled individuals by 50%, the likelihood of finding employment increases by 33 and 25 percent points respectively, while there is, as noted above, no significant effect for those with higher education.

Heckman and Borjas (1980) find that there is a stigma associated with participating in activation. If this is also the case in a Danish context, it does not seem to affect those with higher education. That could be due to the points discussed above, namely that people with higher education are good at influencing the type of activation to which they are subjected. Presumable, that makes activation less stigmatizing.

7.2 Motivation effects on wages and the level of education

The results of the motivation effect of activation on wages for the three educational groups are presented in Table 7.2. We have also included in the table some of the control variables of particular interest. The full regression output is shown in the Appendix.

We find no significant effect on the hazard of exit to a higher wage from an increased probability of activation for individuals with a higher education. However, for both the skilled and the unskilled there is a significant increasing hazard of exit to higher wage jobs, although it is only significant at the 10% level for the unskilled group. There is no effect on the exit to lower wages for any of the educational levels.

Table 7.2: The motivation effects on wages for different educational groups

	Unskilled	Skilled	Higher edu
		P(Higher wage)	
P(ALMP)(1-ALMP)	0.39+	0.79***	0.01
Prev. unemployment	-0.005***	-0.005***	-0.005***
Cohabiting	0.10***	0.15***	0.09**
Child at home	0.02	0.05**	-0.07*
ALMP	0.88***	0.76***	0.74***
		P(Lower wage)	
P(ALMP)(1-ALMP)	0.22	0.18	0.26
Prev. unemployment	-0.002***	-0.002***	-0.001*
Cohabiting	0.13***	0.19***	0.06*
Child at home	0.07***	0.09***	0.10***
ALMP	0.97***	0.75***	0.86***
		P(No wage)	
P(ALMP)(1-ALMP)	0.99**	0.66+	1.68***
Prev. unemployment	0.004***	0.003***	0.001
Cohabitating	-0.14**	-0.15**	-0.22**
Child at home	0.037	0.02	0.02
ALMP	1.50***	1.00***	1.45***
Log likelihood	-276,774.26	-310,630.58	-116,966.12
N	705,590	743,071	313,524

Significance levels: *** = 0.1%, ** = 1%, * = 5%, + = 10%

Interestingly enough, there is an increasing rate of exit to both higher and lower wages for all educational groups during activation. Furthermore, previous unemployment decreases the hazard of exit to both lower-paying and higher-paying jobs, independently of educational level.

Table 7.3 shows the motivation effect on wages for a 12.5% random sample of both men and women. These results are presented as a final robustness test to check whether the exclusion of women in the sample has any noticeable impact on the results.

Table 7.3: The motivation effects on wages for different educational groups - both men and women

	Unskilled	Skilled	Higher edu
P(Higher wage)	0.50+	0.84**	0.65
P(Lower wage)	-0.28	0.40+	0.46
P(No wage)	1.05*	0.67	0.75
Log likelihood	-141,365.79	-141,158.71	-68,679.797
N	376,058	369,712	192,448

Significance levels: *** = 0.1%, ** = 1%, * = 5%, + = 10%

When including women in the sample there is a significant motivation effect on exit to a lower wage for individuals with vocational training, although it is only significant at the

10% level. Still there is no effect for the higher educated, and now there is only a higher exit rate to no-wage for unskilled individuals.

These effects on employment and wages are consistent and suggest that activation is not as unattractive to individuals with higher education as it seems to be for many skilled and unskilled workers. The skilled and unskilled react to an increasing probability of being enrolled in activation programs mainly by searching for work more intensively, but possibly also by reducing their reservation wage, which is a decreasing function of the length of the unemployment spell. As a consequence, they exit to employment faster as activation becomes more likely, but they exit more frequently to higher wages and equally frequently to lower wages.

8 Summary and Discussion

In this section we present an overview of the results and discuss possible limitations of the analysis.

8.1 The aggregate results

In section 5 and 6 we estimated the employment and wage effects of ALMP activation programs on a sample of individuals who had all been unemployed at some time betwen 1 January 1998 and 31 December 2001. The average results for the entire sample are presented in Table 8.1. We also present the employment effects on a sample restricted to include only spells of unemployment for which we have information on wages before unemployment.

Table 8.1: Employment effects and wage effects, males aged 25-50.

	Threat	S.E.
Employment	0.53***	0.056
Employment with wage information	0.50***	0.052
Higher wage	0.50***	0.13
Lower wage	0.15	0.12
No wage	1.02***	0.21

Significance levels: *** = 0.1%, ** = 1%, * = 5%, + = 10%

We identified a significantly increased hazard of employment as a response to an increase in the probability of activation. In other words, activation motivates unemployed workers to find jobs faster than they would have done without the prospect of having to participate in activation. We furthermore found a significantly higher hazard of exit to better-paid jobs as a response to an increase in the probability of activation.

These results are robust to the elimination of potentially temporary unemployment spells. They are also robust to the exclusion of the individuals for whom we do not have any information on the pre-unemployment wages.

The positive employment effect indicates that at least some unemployed individuals perceive program participation as undesirable. Our interpretation of the results is that the unemployed individuals react to the increasing probability of activation by increasing their job search intensity and possibly also by reducing their reservation wage schedule. The reservation wage is a decreasing function of the spell length, but the higher level of search intensity implies a higher rate of exit to higher wages and the same exit frequency to lower wages, and thus promodes exit to better paying jobs. In a study using the Danish Labor Force Survey, Amilon (2010) finds that search activity does indeed increase as mandatory activation approaches.

We also found that individuals who react to the threat of activation have an increased hazard of exit to a job with no wage information. Around 80% of the no wage information exits represent a reduction in gross income.

8.2 The motivation effect and education

The results of the motivation effect on employment and wages for the three educational groups that we consider are summarized in Table 8.2

Table 8.2: Employment and wage effects, males aged 25-50, unskilled, skilled and with higher education

		Threat	S.E.
Higher education	Employment	0.09	0.13
	H	0.009	0.32
	L	0.26	0.27
	N	1.68***	0.44
Skilled	Employment	0.64***	0.089
	H	0.79***	0.19
	L	0.18	0.19
	N	0.66+	0.35
Unskilled	Employment	0.98***	0.26
	H	0.39+	0.20
	L	0.22	0.20
	N	0.99**	0.37

Significance levels: *** = 0.1%, ** = 1%, * = 5%, + = 10%

We found that the hazard of exit to employment increased significantly for both skilled and unskilled individuals as a response to an increasing probability of having to participate in activation programs. A 50% increase in the hazard of program participation increases the odds of finding a job by 38% and 63% for skilled and unskilled individuals respectively. This suggests that many of the unemployed perceive activation as something undesirable.

The results for the wage effect again show that skilled and unskilled men react the most strongly. Both groups exit more frequently to higher paying jobs when the probability of activation increases; however, for the unskilled the effect is only significant at the 10% level. For individuals with higher education we found no motivation effect on wages, just as we found none for employment. This picture also holds when we include women in the sample, although there is then a weakly significant higher exit rate also to lower wages for skilled workers.

Overall, the picture of the employment and the wage effects of an increasing probability of activation makes good sense. For those with higher education, there is not much of an effect in either of these dimensions. These individuals might be better at influencing what type of activation they have to submit to, and hence, of course, participation is less of a threat. This interpretation is in line with there being a significant lock-in effect for these groups; this is something which is usually found empirically (see e.g., Christensen and Jacobsen (2009)), and our results suggest the same. There could be two motives for wanting to participate in these programs: an investment motive and a consumption motive. The fact that the program effect is usually very weak for these groups suggests that the consumption motive plays at least some role.

We find an increasing hazard of exit to employment without wage information if the probability of activation program participation increases. This indicates that if individuals with higher education exit prior to program participation, they are more likely to find jobs for which we have no wage information. These could be self-employment, for example, or jobs with capital income as the main source of income. Emigration will also result in an exit with no wage information. All we know about this group is that they do not receive any kind of benefit payments.

9 Conclusion

In this paper we have identified the motivation effects of activation on employment and wages, where wages are measured by their position in the overall wage distribution. Thus, we have estimated the wage effect for treated workers relative to the wage changes of all workers, and thereby controlled for general effects, including general equilibrium effects initiated by the reform which is used to identify the causal effect on reemployment wages of the probability of activation.

We used duration analysis and utilized a reform of the Danish UI system in 1998 to create exogenous variation in the hazard of participation in ALMP activation programs, and we showed that this is indeed a valid instrument. Using a single risk model, we identified a motivation effect of activation on employment. To estimate the wage effect, we used a competing risk model with three exit states: exit to employment with a higher wage, a lower wage or no wage information compared to the wage before unemployment. In both analyses, we modeled the hazard of activation and the hazard of moving out of unemployment simultaneously.

With regard to employment, we found an increased hazard of exit to employment as the probability of activation increased. If the probability of activation increased by 50 percentage points, the odds of finding employment increased by 25 percent. This is a considerable motivation effect of activation, and it is consistent with other findings from studies of both Danish and foreign data. The effect is not equally great across the labor force; it is mainly to be found among those with medium and lower levels of education. In fact, there are significant employment effects only for unskilled and skilled workers.

In reaction to an increasing probability of activation we found an increased hazard of exit to higher wage jobs, but not to lower wage jobs. As the average wage change up and down are of the same magnitude, both before and after the reform, this suggests that increases in the probability of activation counteract the wage decrease that is generally associated with being made redundant. However, the average wage effect is not identified by the reform. Again, these effects are not found for individuals with a higher education.

These differences are likely to be caused by differences in the expected value of program participation. Some individuals seem to expect a gain from participation in activation programs in the form of either better skills or a good experience. In particular, individuals with higher education seem not to be motivated by activation to find work faster, which is the case for individuals with a shorter education.

Overall, this picture makes good sense. For those with higher education, there is no motivation effect; they do not find jobs faster, and they do not change the types of job that they exit to in that they exit to jobs that pay the same wages. People with a higher education (a college degree or more) might be better at influencing what type of activation they have to submit to, and hence, of course, participation is less of a threat. This interpretation is in line with there being a significant lock-in effect for these groups (see e.g. Christensen and Jacobsen (2009)), and our results suggest the same. Furthermore, the fact that studies usually do not find any program effect for individuals with higher education suggests that what makes the programs attractive, or at least not so unattractive, is not so much the improvement in prospects for future employment, i.e. the investment element, but probably more the consumption element.

Bibliography

Allison, Paul D. (1982), “Discrete-time methods for the analysis of event histories.” *Sociological Methodology*, 13.

Amilon, A. (2010), “Active labour market programmes, job search and job finding in Denmark.” *Journal of Labour Economics*, 3.

Andersen, Signe Hald (2013), “How scary is it? - review of litterature on the threat effect of active labor market programs.” *The Rockwool Foundation Research Unit Study Paper Series*, 48.

Bennmaker, Helge, Osker Nordström Skans, and Ulrika Vikman (2012), “Workfare for the old and long-term unemployed.” *Institute for Evaluation of Labour Market and Education Policy Working Paper Series*, 7.

Black, Dan A., Jeffrey A. Smith, Mark C. Berger, and Brett J. Noel (2003), “Is the threat of reemployment service more effective than the service themselves.” *The American Economic Review*, 93.

Christensen, R. and R. H. Jacobsen (2009), “Analyse af effekten af aktivering og voksen- og efteruddannelses for forsikrede ledige.” Centre for Economic and Business Research.

DØR (2007), “Dansk økonomi, Forår 2007.” De Økonomiske Råd.

DØR (2012), “Dansk økonomi, Efterår 2012.” De Økonomiske Råd.

Gautier, Pieter, Paul Muller, Bas van der Klaauw, Michael Rosholm, and Micahel Svarer (2012), “Estimating equilibrium effects of job search assistance.” *IZA Discussion Paper*, 6748.

Geerdsen, Lars Pico (2006), “Is there a threat effect of active labour market programmes? a study of almp in the danish ui system.” *The Economic Journal*, 116.

Geerdsen, Lars Pico and Anders Holm (2006), “Duration of ui periods and the percieved threat effect from labour market programmes.” *Labour Economics*, 14.

Graversen, Brian Krogh and Jan C. Van Ours (2008), “How to help unemployed find jobs quickly: Experimental evidence from a mandatory activation program.” *Journal of Public Economics*, 92.

Heckman, J. and B. Singer (1984), "A method for minimizing the impact of distributional assumptions in econometric models for duration data." *Econometrica*, 52.

Heckman, James J. and George J. Borjas (1980), "Does unemployment cause future unemployment? definitions, questions and answers from a continuous time model of heterogeneity and state dependence." *Economica*, 47.

Jacobsen, Louis S., Robert J. LaLonde, and Daniel G. Sullivan (1993), "Earnings losses of displaced workers." *The American Economic Review*, 83.

Jenkins, Stephen P. (2005), "Survival analysis." Unpublished teaching notes.

Jespersen, Svend T., Jakob Roland Munc, and Lars Skipper (2008), "Cost and benefits of danish active labour market programmes." *Labour Economics*, 5.

Lillard, Lee A. (1993), "Simultaneous equations for hazards." *Journal of Econometrics*, 56.

Parsons, Donald O., Torben Tranæs, and Helene Bie Lilleør (2003), "Voluntary public unemployment insurance." *CESifo Working Paper Series*, 1010.

Rosholm, Michael and Michael Svarer (2008), "The threat effect of active labour market programmes." *The Scandinavian Journal of Economics*, 110.

Rosholm, Michael and Michael Svarer (2011), "Effekter af virksomhedsrettet aktivering i den aktive arbejdsmarkedspolitik." Arbejdsmarkedsstyrrelsen. Available from www.ams.dk.

Sørensen, Kenneth (2012), "Effects of intensifying labor market programs on post-unemployment wages: Evidence from a controlled experiment." *KORA and Aarhus University, CAP and CAFE.*

Van den Berg, Gerard J., Annette Bergemann, and Marco Caliendo (2008), "The effect of active labor market programs on not-yet treated unemployed individuals." *IZA Discussion Paper*, November.

10 Appendix

Overview of the appendix:

Table 10.1 and 10.2 show the regression results when excluding spells of four weeks or less.

Table 10.3, 10.4 and 10.5 show the employment regressions for educational groups.

Table 10.6, 10.7 and 10.8 show the wage regressions for educational groups.

Notes on estimation:

Both models are estimated using custom Stata programs. Stata's built-in estimation procedures do not allow for multiple equation hazard models. Both programs utilize the *d1* method of the *ml* command where first derivatives are analytically written into the program. Deriving the first derivatives analytically gives the advantage of more speed, but with the possibility of faulty convergence if the first derivatives are derived wrongly. Thus, the convergence of the program was checked and confirmed using the *debug* command, which compares the likelihood of the analytically-solved first derivatives to those found numerically. The likelihood function was optimized using Stata's modified Newton-Rhapson algorithm.

Table 10.1: Employment regression excluding spells of four weeks or less

Variable	P(ALMP)	P(EMP)
week 14-26	1.32***	0.24***
week 27-39	1.91***	-0.11***
week 40-52	2.39***	-0.41***
week 53-65	2.71***	-0.57***
week 66-88	3.50***	-0.82***
week 89-101	4.50***	-0.95***
week 102+	5.46***	-1.14***
D1999	-0.04**	
D2000	-0.26***	
D2001	0.16***	
week 14-26 * D1999	-0.18***	
week 27-39 * D1999	-0.34***	
week 40-52 * D1999	-0.49***	
week 53-65 * D1999	-0.19***	
week 66-88 * D1999	0.62***	
week 89-101 * D1999	0.85***	
week 102+ * D1999	0.13***	
week 14-26 * D2000	-0.20***	
week 27-39 * D2000	-0.14***	
week 40-52 * D2000	0.03	
week 53-65 * D2000	0.90***	
week 66-88 * D2000	1.60***	
week 89-101 * D2000	1.19***	
week 102+ * D2000	-0.18***	
week 14-26 * D2001	0.02	
week 27-39 * D2001	0.17***	
week 40-52 * D2001	0.36***	
week 53-65 * D2001	1.37***	
week 66-88 * D2001	1.62***	
week 89-101 * D2001	0.63***	
week 102+ * D2001	-0.74***	
Previous unemployment	0.01***	-0.005***
Cohabitating	0.06***	0.14***
Child at home	0.10***	0.05***
Vocational education	0.07***	0.16***
Short further	0.25***	0.05**
Medium further	0.04**	-0.01
Long further	0.03**	-0.14***
Age	-0.14***	-0.003
Age squared	0.002***	0.00
Unemployment rate	-0.06***	0.003
P(ALMP)(1-ALMP)		0.45***
ALMP		-0.04+
Constant	1.43***	-4.18***
N	3,061,494	
Log likelihood	-1,082,043.5	

*** represents a significance level of 0.1%, ** is 1%, * is 5% and + is 10%

Table 10.2: Wage regression excluding spells of four weeks or less

Variable	P(ALMP)	P(Higher wage)	P(Lower wage)	P(No wage)
week 14-26	1.46***	0.36***	0.29***	0.65***
week 27-39	2.08***	0.13***	0.05**	0.75***
week 40-52	2.45***	-0.03	-0.11***	0.89***
week 53-65	2.78***	-0.16***	-0.10**	1.02***
week 66-88	3.80***	-0.46***	-0.31***	1.23***
week 89-101	5.33***	-0.61***	-0.32***	1.21***
week 102+	6.67***	-0.94***	-0.54***	1.13***
D1999	0.06*			
D2000	-0.09**			
D2001	0.21***			
week 14-26 * D1999	-0.24***			
week 27-39 * D1999	-0.36***			
week 40-52 * D1999	-0.39***			
week 53-65 * D1999	-0.37***			
week 66-88 * D1999	0.37***			
week 89-101 * D1999	0.37***			
week 102+ * D1999	-0.44***			
week 14-26 * D2000	-0.39***			
week 27-39 * D2000	-0.39***			
week 40-52 * D2000	-0.26***			
week 53-65 * D2000	0.56***			
week 66-88 * D2000	1.43***			
week 89-101 * D2000	0.56***			
week 102+ * D2000	-0.93***			
week 14-26 * D2001	-0.07+			
week 27-39 * D2001	0.13**			
week 40-52 * D2001	0.49***			
week 53-65 * D2001	2.28***			
week 66-88 * D2001	2.51***			
week 89-101 * D2001	0.91***			
week 102+ * D2001	-0.64***			
Previous unemployment	0.01***	-0.004***	-0.001***	0.002***
Cohabitating	0.07***	0.08***	0.11***	-0.17***
Child at home	0.02	-0.005	0.06***	0.03
Vocational education	0.25***	0.07***	0.15***	-0.05
Short further	0.65***	-0.07*	-0.02	0.02
Medium further	0.27***	-0.11***	-0.06**	-0.02
Long further	0.01	-0.21***	-0.21***	0.24***
Age	-0.30***	-0.06***	0.04***	-0.04*
Age squared	0.004***	0.0006***	-0.0004***	0.0005+
Unemployment rate	-0.06***	-0.006*	-0.01***	-0.05***
P(ALMP)(1-ALMP)		0.64***	0.18	1.19***
ALMP		0.94***	0.92***	1.33***
Constant	4.17***	-3.51***	-5.54***	-6.33***
N	1,666,453			
Log likelihood	-556,289.24			

*** represents a significance level of 0.1%, ** is 1%, * is 5% and + is 10%

Table 10.3: Employment regression for individuals with only compulsory education

Variable	P(ALMP)	P(EMP)
week 14-26	1.13***	-0.28***
week 27-39	1.50***	-0.63***
week 40-52	2.01***	-1.05***
week 53-65	2.22***	-1.08***
week 66-88	2.86***	-1.36***
week 89-101	3.98***	-1.02***
week 102+	5.10***	-1.44***
D1999	0.05	
D2000	-0.22***	
D2001	0.06	
week 14-26 * D1999	-0.06	
week 27-39 * D1999	-0.22*	
week 40-52 * D1999	-0.56***	
week 53-65 * D1999	-0.24*	
week 66-88 * D1999	0.25*	
week 89-101 * D1999	0.68***	
week 102+ * D1999	-1.10***	
week 14-26 * D2000	0.005	
week 27-39 * D2000	0.22*	
week 40-52 * D2000	0.36**	
week 53-65 * D2000	1.29***	
week 66-88 * D2000	1.86***	
week 89-101 * D2000	1.20***	
week 102+ * D2000	-0.59**	
week 14-26 * D2001	0.25**	
week 27-39 * D2001	0.70***	
week 40-52 * D2001	1.02***	
week 53-65 * D2001	2.08***	
week 66-88 * D2001	2.34***	
week 89-101 * D2001	1.35***	
week 102+ * D2001	0.59**	
Previous UI	0.014***	-0.005***
Cohabitating	-0.054+	0.15***
Child at home	0.47***	0.01
Age	-0.27***	0.04
Age squared	0.003***	0.00
Unemp. rate	-0.05***	-0.007
ALMP		0.13
P(ALMP=1)(1-ALMP)		0.98***
Constant	3.77***	-4.73***
N		
Log likelihood		

*** represents a significance level of 0.1%, ** is 1%, * is 5% and + is 10%

Table 10.4: Employment regression for individuals with vocational education

Variable	P(ALMP)	P(EMP)
week 14-26	1.50***	-0.40***
week 27-39	2.26***	-0.77***
week 40-52	2.81***	-1.09***
week 53-65	3.12***	-1.30***
week 66-88	3.92***	-1.55***
week 89-101	4.77***	-1.61***
week 102+	6.20***	-1.90***
D1999	-0.05*	
D2000	-0.12***	
D2001	0.32***	
week 14-26 * D1999	-0.24***	
week 27-39 * D1999	-0.52***	
week 40-52 * D1999	-0.69***	
week 53-65 * D1999	-0.43***	
week 66-88 * D1999	0.39***	
week 89-101 * D1999	0.80***	
week 102+ * D1999	-0.02	
week 14-26 * D2000	-0.34***	
week 27-39 * D2000	-0.45***	
week 40-52 * D2000	-0.29***	
week 53-65 * D2000	0.60***	
week 66-88 * D2000	1.30***	
week 89-101 * D2000	0.99***	
week 102+ * D2000	-0.66***	
week 14-26 * D2001	-0.16***	
week 27-39 * D2001	-0.08*	
week 40-52 * D2001	-0.07	
week 53-65 * D2001	1.10***	
week 66-88 * D2001	1.32***	
week 89-101 * D2001	0.33***	
week 102+ * D2001	-1.36***	
Previous UI	-0.014***	-0.007***
Cohabitating	0.11***	0.19***
Child at home	0.02	0.10***
Age	-0.20***	-0.02**
Age squared	0.003***	0.00
Unemp. rate	-0.03***	0.006**
ALMP		-0.10**
P(ALMP=1)(1-ALMP)		0.64***
Constant	2.05***	-3.14***
N	1,237,627	
Log likelihood	-476,296.77	

*** represents a significance level of 0.1%, ** is 1%, * is 5% and + is 10%

Table 10.5: Employment regression for individuals with further education

Variable	P(ALMP)	P(EMP)
week 14-26	1.25***	-0.35***
week 27-39	1.89***	-0.58***
week 40-52	2.39***	-0.84***
week 53-65	2.74***	-0.81***
week 66-88	3.64***	-1.07***
week 89-101	4.52***	-1.33***
week 102+	5.47***	-1.33***
D1999	-0.12***	
D2000	-0.49***	
D2001	-0.04	
week 14-26 * D1999	-0.09*	
week 27-39 * D1999	-0.18***	
week 40-52 * D1999	-0.31***	
week 53-65 * D1999	-0.07	
week 66-88 * D1999	0.67***	
week 89-101 * D1999	0.98***	
week 102+ * D1999	0.34***	
week 14-26 * D2000	-0.12**	
week 27-39 * D2000	0.12*	
week 40-52 * D2000	0.34***	
week 53-65 * D2000	1.15***	
week 66-88 * D2000	1.68***	
week 89-101 * D2000	1.35***	
week 102+ * D2000	0.08	
week 14-26 * D2001	0.26***	
week 27-39 * D2001	0.39***	
week 40-52 * D2001	0.55***	
week 53-65 * D2001	1.56***	
week 66-88 * D2001	1.72***	
week 89-101 * D2001	0.91***	
week 102+ * D2001	-0.69***	
Previous UI	0.01***	-0.004***
Cohabitating	0.25***	0.13***
Child at home	-0.03+	0.03
Age	-0.007	-0.11***
Age squared	-0.0001	0.001***
Unemp. rate	-0.06***	0.007+
ALMP		-0.22***
P(ALMP=1)(1-ALMP)		0.094
Constant	-0.95***	-1.41
N	592,107	
Log likelihood	-223,544.6	

*** represents a significance level of 0.1%, ** is 1%, * is 5% and + is 10%

Table 10.6: Wage regression for individuals with only compulsory education

Variable	P(ALMP)	P(Higher wage)	P(Lower wage)	P(No wage)
week 14-26	1.42***	-0.13***	-0.20***	0.30***
week 27-39	1.87***	-0.38***	-0.48***	0.43***
week 40-52	2.19***	-0.52***	-0.60***	0.55***
week 53-65	2.49***	-0.58***	-0.68***	0.56***
week 66-88	3.02***	-0.81***	-0.80***	0.87***
week 89-101	3.99***	-0.97***	-0.69***	0.93***
week 102+	5.35***	-1.37***	-1.06***	0.81***
D1999	0.06			
D2000	-0.04			
D2001	0.22***			
week 14-26 * D1999	-0.23***			
week 27-39 * D1999	-0.26***			
week 40-52 * D1999	-0.31***			
week 53-65 * D1999	-0.40***			
week 66-88 * D1999	-0.17+			
week 89-101 * D1999	0.53**			
week 102+ * D1999	0.67***			
week 14-26 * D2000	-0.34***			
week 27-39 * D2000	-0.25***			
week 40-52 * D2000	-0.28***			
week 53-65 * D2000	0.61***			
week 66-88 * D2000	1.55***			
week 89-101 * D2000	0.97***			
week 102+ * D2000	0.37*			
week 14-26 * D2001	-0.11+			
week 27-39 * D2001	0.14*			
week 40-52 * D2001	0.15+			
week 53-65 * D2001	1.54***			
week 66-88 * D2001	2.22***			
week 89-101 * D2001	1.08***			
week 102+ * D2001	0.15			
Previous UI	0.015***	-0.005***	-0.002***	0.004***
Cohabitating	-0.18***	0.096***	0.13***	-0.14***
Child at home	0.28***	0.02	0.07***	0.04
Age	-0.19***	-0.075***	0.064***	-0.09**
Age squared	0.002***	0.0009***	-0.00075***	0.001*
Unemp. rate	-0.05***	-0.003	-0.006+	-0.05***
ALMP		0.88***	0.97***	1.50***
P(ALMP=1)(1-ALMP)		0.39+	0.22	0.99**
Constant	2.06***	-2.68***	-5.52***	-5.08***
N	705,590			
Log likelihood	-276,774.26			

*** represents a significance level of 0.1%, ** is 1%, * is 5% and + is 10%

Table 10.7: Wage regression for individuals with vocational education

Variable	P(ALMP)	P(Higher wage)	P(Lower wage)	P(No wage)
week 14-26	1.64***	-0.26***	-0.34***	0.28***
week 27-39	2.37***	-0.51***	-0.56***	0.34***
week 40-52	2.61***	-0.65***	-0.78***	0.56***
week 53-65	3.04***	-0.90***	-0.77***	0.76***
week 66-88	4.83***	-1.23***	-1.00***	0.95***
week 89-101	6.14***	-1.04***	-1.06***	1.04***
week 102+	7.95***	-1.61***	-1.11***	0.95***
D1999	0.18***			
D2000	0.03			
D2001	0.38***			
week 14-26 * D1999	-0.32***			
week 27-39 * D1999	-0.52***			
week 40-52 * D1999	-0.9***			
week 53-65 * D1999	-0.42**			
week 66-88 * D1999	-0.21+			
week 89-101 * D1999	-0.60***			
week 102+ * D1999	-0.71***			
week 14-26 * D2000	-0.53***			
week 27-39 * D2000	-0.70***			
week 40-52 * D2000	-0.34***			
week 53-65 * D2000	0.67***			
week 66-88 * D2000	1.13***			
week 89-101 * D2000	0.72***			
week 102+ * D2000	-1.91***			
week 14-26 * D2001	-0.23***			
week 27-39 * D2001	-0.13+			
week 40-52 * D2001	0.48***			
week 53-65 * D2001	2.35***			
week 66-88 * D2001	1.90***			
week 89-101 * D2001	0.15			
week 102+ * D2001	-3.52***			
Previous UI	0.012***	-0.005***	-0.002***	0.003***
Cohabitating	-0.01	0.15***	0.19***	-0.15**
Child at home	0.09***	0.05**	0.09***	0.015
Age	-0.40***	-0.05***	-0.006	-0.01
Age squared	0.005***	0.0004**	0.00	0.00
Unemp. rate	-0.06***	0.003	-0.01***	-0.06***
ALMP		0.76***	0.75***	1.00***
P(ALMP=1)(1-ALMP)		0.79***	0.18	0.66+
Constant	5.66***	-3.03***	-3.81***	-6.16***
N	743.071			
Log likelihood	-310,630.58			

*** represents a significance level of 0.1%, ** is 1%, * is 5% and + is 10%

Table 10.8: Wage regression for individuals with further education

Variable	P(ALMP)	P(Higher wage)	P(Lower wage)	P(No wage)
week 14-26	1.34***	-0.28***	0.28***	0.13*
week 27-39	2.06***	-0.37***	-0.42***	0.23**
week 40-52	2.51***	-0.57***	-0.53***	0.27**
week 53-65	2.54***	-0.54***	-0.36***	0.61***
week 66-88	2.81***	-0.88***	-0.60***	0.78***
week 89-101	3.79***	-1.57***	-0.60***	0.72**
week 102+	5.00***	-0.95***	-0.66***	0.96***
D1999	-0.007			
D2000	-0.44***			
D2001	-0.22***			
week 14-26 * D1999	-0.28***			
week 27-39 * D1999	-0.41***			
week 40-52 * D1999	-0.46***			
week 53-65 * D1999	-0.03			
week 66-88 * D1999	2.00***			
week 89-101 * D1999	1.92***			
week 102+ * D1999	1.29***			
week 14-26 * D2000	-0.20*			
week 27-39 * D2000	0.05			
week 40-52 * D2000	0.49***			
week 53-65 * D2000	1.36***			
week 66-88 * D2000	3.05***			
week 89-101 * D2000	1.57***			
week 102+ * D2000	0.62**			
week 14-26 * D2001	0.16+			
week 27-39 * D2001	0.16			
week 40-52 * D2001	0.30*			
week 53-65 * D2001	1.85***			
week 66-88 * D2001	3.53***			
week 89-101 * D2001	3.12***			
week 102+ * D2001	3.04***			
Previous UI	0.01***	-0.005***	-0.001*	0.001
Cohabitating	0.31***	0.09**	0.06*	-0.22**
Child at home	-0.26***	-0.07*	0.10***	0.02
Age	-0.12***	-0.14***	-0.06**	-0.11*
Age squared	0.001***	0.001***	0.001**	0.001*
Unemp. rate	-0.11***	-0.008	-0.006	-0.003
ALMP		0.74***	0.86***	1.44***
P(ALMP=1)(1-ALMP)		0.009	0.26	1.68***
Constant	1.68***	-1.04**	-3.40***	-5.05***
N	313,524			
Log likelihood	-116,966.12			

*** represents a significance level of 0.1%, ** is 1%, * is 5% and + is 10%