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Employment behaviour of marginal workers

The roles of preferences and opportunities

Morten Nordberg*

Ragnar Frisch Centre for Economic Research, Gaustadalléen 21, N-0349 Oslo.

Abstract

We use structural estimation techniques to analyze labour supply effects of changes in economic incentives for individuals who have just finished vocational rehabilitation in Norway. The complicated and sometimes non-convex budget sets for this group are accounted for. Focus is also on the limitation in the choice sets this group face. Parametric bootstrap and simulation techniques are applied to construct confidence intervals for the predicted impacts of changes in the economic environment. The results show that there is a small to moderate effect of changes in economic incentives on the extent to which vocational rehabilitation brings individuals back to work. We also find that individual health status and local labour market conditions are the most important factors affecting the transition from rehabilitation to work.

1. Introduction

Over the last decades, many countries have experienced a rise in health-related withdrawals from the labour force; see, e.g., Bound and Burkhauser (1999), Autor and Duggan (2003), OECD (2003), and Bell and Smith (2004). In Norway, the proportion of the working age population claiming a disability benefit has risen sharply during the last decade, from 8.3 per cent in 1994 to 10.9 per cent in 2005. For most claimants, disability is an absorbing state; the rate of return to the labour market is close to nil. Given the demographic challenges ahead, it has become a major government priority to curb the flows into disability benefits as well as to re-integrate already disabled individuals into the labour force. An important part of the strategy has been to offer medical and

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vocational rehabilitation programmes to individuals with serious health problems. The number of participants in such programmes has increased by 77 per cent during the past ten years, and there are now more individuals participating in various vocational rehabilitation programmes than there are ordinary unemployed. Recent empirical evidence (Ekhaugen, 2006) shows that approximately half of the participants return to ordinary employment within a year after completion of vocational rehabilitation. Around 20 per cent make a transition to permanent disability. A substantial fraction of the entrants into permanent disability in Norway have been through a vocational rehabilitation attempt. Among young (below 40 years) entrants, almost 40 per cent participated in a vocational rehabilitation programme one year before entry to permanent disability. Norwegian legislation actually implies that vocational rehabilitation shall *always be considered* before a disability application is approved.

What are the factors that determine whether a vocational rehabilitation attempt ends up as a success or a failure? The capabilities of the participants as well as the quality of the rehabilitation programmes and their ability to match labour market demands are obviously important factors. But, as empirical evidence accumulates regarding the moral hazard problems embedded in the Norwegian unemployment insurance systems (see, e.g., Røed and Zhang, 2003; 2005), the political attention has turned towards the impact of economic incentives facing temporary disabled job-seekers also. Fevang *et al.* (2005) show that a non-trivial fraction of social security claimants in Norway actually receive a higher net income as disability pensioners than as full-time workers. In a recent country study, OECD (2006) highlights improved work-incentives as a key to more successful rehabilitation of individuals with health problems in Norway. However, to our knowledge, no scientific evidence exists regarding the impact of individual economic incentives on the success/failure rate of Norwegian vocational rehabilitation programmes. And the fact that the rise in Norwegian disability rolls has occurred in a period without significant changes in the social security system casts some doubt on the empirical relevance of the incentives-explanation. Moreover, there is some recent empirical evidence indicating that organizational changes and downsizings have contributed significantly to the rise in Norwegian disability rates (Rege *et al.*, 2005; Røed and Fevang, 2007).

The aim of the present paper is to provide more direct evidence regarding the impact of economic incentives for this type of ‘marginal workers’ by means of estimating a structural discrete choice model for individuals who have just completed a vocational rehabilitation programme, explicitly taking into account that some of the individuals may face very restricted choice sets. We study nearly 14,000 persons who finished this kind of rehabilitation in 1999.

The transition process that we model in this paper can be described as follows: A rehabilitation programme is considered to be completed when all programme activities involving temporary social security benefits have been terminated for at least six months. This implies that the individuals we look at either gets some employment or they move out of the labour force, with or without a full or partial permanent disability benefit.

The structural model we set up and estimate draws on a methodological framework established to analyse labour supply when non-pecuniary attributes are present, and when the choice set differs across individuals. This framework is described in Dagsvik (1994), Aaberge *et. al.* (1995), (1999), (2000) and Dagsvik and Strøm (2006). A key property of the model in the present paper is that it views the alternative labour market outcomes as resulting from a combination of individual optimization (choices) and external constraints. The constraints exist in two forms: First, a disability benefit is not a matter of choice only. A disability application can be (and quite often is) rejected by social security authorities. Second, labour market opportunities may be restricted, and some individuals may have difficulties with obtaining realistic job opportunities at all. Lack of job offers is likely to be particularly relevant for the population analysed in this paper, since a history of sickness, unemployment, and vocational rehabilitation may entail a substantial stigma. Our goal is to account for the variation in individual constraints when modelling individual choices in a way that make it possible to predict the impact of changes in economic incentives, not only in preferred, but also in realized outcomes. Such a separation then enables us to study the impact of alternative tax- and benefit reforms on the predicted work pattern and disability rates. This is of course a difficult task, since the distribution of preferences and constraints in the population is likely to be highly interrelated, and hence almost inseparable from an empirical point of view. As we return to in Section 3, non-parametric identification of the separate roles of preferences and constraints requires access to observed explanatory variables (instruments) that affect one of these factors, but not the other. Such variables are hard to find. However, we have at our disposal a unique dataset. Based on administrative registers, we are able to characterize each individual's health status (in terms of diagnosis and past sickness absence), human capital resources (in terms of education and work experience), family situation (in terms of spouse and children), age, and local labour market opportunities (in terms of unemployment rates).

The present paper contributes with two novel extensions to the existing literature regarding discrete labour supply models. First we separate between choices and constraints in a more comprehensive manner than what has been done in previous work. This extension is motivated by the particularities of the marginal group considered in this paper (for which constraints are likely to be of paramount importance), but may also be of more general interest. Second we present measures of statistical uncertainty (confidence intervals), not only for the estimated parameters, but also for model and policy predictions. This is achieved through a combination of parametric bootstrap and repeated simulation.

The rest of the paper is organized as follows: Section 2 describes institutions and data. Section 3 describes both how we manage to characterise each individual's economic incentives (i.e. their net incomes associated with each of the seven possible states) and the setup of the labour supply model. In Section 4 we present the results from a 'preferred' version of the model. A sensitivity analysis is described in Section 5, and Section 6 concludes.

2. Institutions and data

The Social Security System is the main source of insurance against income loss during unemployment and sickness for Norwegian citizens. The largest expenditures are due to payments to persons who are unable to work (full-time) for health related reasons. This group ranges from persons who are unable to work for a very limited period to persons who leave the labour force permanently, typically receiving disability pension. A typical entry into the state of disability pension starts with the person becoming sick and receiving sick leave benefits. During the first 16 days of sick leave, the employer are responsible for the payments. The rest of the period is paid by the public social security system. For most workers sick leave benefits have a 100% replacement rate limited to a period of one year. A person must then be at work for at least 6 months in order to become eligible for a new period of sick leave payments. If a person is not ready to return to work when the sick leave payment period runs out, some kind of medical- and/or vocational rehabilitation may be activated. For the latter to be implemented there should be a realistic chance for a re-entry to the labour force to take place. The replacement rate during rehabilitation was in the actual period normally around 66 percent (less for some high income workers). When a rehabilitation program ends, the participant typically either returns to the labour force or applies for disability pension, which until 2002 had the same replacement rate as the rehabilitation programs. The application for disability pension is then either accepted or rejected by the social security authorities. Acceptance could mean that a person is considered being between 50 % and 100 % disabled.

The data available are well suited to highlight some of the economic mechanisms working in the system described above. We have register data containing individual information about public paid benefits. This includes sick leave payments, medical and vocational rehabilitation, and disability pension for the period 1992-2003. We also have information about diagnoses (from 1994), and information about each person's unemployment record from 1989 to 2003. In addition we have demographic information like gender, age, municipality (residence) and education. Labour income information is available for several years, and hours worked is available in 3 (broad) categories: 4-19 hours a week, 20-29 hours a week, and more than 29 hours a week.

The data described above come from different sources, but we are able to combine the data for each individual through (anonymous) id-numbers. The rich data enable us both to use the established structural modelling framework on an important group, and to extend the model to capture this group's decision problem, and control for factors we expect affects the choice set different people face.

Table 1 contains characteristics of the population studied in this paper, which is those finishing vocational rehabilitation in 1999[1] (all numbers except experience and education are in percent). The largest diagnose groups are mental health related, and muscular- and skeleton related. In particular for women the latter group is large. Note that men have experienced more unemployment than women, reflecting a stronger connection to the labour market for this group. In Norway, a person accumulates pension points if income is above one "base amount" (BA). The BA is about 62000 NOK[2] in 2006, and income below one BA is not registered. We measure work experience by number of years with income above one BA or, alternatively two BAs during the last 20 years. We see that men have more experience, in particular if measured by the two-BA measure.

In this article we present a model where we estimate the probability of being in one of seven states a period after the rehabilitation program has ended. Each state is a combination of hours worked and whether or not disability pension is received. We see that as many as 57.6 % are not registered in the employee register 12 months after they leave the Employment Service's register[3]. This number hardly changes it we extend the evaluation period to 24 months after the register is left. The fraction working full-time is just above 30 %, and there is about 36 % receiving disability- or rehabilitation benefit after 12 months. The latter fraction increases to 41 % percent when we extend the evaluation period. There is about 11 percent working part-time. "Some part-time" means that a person is working between 4 and 19 hours a week, where as "much part-time" refers to working from 20 to 29 hours a week.

[1] We condition on leaving the Employment Service's register, having participated in a vocational rehabilitation program for at least 3 months during the last 12 months before exit. The register contains information about unemployment, vocational rehabilitation and labour marked programs.
[2] Nov 1, 2006 1 USD is about NOK 6.70

Table 1 **Descriptive statistics**

	All, 13588 persons	Men, 7187 persons	Women, 6401 persons
Health and unemployment			
Mental health related diagnose	23,00	21,57	24,61
Muscular and/or skeleton related diagnose	36,89	32,54	41,76
Neurological related diagnose	3,58	3,69	3,45
Not received sick leave benefits last three years	45,29	46,61	43,81
Sick leave 1-3 months last three years	8,04	8,65	7,34
Sick leave 4-11 months last three years	13,75	13,77	13,73
Sick leave more than 11 months last three years	32,92	30,96	35,12
Not unemployed last three years	51,51	47,04	56,52
Unemployed 1-3 months last three years	20,64	21,14	20,09
Unemployed 4-11 months last three years	18,44	20,51	16,11
Unemployed more than 11 months last three years	9,41	11,31	7,28
Average local unemployment rate	3,32	3,35	3,29
Demography and experience			
Average age	36,5	36,0	37,1
Fraction women	47,11		
Married	33,46	28,58	38,93
Immigrant from non-OECD country	7,96	9,06	6,73
Having children less than 4 years old	17,63	18,42	16,73
Having children 4-7 years old	19,54	18,51	20,70
Having children 8-11 years old	18,21	15,68	21,04
Having children 12-18 years	22,70	17,53	28,50
Average years of education	11	11	11
Years of experience (Income above one BA)	10,70	11,31	10,02
Years of experience (Income above two BA)	9,40	10,76	7,88
State after rehabilitation			
Not working 12 months later	57,61	57,81	57,38
Fraction working some part-time 12 months later	6,01	3,05	9,33
Fraction working much part time 12 months later	5,67	2,31	9,44
Fraction working full-time 12 months later	30,72	36,83	23,86
Not working 24 months later	56,30	55,99	56,65
Fraction working some part-time 24 months later	5,41	2,91	8,22
Fraction working much part time 24 months later	6,01	2,49	9,95
Fraction working full-time 24 months later	32,29	38,61	25,18
Fraction receiving disability- or rehabilitation benefits 12months later	36,47	32,46	40,96
Fraction receiving disability- or rehabilitation benefits 24 months later	41,27	37,92	45,04

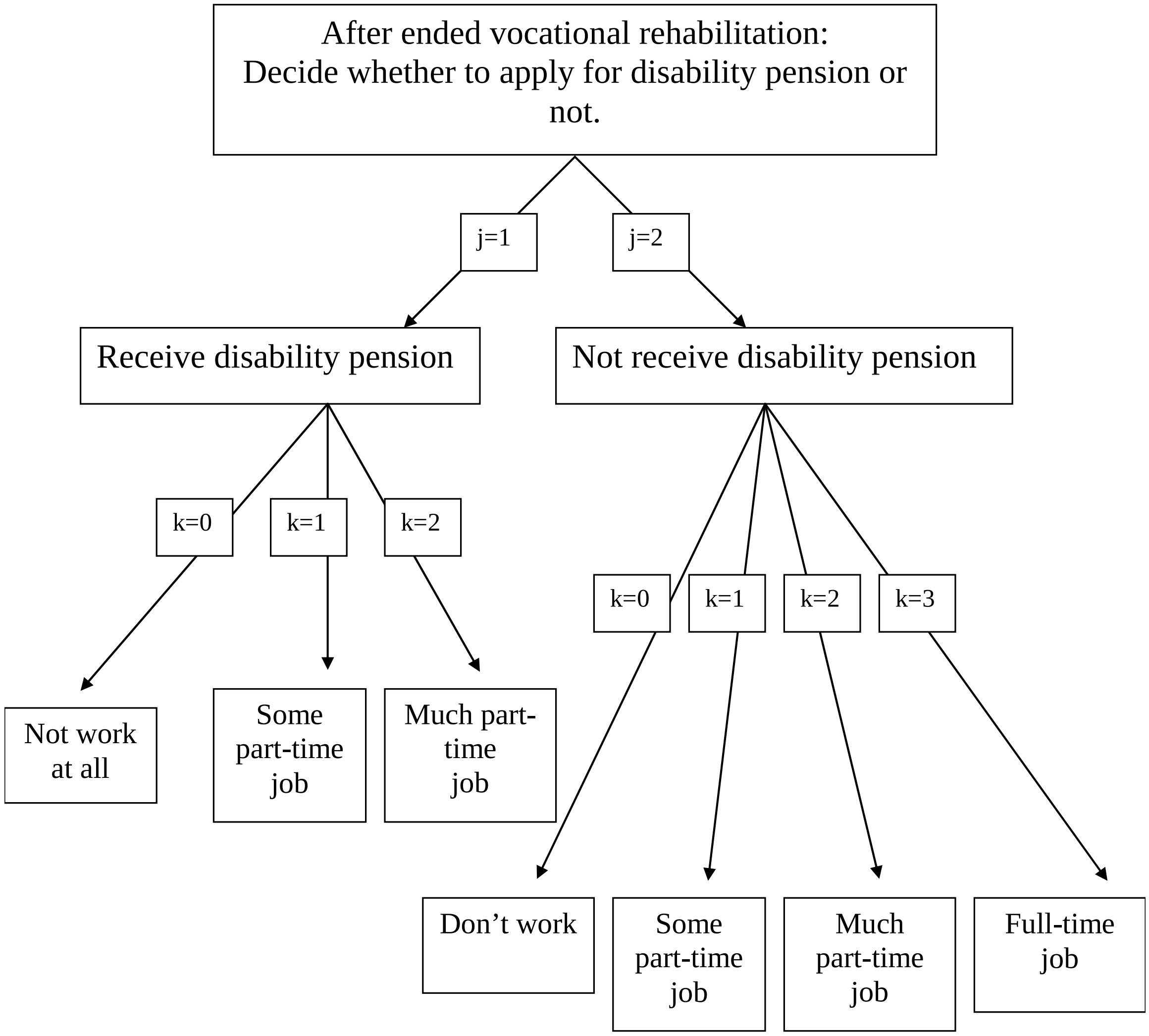
3. The model

Estimating labour supply when budget sets are non convex originated with 'The Hausman approach' see e.g. Hausman (1980), (1981), (1985), Hausman and Ruud (1984) and Mofitt (1986). The present model is in line with another and more recent structural discrete labour supply modelling tradition; see Dagsvik (1994), Aaberge et. al. (1995), (1999), (2000) and Dagsvik and Strøm (2006). As mentioned in the introduction we study a population participating in a vocational rehabilitation program and when the rehabilitation period ends, each person has to "decide" whether to apply for disability pension and how much to work. However, the person's choice opportunities are restricted and these restrictions are of significant importance for whether a person will work, receive benefits, or combine the two. These restrictions are, however, unobserved by the researcher. Disregarding heterogeneity in choice sets may clearly lead to invalid inference regarding the preference structure. During the model presentation it is explained how this problem is handled. Note that we first present the model, pretending that income/ consumption associated with each of the seven potential labour market states is known; thereafter we demonstrate how hypothetical income for each state is estimated.

The way we think of the decision problem is illustrated in Figure 1: First the person decides whether to apply for a disability pension or not[4]. An application is either accepted or rejected. Second, he/she decides how much labour to supply in the market. The data allow us to distinguish between the following broad work-hours categories: i) no work at all, ii) some part-time work, iii) much part-time work, and iv) full-time work. If the person has been granted a disability pension, the option of full-time work is not available. As illustrated in the figure, this leads to seven different possible outcomes.

[4] Note that we do not observe who applies and who does not, so those not receiving benefit consist of those not applying, and of those applying but rejected. If we look at the period 1993 to 1997, 16.7 % of the applications where rejected. Some of these rejections where temporarily, according to Fevang et al. (2004) 33% did receive disability two years after their application had been turned down.

Figure 1



Let U_{ijkr} be agent *i*’s utility of alternative (*j*,*k*,*r*), where *j=1,2*. *j*=1 represent disability pension alternatives, where as *j*=2 represents non-disability pension alternatives. *k* represents hours of work levels, where *k*=0 means “no work”, *k*=1 means “some part-time”, *k*=2 means “much part-time”, whereas *k*=3 means “full-time”. *r* indexes unobserved job opportunities within each category. When *k*=0, *r*=0 (not working). This notation corresponds to the 7 states described in Figure 1. Let B_{ijk} denote the set of jobs with hours of work level *k* within disability/no-disability category *j* that is available to agent i. Let H_k denote the hours of work levels corresponding to category k with $H_0 = 0$. These hour levels are assumed fixed and determined by the employees. Let W_i denote the wage rate agent i face. Given that agent i has a job that belongs to B_{ijk} her (yearly) gross wage income will be $W_i H_k$ and her disposable income will be

$$(1)\, C_{ijk} = W_i H_k + \varphi_j(W_i H_k) - T(W_i H_k, \varphi_j(W_i H_k))$$

where $\varphi_j(.)$ is the function that assigns benefits to income for disability alternatives, so that $\varphi_1(.)$ is the disability pension if disabled, and $\varphi_2(.) = 0$. T(.) is the tax function which depends on wage income and benefits (both labour income and benefits are taxed). Notice that W_i is fixed for person i, it does not depend on hours chosen, and it will not be estimated simultaneously with hours chosen. Benefits depend on hours because there is a curtailment in benefits if a person works (too much). The tax and benefit function may imply that the effective marginal tax rate is not uniformly increasing with wage income and hence non-convexity in the budget constraint may occur.

We assume that the utility function has the structure

$$(2)\, U_{ijkr} = u_{ij}(C_{ijk}, H_k)\varepsilon_{ijkr}$$

where u_{ij} is a positive deterministic function that is quasi-concave, increasing in the first argument and decreasing in the second and that $\varepsilon_{\mathrm{ijkr}}$ are an i.i.d. positive random variable with c.d.f.

$$(3) \quad P(\varepsilon_{ijkr} \le x) = \exp\left(-\frac{1}{x}\right)$$

for x>0. See e.g. McFadden (1973) and Yellott (1977) for justification of the extreme value distribution. Let m_{ijk} denote the number of available alternatives within B_{ijk}. Then it follows readily (cf. Dagsvik and Strøm, 2006) that utility maximization and the restriction given in (1)-(3) implies that the probability, P_{ijk}, that individual *i* chooses a job within B_{ijk}, is equal to

$$(4)\ \ P_{ijk} = \frac{m_{ijk} u_{ij} \left(C_{ijk}, H_k \right)}{\sum_{s=1}^{2} \sum_{q=0}^{M_s} m_{isq} u_{is} \left(C_{isq}, H_q \right)}$$

where $M_1 = 2$ and $M_2 = 3$. Without loss of generality we normalize such that $m_{i20} = 1$. m_{i10} will be less than or equal to one, and can be interpreted as the degree of which the disability alternative with zero working hours is available. We assume furthermore that

$$(5)\ \ \log u_{ij} \left(C, H \right) = \alpha_0 \frac{\left(\left(10^{-5} C + \alpha_1 G \right)^{\lambda} - 1 \right)}{\lambda} + v_{ij}(H)$$

where G_i is equal to one if a person is married to a person with labour income above 200 000 NOK, and zero otherwise, λ is a shape coefficient to be estimated. Thus, the deterministic part of the utility function is assumed to be Box-Cox transformation of consumption, whereas the function $v_{ij}(H)$ is allowed to be semi parametric and will be specified empirically below. A justification for the Box-Cox transformation is found in Dagsvik and Strøm (2006). This specification is also used by Heckman and McCurdy (1980), and Aaberge et. al. (1995, 2000). The deterministic element is, as shown in equation (5), separated in two parts. The first part is related to consumption or income, and the second part is related to other factors. We will see that the specification above enables us, at least partly, to separate between choices and limitations.

We shall call m_{ijk} ”opportunity restrictions measure”. From (4) we notice that this measure enters in a way that weights the utility of a particular alternative. In the present paper a major emphasis is made on obtaining an appropriate specification on the opportunity functions to fit the problem of the group described. These weighting functions come from factors related to the availability of choice alternatives, meaning that they are related to opportunities, and not to choices.

Let

(6) $$g_i = \frac{\sum_{q=0}^{M_1} m_{i1q}}{\sum_{q=0}^{M_2} m_{i2q}},$$

(7) $$f_{i1k} = \frac{m_{i1k}}{\sum_{q=0}^{M_1} m_{i1q}} = \frac{m_{i1k}}{g_i \sum_{q=0}^{M_2} m_{i2q}}$$ and

(8) $$f_{i2k} = \frac{m_{i2k}}{\sum_{q=0}^{M_2} m_{i2q}}.$$

The measure g_i in (6) is the number of feasible opportunities within the disability category relatively to the number of feasible opportunities within the non-disability category, and capture to what extent disability is an option that is available for person *i* (the disability benefit acceptance probability). The measure f_{ijk} in (7) and (8) is the fraction of feasible jobs within B_{ijk} among all the feasible jobs within $B_{ij} = \bigcup_k B_{ijk}$.

If follows from (6)-(8) that we can write

(9) $$m_{i1k} = f_{i1k} g_i \sum_{q=0}^{M_2} m_{i2q}$$ and

(10) $$m_{i2k} = f_{i2k} \sum_{q=0}^{M_2} m_{i2q}.$$

With this notation we rewrite (4) so that

(11) $$P_{i1k} = \frac{g_i f_{i1k} u_{i1}(C_{i1k}, H_k)}{g_i \sum_{q=0}^{2} f_{i1q} u_{i1}(C_{i1q}, H_q) + \sum_{q=0}^{3} f_{i2q} u_{i2}(C_{i2q}, H_q)}$$

and

(12) $$P_{i2k} = \frac{f_{i2k}u_{i2}(C_{i2k}, H_k)}{g_i \sum_{q=0}^{2} f_{i1q}u_{i1}(C_{i1q}, H_q) + \sum_{q=0}^{3} f_{i2q}u_{i2}(C_{i2q,} H_q)}$$

The part of the utility function that depend on hours, $v_{ij}(H)$, has not yet been characterized. Note that since there might be differences in the type of jobs typically combined with disability and those not combined with disability we let *v* depend on *j*. Because availability of working hours is present in the *f*(.) function, the question of identification arises. If the purpose of the model is to simulate the effect of changes in the tax- and benefit system, it is however, not necessary to identify v_j completely separated from f_{ijk} in equation (11) and (12) if we are only interested in simulating reforms in the economic budget constraint. On the other hand, if one wishes to make simulations with changes in the opportunity measure identification is necessary. What we need for this purpose are some explanatory variables that can reasonably be assumed to affect preferences, but not opportunities, and some variables that affect opportunities, but not preferences. Based on out rich data set, we will argue that such variables exist, although identification clearly hinges on some non-testable exclusion restrictions. As mentioned above we shall apply a semiparametric specification so that

(13) $$v_{ij}(H_k) + \log f_{ijk} = \theta_{0jk} + \theta_{i1j} X_i \beta + \theta_{2jk} V_i \gamma$$

where X_i is a vector containing variables related to preferences and V_i is a vector containing variables related to choice restrictions. In this case none of the variables included in X_i can be included in V_i. One of the betas, one of the gammas, and 6 of the thetas need to be normalized. This is done by setting $\beta_1 = \gamma_1 = 1$, and by setting $\theta_{0j0} = \theta_{1j0} = \theta_{2j0} = 0$, for j={1, 2}. This means that the no-work alternative is the reference case both for those receiving benefits and for those who do not. v_{ij} is not completely separated from f_{ijk} in this specification but $\theta_{i1j} X_i \beta$ has a structural interpretation related to preferences and $\theta_{2jk} V_i \gamma$ has a structural interpretation related to possibilities, whereas θ_{0jk} is related to both preferences and possibilities.

To be able to estimate the model we need to specify which factors that is supposed to affect preferences and which factors that is supposed to affect choice restrictions. More specific we need to specify which variables to include in the X-vector, the V-vector, and also which variables to include in the g-function, that we will call the Z-vector. First we justify and estimate a benchmark model, but since such choices can always be questioned, we report the results from several alternative specifications in Section 5.

In the benchmark model, preferences are described by age, gender and family situation. More specific we assume that

$$(14) \quad \begin{aligned} & X_i \beta = \beta_1 (Age20-35) + \beta_2 (Age50+) + \beta_3 Children(Man) \\ & + \beta_4 Children(Woman) + \beta_5 Woman \end{aligned}$$

Where Age20-35 is a dummy-variable equal to one if a person is less than 35 years old. Age50+ is equal to one if a person is more than 49 years old. This implies that “prime age” is the reference group. Woman is a dummy variable equal to one if the person is a woman, and Children(Woman) is a dummy variable equal to one if the woman has children under the age of 12 years old. Children (Man) is a dummy equal to one if a man has children under the age of 12. This implies that men without children are the reference group. All dummy variables equal zero it they do not equal one.

In this benchmark model the job opportunity set, on the other hand, is described by work experience, educational attainment, immigrant status, business cycle indicators and experienced unemployment. We let

$$(15) \quad \begin{aligned} & V_i \gamma = \gamma_1 Fraction0 + \gamma_2 (Un1-3) + \gamma_3 (Un4-11) + \gamma_4 (Un12+) + \gamma_5 Localur \\ & + \gamma_6 NoOECD + \gamma_7 Education \end{aligned}$$

Fraction0 is the fraction of a person's potential labour force participation period[5] where yearly income was below 2 base amounts. (One base amount is about 63000 NOK in 2006) fraction0 is between zero and one, where Fraction0=1 means that the person was not working at all during the whole potential period, and Fraction0=0 means that a person had labour income every year. Un1-3 is a dummy variable equal to one if a person is registered as unemployed 1-3 months during the last three years, zero otherwise. Un4-11 equals one if unemployed 4-11 months and Un12+ is one if unemployed more than 11 months during the last three years. The reference group are those not registered as unemployed the last three years. Localur is the local-unemployment rate (municipality level), constructed as fraction of the population between 20 and 67 registered as unemployed. NoOECD is a dummy equal to one if the person has immigrated from outside the OECD area, and Education is years of education[6].

As described above we also take into account that access to disability pension is limited; e.g. that there is an institution who decides whether a person qualifies for disability pension or not. The access to disability depends on a person's health status, in this model captured by length of sick leave period and medical diagnosis. We also suspect that business cycles, and a person's previous unemployment record is taken into account when an application is considered. Let the *g*-function for the benchmark model be:

$$
\begin{aligned}
& g_i = g(Z_i) = \exp(g_0 + g_1(\text{Sick4}-11) + g_2(\text{Sick12+}) \\
(16) \qquad & + g_3(\text{Un1}-3) + g_4(\text{Un4}-11) + g_5(\text{Un12+}) + g_6\text{Localur} \\
& + g_7\text{Muscular} + g_8\text{Mental} + g_9\text{Neurologic})
\end{aligned}
$$

Sick4-11 is a dummy variable equal to one if the person is registered as sick 4-11 months during the last 3 years. Sick12+ equals one if a person is registered sick more than 11 months during the last three years. The reference group is those registered sick for less than four months during the last three years. The unemployment related variables (business cycle and experienced unemployment) are the same as in equation (15). "Muscular" is a dummy equal to one if there is a medical diagnosis related to muscular-

[5] The potential income period is the period after the completion of education to the end of 1999. For immigrants we use the period from when they arrived if they do not have education from Norway.
[6] Missing education or education less than 9 year is set to 9 years, education above 18 years is set to 18 years.

or skeleton related disease, “Mental” is one if a diagnosis related to mental sufferings is observed, and “Neurologic” is a dummy equal to one in the case of a neurological diagnosis.

If $\lambda < 1$, and $\alpha_0 > 0$ the deterministic part of the utility function is increasing and strictly quasi concave in consumption. As we will se in the next section the parameters related to the structural part of the utility function have the theoretical correct signs, and are typically estimated very precisely. However, we first describe how labour income is estimated.

Estimation of the wage function

So far we have pretended that consumption in all of the states a person can be in is easily accessible information. In reality this is not the case. Deriving state specific “consumption” or net-income for those on rehabilitation faces three potential problems. First we need to know labour income, second the amount received if disabled, and third how the tax system affects (combinations of) these two income components. The tax component is trivial in the sense that once benefits and labour income are determined we are able to calculate the tax rather exactly. Disability pension and (rehabilitation benefits) for the present group can be found based on received rehabilitation benefits which are calculated in the same way as disability pension until 2002. By recording for how long and to what extent a person is registered on rehabilitation we can calculate disability pension from the income files[7]. This means that even if a person is not receiving the benefit today we could tell what she would receive if an application for disability pension was accepted. The real challenge in this setting is to estimate the wage rate. It is always difficult to predict wages for individuals who do not work, since we expect those who actually end up working to be a selected group. In the present context, this problem is potentially even larger than in “standard” wage regressions, since the fractioned censored in this study is much larger than in other labour supply studies. The data problem is caused by a combination of the relatively low fraction returning to work, and the fact that “hours worked” are only available in broad categories with “more than 30 hours a week”

[7] Some have occupational pensions, and this method enables us at (least partly) to include this in the pension payments.

as the top category. In fact only 24.9 % are registered with a fulltime job for a whole year twelve months after the rehabilitation ends. Since we do not observe hourly wages, but rather yearly earning, we can only use workers who have worked full time a whole year to infer hourly wages. These problems imply that standard wage estimation techniques are problematic. To cope with this we use previous income as a proxy for future income, as described in Fevang et. al. (2005). The idea is that previous income is a proxy for future income potential, adjusted for the impact of the rehabilitation experience. We assume that fulltime work an entire year is the credible earnings-potential information, and we search for a fulltime job during the last 5 years prior to the end of the rehabilitation program. If several previous full time incomes are observed, we use the highest income. This is done to increase the probability that a fulltime job is being observed.

Even when we search for fulltime job in a period of five years as much as 62.8 % of the population is not registered with income from fulltime work during a whole year. For the group where a fulltime job is not observed we estimate their earnings potential with a Full-Information Maximum Likelihood method where we try to control for the selection problem. In the model below w_i is the individual wage potential, h^* is the hours related to fulltime work. $h^* w_i$ is the income potential at fulltime work. y^* is a latent variable reflecting the probability of being observed with a full-time income, and y is a dummy for whether such an income is observed or not. M includes the variables we assume affect this previous fulltime labor income, while N is all the variables included in M plus some variables only assumed to affect whether previous income is observed or not, (the instruments). Such instruments are assumed not to effect income directly, only through the participation decision. Whether to include such instruments, and if included, which variables to use as instrument can always be debated. We therefore report the result from an alternative specification in the sensitivity check section (Section 5), where the income potential if not observed, is estimated with an OLS regression.

In this study, marital status, spouse’s income, and whether the person has children or not, only affects whether fulltime income is observed or not. These are variables not included in the wage equation and previously used as instruments in labour supply studies. The estimation results are given in Appendix 1.

(17) $\log h^* w_{\mathrm{i}} = M_i \mu + v_i$,

(18) $y_i^* = N_i \varpi + u_i$,

Let $y_i = 1$ if $y_i{*} > 0$ and $y_i = 0$ otherwise. We observe y_i but not $y*$.

(v_i, u_i) are assumed to be jointly normally distributed with expectations equal to zero. σ is the standard deviation of v ,

If previous income is not observed we predict the fulltime income potential to be

(19) $\overline{h^* w_{\mathrm{i}}} = M_i \hat{\mu} + \psi m_i$

where $\psi = \rho\sigma$, $\rho = corr(v,u)$ and m is the inverse Mill's Ratio. Note that we include ψm_i in the predictions, since the information that a person has not been employed in the past contains valuable information regarding that individual's wage prospects in the future. It is the conditional wage predictions that is relevant our model, since the conditioning only relates to the past, and not to the outcomes that will be modelled as a function of this predictions.

The main results from the income estimation are summarized in Table 2. We see that for 56 % of the men and 70 % of the women a fulltime- job is not observed during the last 5 years, and hence the earnings potential has to be based on the regression described above. The table shows that the standard deviation is much smaller for those where income is predicted from the regression, indicating that the regression model is not able to reproduce the individual variation in the earnings potential. On average, observed previous income seems to be a good instrument for future income, while the regression model seems to underestimate income for men and overestimate income for women. Note that the fraction working full time after the rehabilitation has ended is low for both men and women. 21% of the men who was not working fulltime during the last 5 years are registered with a full-time job one year after the rehabilitation ends. The corresponding number for women is as low as 14.32 %

Table 2
Income estimation and observed income: Main results

	Men		Women	
	Censored	Uncensored (Income observed)	Censored	Uncensored (Income observed)
Number	4188	3268	4602	1945
Censored (%)	56,17	43,83	70,29	29,71
Average predicted gross income potential in fulltime job (NOK)	226606	274179	272652	238322
Standard deviation	24051	76711	28686	53761
Fraction with observed income ("next year")	21,04	46,79	14,32	33,62
Average observed gross income (NOK)	258616	269260	236129	239753
Average predicted gross income "next year" (NOK)	240369	278271	254792	232012

As mentioned we use the highest yearly income (actual or predicted) in this period as the proxy for future yearly income. However, since we use a maximum of yearly income for several years, and because we might expect that the rehabilitation process affect potential wages in a negative way, we scale down the full-time income so the income on average fits the actual income for those who do work fulltime after the rehabilitation period. This downscaling is done separately for men and women and 7 age groups, that is 14 groups altogether. We then use this downscaled income and the calculated benefits to calculate net income for the different states described earlier in this section. The state "some part-time" relates to income if working 30 %, while "much part-time" is related to working 50%. We also need to assume that those not working and not receiving disability pension or rehabilitation benefit receive at least some income. For now we assume that this income is 30000 NOK, and we later (Section 5) show that precise determination of this number is of minor importance for our main results.

Table 3 shows average net income for men and women in the states described above. We see that men have a higher net-income than women in all the states, but that this difference is very small.

Table 3

Predicted net-income (NOK[8]) in the different states

	All	Men	Women
Average net income working full-time	179076	182607	175111
Average net income combining some part-time work and benefits	127772	129372	125976
Average net income combining much part-time work and benefits	136242	138575	133622
Average net income 100% disabled	99454	99864	98995
Average income some part-time work, no benefits	64909	66213	63445
Average income much part-time work, no benefits	97654	99818	95225

4. Results

In this chapter we present the estimates from the benchmark model, and study how several variables affect the probability of being in each of the seven states. The main focus is on how the model predicts the effect of changes in economic incentives, and changes in business cycles. In particular we are interested in the effect on the fraction of the group working, and on the fraction receiving disability pension. We also examine the statistical uncertainty of these results by using parametric bootstrap and simulation techniques. In the next section (Section 5) we examine the robustness of this benchmark model by estimating alternative models to test to what extent the results presented here are sensitive to the particular specification described above. The estimates of the benchmark model are presented in table 4.

[8] Nov 1, 2006 1 USD is about NOK 6.70

Table 4
Estimation results of the standard model[9]

			Coefficient	Standard error
Parameters related to job restriction	Fraction of potential years not working (normalized)	γ_1	1	
	Unemployed 1-3 months last three years	γ_2	0,02	0,03
	Unemployed 4-11 months last three years	γ_3	0,05*	0,03
	Unemployed more than 11 months last three years	γ_4	0,17***	0,04
	Local unemployment rate	γ_5	0,04***	0,01
	Immigrant from non-OECD country	γ_6	-0,12***	0,03
	Years of education	γ_7	-0,10***	0,01
	State parameter related to fulltime alternative	θ_{223}	-2,34***	0,08
	State parameter related to much part-time, no pension	θ_{222}	-1,59***	0,13
	State parameter related to some part-time, no pension	θ_{221}	-0,87***	0,14
	State parameter related to much part-time, pension	θ_{212}	-1,32***	0,23
	State parameter related to some part-time, pension	θ_{211}	-1,06***	0,16
Parameters related to preferences	Less than 35 years old	β_1	1	
	More than 49 years old	β_2	-0,73*	0,38
	Having children below 12 years old (men)	β_3	1,33***	0,43
	Having children below 12 years old (women)	β_4	-0,99***	0,31
	Women	β_5	-4,13***	0,94
	Constant utillity term, consumption	α_0	0,97***	0,08
	Married to person with labour income above 200000 NOK	α_1	-0,02**	0,01
	Shape coefficient	λ	-1,40***	0,31
	State parameter related to fulltime alternative	θ_{123}	0,06***	0,01
	State parameter related to much part-time, no pension	θ_{122}	-0,33***	0,07
	State parameter related to some part-time, no pension	θ_{121}	-0,23***	0,05
	State parameter related to much part-time, pension	θ_{112}	-0,18***	0,05
	State parameter related to some part-time, pension	θ_{111}	-0,25***	0,06
Parameters related to pension restrictions	Constant term	g_0	-3,23***	0,67
	Sick 4-11 months last 3 years	g_1	0,20***	0,06
	Sick more than 11 months last 3 years	g_2	0,46***	0,04
	Unemployed 1-3 months last three years	g_3	-0,60***	0,06
	Unemployed 4-11 months last three years	g_4	-0,26***	0,06
	Unemployed more than 11 months last three years	g_5	0,16**	0,08

[9] * is significant at a 10 % level, ** at 5 % level and *** at the 1 % level.

			Coefficient	Standard error
	Local unemployment rate	g_6	0,03**	0,02
	Muscular or skeleton related diagnose	g_7	0,43***	0,05
	Diagnose related to mental sufferings	g_8	0,85***	0,05
	Neurological related diagnose	g_9	0,86***	0,10
Common constant term of preferences and job opportunities	Constant term related to fulltime alternative	θ_{023}	-4,26***	0,69
	Constant term related to much part-time, no pension	θ_{022}	-6,25***	0,70
	Constant term related to some part-time, no pension	θ_{021}	-5,21***	0,64
	Constant term related to much part-time, pension	θ_{012}	-4,43***	0,19
	Constant term related to some part-time, pension	θ_{011}	-3,85***	0,15

Interpreting the estimated coefficients is not straightforward. Not only are the probabilities in (11) and (12) complicated expressions, but from (13) we see that telling the estimated sign of a particular effect is tricky since we have to consider both the relevant θ and the γ or β simultaneously. Since γ_1 is normalized to 1, θ_{2jk} reflects the impact of the fraction of years with low (or no) labour income on job opportunities. We see that θ_{2jk} is negative for all j and *k*. In other words, we find that years with no/low income have a negative impact on the opportunities in the labour market in general. More individual unemployment experience ($\gamma_2, \gamma_3\ \gamma_4$) and higher local unemployment rate (γ_5) reduce the job opportunities. Surprisingly, being a No-OECD immigrant (γ_6) increases the job opportunities. γ_6 change sign if the experience variable is left out of the regression, suggesting that among the present group, immigrants have less opportunities because they have less experience (see Table A3 in the appendix). Not surprisingly more education (γ_7) increases the opportunities for work.

We see that θs related to preferences (θ_{1jk}) change signs between the full-time alternative and the part-time alternatives. Since the θ related to preferences and the fulltime alternative (θ_{113}) is positive, and the θ_1s related to the part-time alternative is negative, the youngest group prefer working full-time. The negative sign of β_2 and the shifting sign of θ_{1jk}, means that those in the oldest group prefer full-time work even less than the prime aged. Women prefer fulltime work less than men (β_5), and their preference for leisure is stronger if they have children below 12 years (β_4). Men prefer to work more when they have children (β_3).

When it comes to factors that limit the disability pension alternative, we can interpret the estimated parameter signs as more directly related to effect of variables. E.g., we see that the corresponding coefficient to a long sick leave record in the recent years (g_1, g_2) is positive, meaning that it increases the possibility of getting an application approved. The signs related to "some" experienced unemployment (g_3, g_4) is negative while the sign related to 12 months experienced unemployment last three years (g_5) is positive. This might indicate that some unemployment reveal some connection to the labour market, while those without job experience at all are in the no-unemployment group. The higher the local unemployment rate (g_6) the higher the possibility of getting a disability pension application approved, and having a diagnose related to mental health (g_7), muscular or skeleton system (g_8), or the neurological system (g_9), all increases the possibility of receiving disability pension, that is compared to having any other diagnose.

The ambition, and one main advantage, of structural estimation techniques, is the ability to predict the effect of changes in external variables. To study the aggregate effect of policy-, health-, or business cycles changes we need an uncertainty measure. One could argue that the significance of each estimate should not be the main focus in this kind of study (particularly if insignificant parameters are caused by including correlated variables). The most important significant measure in this setting would be uncertainty regarding the effects of changes in the external variables described above, and in particular behavioural changes due to changes in economic incentives. We study this by using Monte Carlo simulations, where we take into account that estimates are correlated (using a so called Choleski decomposition of the covariance matrix before we draw parameter vectors). Based on the variance of each parameter and the covariance between the parameters, we draw 100 parameter vectors. For each of these vectors we calculate the probability of being in each of the seven labour market states, given the change in the variable we want to study the effect of. By deleting the 5 highest and 5 lowest probabilities for each category, we calculate a 90 % confidence interval of the fraction of persons in each state e.g. after a reform. Using this method we are able to say something about the size of the predicted response to a change in incentives for the group as a whole, and its corresponding statistical uncertainty, given of course that the model is correctly specified. We show the results of alternative model specifications, and we study the effects for different income-, and education groups based on separate estimations for these groups.

In all tables reporting simulated effects of changes in incentives, unemployment and health, a 90 % confidence interval is predicted and reported. The limits of this interval are labelled P5 and P95. We also see that the model with the true explanatory variables is able to predict the fractions in each state rather precisely. For all simulations based on counterfactual explanatory variables, we report the results from statistical significance tests based on pairwise comparisons with predictions from a model based on factual data. If the model predict an increase/decrease of persons in a state, compared to the case where the true explanatory variables are used, in more than 95 % of the cases (drawn parameter vectors) we call this significant at the 5 % level (marked ** in the tables). A 10 % significant level is marked *. We shall look at the impact of three types of interventions/shock. The first is related to changes in economic incentives, connected to the preferences part described above. The second shock is related to business cycles, which will affect the opportunities each person face. Third we will change health status (medical diagnoses) which affects the disability eligibility. The latter is not meant as a policy relevant change, but included to study the importance of this factor in the model.

To study these shocks we modify the explanatory variables. Changes in incentives are studied by increasing the net income if working by 10 %, decreasing the disability pension for the 100% disabled by 10%, and combinations of the two. The effect of business cycles is studied by increasing the local unemployment rate by 3 percentage points, and the effect of health status is studied by giving those having a medical diagnose related to a high probability for disability, a diagnose with a “low” probability for disability[10].

[10] Based on a simple regression where we study the probability of being disabled against different diagnoses, controlling for several other factors we find that the diagnoses included in the model (mental health, muscular-or skeleton related, and neurological related diagnoses) gives the highest probabilities for

Table 5

Simulation results reference model
Predicted probabilities (fractions) in percent

		No work, no pension	Some part-time, no pension	Much part-time, no pension	Full-time	100% disabled	Combining some part-time and pension	Combining much part-time and pension
Observed fraction in each state (13588 persons)		25	3.5	4.33	30.72	32.62	2.51	1.34
Simulation with true value of explanatory variables	P5	20.19	3.02	3.32	29.90	31.89	2.13	1.14
	Mean	23.98	3.47	4.12	31.31	33.26	2.50	1.35
	P95	26.01	3.85	4.69	33.08	35.07	2.87	1.62
Increase net income if working by 10 percent	P5	19.81	3.49	3.72	30.36	31.12	2.09	1.08
	Mean	23.52*	4.00*	4.41	31.79	32.55	2.43	1.30
	P95	25.52	4.55	4.99	33.41	34.27	2.76	1.54
Reduce disability pension by 10 percent	P5	20.67	3.09	3.67	31.01	29.57	2.15	1.15
	Mean	24.98**	3.62	4.31	32.31**	30.83**	2.56	1.39
	P95	27.27	4.03	4.87	34.16	33.10	2.96	1.62
Increase income and reduce pension by 10 percent	P5	20.30	3.64	3.71	31.41	28.44	2.11	1.13
	Mean	24.36	4.14**	4.56**	32.84**	30.23**	2.51	1.36
	P95	26.35	4.69	5.25	34.89	32.06	2.83	1.64
Increase local unemployment rate by 3 percentage points	P5	21.26	2.85	2.98	24.57	35.48	2.14	1.05
	Mean	25.17*	3.35	3.65*	26.05**	37.95**	2.52	1.32
	P95	27.59	3.78	4.27	27.51	40.32	2.89	1.62
Adjust medical diagnoses from high risk to low risk	P5	23.44	4.05	4.11	35.01	21.60	1.63	0.81
	Mean	27.74**	4.74**	5.16**	36.46**	22.96**	1.91**	1.03**
	P95	30.13	5.35	5.89	38.56	24.70	2.24	1.23

Starting with “the main model” specified in Chapter 3, we see from the first rows in table 5 that the fractions in each state predicted from the model, are very close to the true outcomes. “Simulation on the true explanatory variables” in Table 5 shows that the confidence interval covers the true value for each of the seven categories[11]. Second, from the same table and the “increase net income if working by 10 percent”, we see that a 10 % increase in net income have a rather small effect on the fraction ending up in each

disability. This is what we call high-risk diagnoses. The low-risk category contains all other diagnoses and not being registered with a diagnose.

[11] Other, more flexible, specifications of the model are tested. This typically leads to uncertain estimated parameters. The predicted effect of changes in economic incentives is typically similar to those reported in this article, but the estimated confidence intervals are typically much larger.

state, when we compare with the predictions based on the real data (true explanatory variables). The next line shows that reducing the disability pension by 10 % (for those being 100 % disabled) will reduce the fraction becoming 100% disabled by nearly 2.4 percentage point compared to the mean from the simulation on the real explanatory variables. If we look to the next line in Table 5 we see that the effect of combining a net labour income increase and a net disability reduction the effect is larger, 2.9 percentage points. There are only small changes in the fraction working part-time. When turning to the estimated effects of changes in the local unemployment rate, the size of this effect will of course depend of the size of the change. Here we increase the rate by 3 percentage point, which is meant to be a large but realistic recession for the Norwegian economy. Also note from Table 5 that this reduces the fraction in all of the work-related categories, while it increases the fraction being 100% disabled, and the fraction not working and not receiving benefits. Finally we simulate the effect of changing medical diagnoses from high-risk to low-risk. From the last lines in Table 5 we see that having one of the three high risk diagnoses have a large and statistically significant effect on fraction working and fraction disabled.

5. Sensitivity check

In the present section we study how sensitive the results from the benchmark model described in Section 4 is to the model specification and data definitions. The first test is on the sensitivity of the length of the evaluation period. Below we report the result from an estimation identical to the one described above, except that the time period after the exit from the Employment Service’s register, when labour market outcomes are evaluated, are extended. We extend this period from 12 to 24 months and report the results in Table 6.

Table 6

Reference model, evaluation period 24 months after rehabilitation ends

Predicted probabilities (fractions) in percent

		No work, no pension	Some part-time, no pension	Much part-time, no pension	Full-time	100% disabled	Combining some part-time and pension	Combining much part-time and pension
Observed fraction in each state		21.97	2.87	4.14	30.9	35.42	2.69	2.01
Simulation with true value of explanatory variables	P5	19.20	2.47	3.27	30.32	34.98	2.32	1.69
	Mean	21.38	2.82	4.02	31.30	35.86	2.62	1.99
	P95	22.87	3.20	4.51	32.32	36.85	3.01	2.32
Increase net income if working by 10 percent	P5	18.88	2.73	3.71	30.75	34.00	2.25	1.61
	Mean	20.96	3.1*	4.27	32.18*	34.99*	2.57	1.93
	P95	22.52	3.51	4.78	33.46	36.32	2.99	2.26
Reduce disability pension by 10 percent	P5	20.23	2.56	3.42	31.18	32.56	2.33	1.76
	Mean	22.26**	2.92	4.14	32.27**	33.64**	2.71	2.06
	P95	23.66	3.35	4.65	33.45	34.75	3.13	2.35
Increase income and reduce pension by 10 percent	P5	19.44	2.87	3.77	31.65	31.92	2.26	1.67
	Mean	21.77	3.25**	4.39*	33.03**	32.9**	2.65	2.01
	P95	23.33	3.66	4.93	34.38	34.03	3.05	2.34
Increase local unemployment rate by 3 percentage points	P5	18.07	2.29	2.99	26.04	38.14	2.42	1.80
	Mean	20.53	2.67	3.67**	27.89**	40.25**	2.83	2.15
	P95	22.86	3.03	4.19	29.45	42.30	3.28	2.47
Adjust medical diagnoses from high risk to low risk	P5	22.25	3.23	4.23	35.28	25.19	1.77	1.31
	Mean	24.45**	3.68*	4.98**	36.54**	26.57**	2.16**	1.62**
	P95	26.23	4.22	5.60	38.12	27.84	2.54	1.88

We notice by comparing the first lines in Table 6 and Table 5 that the fraction receiving pension increase when we evaluate 24, rather than 12 months after the exit, while the fraction being in the "no work, no pension" category declines. We see that the effect of all the changes in incentives, unemployment and diagnoses, have very similar predicted effect as for the case when "12 months" is the basis for the evaluation.

Each person's experienced unemployment, and the local unemployment rate is included in the opportunity function regarding disability benefits (the g(.)-function). A justification for this assumption is that a caseworker might take into account how hard it is for a person to get an ordinary job when e.g. disability is being assessed. We also argued for including individual specific variables in the job limitation function.

In the reference model we have separated the factors affecting choices from factors restricting choices. In the literature (e.g. in Aaberge et. al. (2000)) most variables are included in the preference part of the model, while the factors limiting choices are limited to comprise external characteristics such as place of residence and local unemployment rates. Let us see what happens if we estimate models where limitations are handled along this line. In Table 7 we present the results from three alternative models where we exclude or limit the functions meant to capture the restrictions in opportunities.

Table 7

	I Only local unemployment in γV		II g(z)=1		III Local unemployment rate in γV, g(z)=1	
	Estimates	Std. Error	Estimates	Std. Error	Estimates	Std. Error
γ_2			-0.152	0.024		
γ_3			-0.060	0.025		
γ_4			0.125	0.035		
γ_5			0.048	0.007		
γ_6			-0.196	0.034		
γ_7			-0.108	0.007		
β_2	-1.018	0.590	-0.978	0.240	-1.013	0.556
β_3	2.765	0.856	0.476	0.185	2.570	0.765
β_4	-1.535	0.548	-0.555	0.154	-1.468	0.505
β_5	-5.645	1.685	-1.239	0.227	-5.378	1.523
g_0	-0.726	0.104				
g_1	0.026	0.057				
g_2	0.221	0.042				
g_3	-0.541	0.051				
g_4	-0.128	0.051				
g_5	0.375	0.067				
g_6	0.033	0.018				
g_7	0.432	0.048				
g_8	0.969	0.051				
g_9	0.881	0.099				
α_0	0.672	0.079	0.462	0.033	0.544	0.030

	I Only local unemployment in γV		II g(z)=1		III Local unemployment rate in γV, g(z)=1	
	Estimates	Std. Error	Estimates	Std. Error	Estimates	Std. Error
α_1	2.673	2.471	-0.300	0.205	1.084	0.257
λ	**1.290**	**0.168**	**0.917**	**0.150**	**1.615**	**0.083**
θ_{023}	-0.516	0.131	-1.731	0.149	-0.238	0.066
θ_{123}	0.059	0.017	0.222	0.032	0.066	0.018
θ_{223}	-0.082	0.018	-2.172	0.078	-0.099	0.015
θ_{022}	-2.707	0.168	-3.202	0.144	-2.478	0.146
θ_{122}	-0.220	0.063	-0.400	0.061	-0.226	0.061
θ_{222}	-0.078	0.035	-1.327	0.119	-0.095	0.034
θ_{021}	-2.644	0.151	-2.649	0.110	-2.466	0.138
θ_{121}	-0.150	0.044	-0.213	0.050	-0.153	0.042
θ_{221}	0.003	0.035	-0.812	0.130	-0.014	0.033
θ_{012}	-3.510	0.215	-7.765	0.232	-3.567	0.213
θ_{112}	-0.109	0.037	-0.270	0.076	-0.120	0.038
θ_{212}	-0.081	0.055	-2.520	0.224	-0.067	0.055
θ_{011}	-3.138	0.158	-3.512	0.140	-3.197	0.156
θ_{111}	-0.166	0.050	-0.440	0.076	-0.179	0.051
θ_{211}	-0.055	0.036	-0.777	0.158	-0.041	0.036
	Log likelihood: -19131		Log likelihood: -19148.1		Log likelihood: -19451.7	

In the first model (I) we include the local unemployment rate in vector V only and keep g(Z) as in the bench-mark model. In the second model (II) we keep V as in the main model and set g(Z) equal to one (Z=0), and in the third case we set g(Z) equal to one and exclude all other variables apart from the local unemployment rate in V. In all three cases we see that λ is no longer significantly less than 1, which means that the utility function is no longer strictly concave in income. This indicates that for the present group it is important how the limitations we believe they face in the labour market, are handled. The results above indicate that limitations are critical in getting sensible results for the present group, and that explaining the disability problem as a choice-only-problem does not give "sensible" results.

As described in Section 3 the wage prediction is associated with great uncertainty for the present group, and one could argue that a regression model controlling for sample selection is problematic when the fraction censored is as large as in this paper. Let's therefore look at the results when we replace income from the Heckman selection based equation with income from an OLS-regression. Otherwise, wages are calculated in the same way as described in Section 3. The variables used in this estimation are the same as in the selection part of the Heckman model. The estimation is done separately for men and women (coefficients in the appendix). Table 5 and Table 8 below shows that the predicted changes of the variables described are not affected by the income estimation methods used, and the conclusions from above are valid.

Table 8

Simulation results, OLS income prediction

Predicted probabilities (fractions) in percent

		No work, no pension	Some part-time, no pension	Much part-time, no pension	Full-time	100% disabled	Combining some part-time and pension	Combining much part-time and pension
Observed fraction in each state (13588 persons)		25	3.5	4.33	30.72	32.62	2.51	1.34
Simulation with true value of explanatory variables	P5	17.47	2.88	3.50	30.08	32.13	2.10	1.11
	Mean	23.31	3.43	4.25	31.63	33.55	2.47	1.36
	P95	25.45	3.95	4.80	34.11	36.19	2.90	1.64
Increase net income if working by 10 percent	P5	16.96	3.44	3.80	30.71	31.47	2.02	1.09
	Mean	22.86	3.96**	4.52	32.09	32.85	2.40	1.33
	P95	25.14	4.63	5.14	34.92	35.26	2.78	1.58
Reduce disability pension by 10 percent	P5	18.63	2.97	3.65	31.16	29.53	2.21	1.17
	Mean	24.44**	3.59	4.39	32.58**	31.02**	2.57	1.42
	P95	27.01	4.24	5.01	35.15	33.57	3.00	1.67
Increase income and reduce pension by 10 percent	P5	18.24	3.51	3.98	31.55	29.06	2.10	1.16
	Mean	23.78	4.12**	4.72*	33.01**	30.49**	2.52	1.37
	P95	26.14	4.7	5.35	35.82	32.74	2.94	1.62
Increase local unemployment rate by 3 percentage points	P5	19.45	2.98	3.28	25.41	34.23	2.02	1.06
	Mean	25.41	3.43	3.9**	27.16**	36.43**	2.39	1.27
	P95	28.05	3.98	4.52	30.19	39.35	2.88	1.51
Adjust medical diagnoses from high risk to low risk	P5	20.21	3.94	4.47	35.10	21.47	1.61	0.80
	Mean	27.04**	4.7**	5.31**	36.76**	23.23**	1.89**	1.06**
	P95	29.49	5.57	6.08	40.01	25.39	2.22	1.24

Another objection to the bench-mark model could be that we have included education in opportunities (the V-vector), and not in the preference part of the model. One could argue that preferences for leisure depend on, or at least is correlated with education, and that the low- educated in general have less interesting jobs, and therefore higher preferences for leisure. In Table 9 below we show the results from a model where education is included in the preference function (X-vector), and excluded from the V-vector. A comparison of the results with the benchmark model shows (Table 9 and Table 5) that the results hardly differ at all.

Table 9

Simulation results when education is part of preferences

Predicted probabilities (fractions) in percent

		No work, no pension	Some part-time, no pension	Much part-time, no pension	Full-time	100% disabled	Combining some part-time and pension	Combining much part-time and pension
Observed fraction in each state (13588 persons)		25	3.5	4.33	30.72	32.62	2.51	1.34
Simulation with true value of explanatory variables	P5	21.95	3.02	3.60	30.12	31.61	2.06	1.14
	Mean	24.22	3.50	4.27	31.16	33.02	2.49	1.34
	P95	25.71	3.91	4.85	32.37	34.75	2.89	1.59
Increase net income if working by 10 percent	P5	21.10	3.47	3.89	30.71	31.07	2.12	1.07
	Mean	23.67	3.93**	4.59*	31.84	32.23*	2.44	1.30
	P95	25.37	4.43	5.13	32.93	33.71	2.80	1.52
Reduce disability pension by 10 percent	P5	22.58	3.12	3.73	30.95	29.61	2.18	1.15
	Mean	25.14**	3.64	4.39	32.14**	30.68**	2.61	1.39
	P95	26.42	4.12	5.02	33.46	32.32	3.05	1.67
Increase income and reduce pension by 10 percent	P5	21.81	3.61	4.02	31.76	28.59	2.12	1.17
	Mean	24.54	4.1**	4.75*	32.8**	29.92**	2.52	1.38
	P95	26.1	4.68	5.38	34.24	31.56	2.86	1.58
Increase local unemployment rate by 3 percentage points	P5	22.10	2.92	3.27	24.91	35.58	2.09	1.10
	Mean	25.01	3.30	3.82**	26.5**	37.54**	2.50	1.34
	P95	27.16	3.79	4.29	27.86	39.45	2.99	1.57
Adjust medical diagnoses from high risk to low risk	P5	24.98	4.01	4.56	35.01	21.55	1.59	0.86
	Mean	27.76**	4.63**	5.38**	36.47**	22.77**	1.92**	1.07**
	P95	29.68	5.24	6.13	38.03	24.27	2.20	1.29

As mentioned there is a group (25 % of the present population when evaluated 12 months after the rehabilitation spell ends) that does not fit into the work-benefit categories constructed in this study. As mentioned in Section 3 we have to assume that the members of this group receive at least some kind of income even if they are not working and not receiving benefits. So far this income has been set to 30000 NOK pr year. Let us test whether the results are sensible to this assumption, and estimate the model when income in this state is raised to 50000. We see from Table 10 that the results change very little, and that the main conclusions hold.

Table 10

Simulation results when income in state no work no disability is increased to 50000

Predicted probabilities (fractions) in percent

		No work, no pension	Some part-time, no pension	Much part-time, no pension	Full-time	100% disabled	Combining some part-time and pension	Combining much part-time and pension
Observed fraction in each state (13588 persons)		25	3.5	4.33	30.72	32.62	2.51	1.34
Simulation with true value of explanatory variables	P5	23.93	3.08	3.42	29.93	31.82	2.02	1.10
	Mean	25.00	3.45	4.13	30.96	32.73	2.42	1.31
	P95	28.98	3.89	4.66	31.78	33.63	2.75	1.54
Increase net income if working by 10 percent	P5	23.61	3.43	3.62	30.28	31.09	2.03	1.06
	Mean	24.47	3.94**	4.43	31.42	32.09	2.37	1.28
	P95	25.29	4.50	5.07	32.66	33.17	2.70	1.54
Reduce disability pension by 10 percent	P5	25.06	3.13	3.63	30.77	29.40	2.17	1.14
	Mean	26.01	3.55	4.26	31.89*	30.39**	2.53	1.37
	P95	26.84	3.97	4.74	32.92	31.27	2.91	1.60
Increase income and reduce pension by 10 percent	P5	24.50	3.49	3.88	31.31	28.79	2.10	1.07
	Mean	25.43	4.09**	4.57*	32.34**	29.79**	2.46	1.32
	P95	26.19	4.67	5.21	33.43	31.01	2.79	1.55
Increase local unemployment rate by 3 percentage points	P5	24.64	2.87	3.18	24.61	35.77	2.08	1.07
	Mean	26.12*	3.29	3.67**	25.74**	37.37**	2.50	1.30
	P95	27.51	3.69	4.13	27.17	38.95	2.91	1.56
Adjust medical diagnoses from high risk to low risk	P5	27.83	4.13	4.54	34.79	21.36	1.52	0.77
	Mean	28.89**	4.67**	5.18**	35.89**	22.5**	1.86**	1.00**
	P95	29.88	5.25	5.77	37.30	23.68	2.20	1.20

The results presented so far have been for the entire population. Next, we study whether the results presented so far is driven by some particular groups. To highlight this issue we estimate the model separately for those with high- and those with low education. We also estimate the model separately for men and women. Table 11 shows the results for those with low education (less than 12 years in this setting) and Table 12 shows the results for those with more than 11 years of education. We see from the "Observed fraction in each state" that the low- educated are highly overrepresented among the 100% disabled, and underrepresented among those working. The effects of changes in economic incentives do not differ much between the two groups, and there is a statistical significant effect of simultaneously increasing net income if working and reducing pension if disabled. Turning to the effect of changes in the unemployment rate we see that the effect is larger for the low-education group. An increase in the (local) unemployment rate of 3 percentage points increased the fraction disabled by 7 percentage point (17%) and decreases the fraction working fulltime by 7 percentage points (28%). In comparison the corresponding numbers for those with more than 11 years of education is 3 percentage points (12%), 3 percentage points (8%).

Table 11

Results for persons with less than 12 years education

Predicted probabilities (fractions) in percent

		No work, no pension	Some part-time, no pension	Much part-time, no pension	Full-time	100% disabled	Combining some part-time and pension	Combining much part-time and pension
Observed fraction in each state (8143) persons		26.83	3.17	3.59	23.7	38.56	2.73	1.43
Simulation with true value of explanatory variables	P5	16.01	1.42	1.25	22.79	38.03	1.10	0.73
	Mean	24.76	2.60	2.80	25.43	40.87	2.25	1.30
	P95	28.75	3.62	4.11	30.38	46.04	3.03	1.80
Increase net income if working by 10 percent	P5	15.34	1.67	1.38	23.08	37.00	1.09	0.71
	Mean	24.46	3.2**	3.04	25.83	40.01	2.20	1.28
	P95	28.66	4.38	4.46	30.62	44.68	3.06	1.80
Reduce disability pension by 10 percent	P5	16.59	1.47	1.34	23.61	35.03	1.23	0.79
	Mean	26.26**	2.81	2.92	26.6**	37.64**	2.41	1.35
	P95	30.35	3.91	4.21	31.41	42.13	3.33	1.93
Increase income and reduce pension by 10 percent	P5	16.25	1.68	1.41	24.27	33.94	1.13	0.76
	Mean	25.83	3.33**	3.17*	27.09**	36.9**	2.35	1.34
	P95	30.01	4.73	4.49	33.00	41.48	3.17	1.89
Increase local unemployment rate by 3 percentage points	P5	16.24	1.32	1.06	16.42	44.09	0.96	0.62
	Mean	25.61	2.33	2.2**	18.79**	47.87**	2.06	1.14
	P95	30.54	3.17	3.15	22.35	53.97	2.89	1.57
Adjust medical diagnoses from high risk to low risk	P5	19.30	2.01	1.57	28.18	25.17	0.81	0.59
	Mean	30.04**	3.92**	3.72*	31.4**	28.14**	1.77**	1.00**
	P95	34.66	5.70	5.35	37.83	33.16	2.45	1.45

Table 12

Results for persons with more than 11 years of education

Predicted probabilities (fractions) in percent

		No work, no pension	Some part-time, no pension	Much part-time, no pension	Full-time	100% disabled	Combining some part-time and pension	Combining much part-time and pension
Observed fraction in each state (5445) persons		22.24	3.99	5.44	41.21	23.72	2.19	1.21
Simulation with true value of explanatory variables	P5	15.34	3.41	4.35	39.90	22.53	1.57	0.84
	Mean	20.62	4.01	5.39	42.16	24.42	2.18	1.24
	P95	23.59	4.67	6.26	45.70	26.28	2.64	1.68
Increase net income if working by 10 percent	P5	14.21	3.73	4.85	41.09	21.75	1.63	0.84
	Mean	19.87	4.48*	5.76	43.02	23.57	2.10	1.20
	P95	22.54	5.25	6.82	46.29	25.26	2.59	1.56
Reduce disability pension by 10 percent	P5	15.67	3.48	4.69	41.09	20.67	1.68	0.91
	Mean	21.24	4.14	5.61	43.20	22.27**	2.26	1.28
	P95	23.78	4.71	6.35	46.65	24.44	2.87	1.68
Increase income and reduce pension by 10 percent	P5	15.06	3.76	5.13	41.81	19.99	1.56	0.85
	Mean	20.44	4.62*	5.89*	44.07**	21.56**	2.20	1.22
	P95	23.14	5.56	6.79	48.18	23.44	2.72	1.66
Increase local unemployment rate by 3 percentage points	P5	14.70	3.29	4.31	35.52	25.25	1.80	0.92
	Mean	20.86	4.02	5.17	38.9**	27.37**	2.36	1.32
	P95	24.91	4.83	6.08	44.24	30.12	3.03	1.70
Adjust medical diagnoses from high risk to low risk	P5	16.77	4.15	5.32	44.80	14.76	1.26	0.70
	Mean	22.28**	5.04	6.35*	47.12**	16.54**	1.71*	0.95
	P95	25.28	5.94	7.34	51.03	18.03	2.26	1.30

Turning to the difference between men and women, we first see that women are over-represented among part-time workers, and among the 100% disabled. Men are overrepresented among the full-time workers and among those neither on disability or working[12]. For both men and women there is a significant effect of changes in economic incentives, and of changes in the unemployment rate. The latter effect is slightly higher for men.

[12] When comparing to the fractions in each state 24 months later the fraction men in each state falls to the level of women. This might indicate that it is particularly for men that it takes time before a more final state is decided.

Table 13

Results for men

Predicted probabilities (fractions) in percent

		No work, no pension	Some part-time, no pension	Much part-time, no pension	Full-time	100% disabled	Combining some part-time and pension	Combining much part-time and pension
Observed fraction in each state (7187) persons)		27.36	1.87	1.49	36.83	30.46	1.18	0.82
Simulation with true value of explanatory variables	P5	19.11	1.57	1.19	35.83	29.53	0.91	0.58
	Mean	24.96	1.97	1.52	37.90	31.57	1.22	0.85
	P95	28.05	2.41	1.85	41.20	34.78	1.56	1.13
Increase net income if working by 10 percent	P5	18.33	1.68	1.29	36.87	28.98	0.88	0.60
	Mean	24.40	2.25	1.66	38.8*	30.84	1.22	0.83
	P95	27.45	2.79	2.06	42.14	34.04	1.58	1.11
Reduce disability pension by 10 percent	P5	20.59	1.65	1.20	37.18	27.08	0.99	0.63
	Mean	26.16*	2.04	1.58	38.99*	29.04**	1.30	0.89
	P95	29.18	2.49	1.98	42.67	31.95	1.68	1.18
Increase income and reduce pension by 10 percent	P5	19.49	1.82	1.31	38.15	26.14	0.98	0.59
	Mean	25.48	2.33*	1.74	40.08**	28.21**	1.26	0.89
	P95	28.54	2.75	2.11	44.20	31.07	1.61	1.18
Increase local unemployment rate by 3 percentage points	P5	20.84	1.54	1.09	28.57	32.52	0.95	0.56
	Mean	27.32**	2.00	1.42	30.97**	36.18**	1.27	0.84
	P95	31.31	2.46	1.75	34.10	39.82	1.59	1.12
Adjust medical diagnoses from high risk to low risk	P5	21.21	2.07	1.41	40.32	21.20	0.81	0.49
	Mean	27.62**	2.57	1.83	42.9**	23.28**	1.06	0.73
	P95	31.06	3.26	2.21	47.46	26.38	1.32	1.02

Table 14

Results for women

Predicted probabilities (fractions) in percent

		No work, no pension	Some part-time, no pension	Much part-time, no pension	Full-time	100% disabled	Combining some part-time and pension	Combining much part-time and pension
Observed fraction in each state (6401) persons)		22.34	5.33	7.51	23.86	35.04	4	1.92
Simulation with true value of explanatory variables	P5	12.87	4.39	6.22	23.84	33.72	2.89	1.22
	Mean	20.20	5.09	7.07	25.93	36.32	3.63	1.76
	P95	24.21	6.24	8.07	28.59	40.05	4.33	2.23
Increase net income if working by 10 percent	P5	12.32	5.17	6.52	23.92	33.39	2.91	1.35
	Mean	19.68	5.94**	7.52	26.02	35.58	3.53	1.73
	P95	24.00	6.97	8.37	28.71	38.86	4.24	2.18
Reduce disability pension by 10 percent	P5	12.90	4.69	6.51	24.83	31.51	3.22	1.40
	Mean	21.00	5.38	7.40	26.77*	33.83**	3.79	1.83
	P95	25.49	6.04	8.21	29.22	37.99	4.34	2.34
Increase income and reduce pension by 10 percent	P5	12.63	5.35	6.91	24.71	30.62	3.10	1.41
	Mean	20.52	6.17**	7.86*	26.82*	33.12**	3.69	1.82
	P95	24.61	7.10	8.89	29.90	36.39	4.36	2.33
Increase local unemployment rate by 3 percentage points	P5	11.73	4.10	5.34	20.00	37.99	3.21	1.41
	Mean	19.53	4.70	6.36**	22.42**	41.23**	3.90	1.88
	P95	23.60	5.47	7.37	25.64	48.90	4.61	2.35
Adjust medical diagnoses from high risk to low risk	P5	15.65	6.55	7.97	28.59	21.00	2.16	0.95
	Mean	24.74**	7.33**	9.25**	31.29**	23.51**	2.62**	1.27**
	P95	29.28	8.58	10.46	35.89	27.57	3.16	1.65

Conclusion

In the present paper we extend an established method in the labour supply literature to fit a group where claiming social security benefit is a realistic alternative to market work. Distinguishing between variations in individual preferences on the one hand and variations in choice sets on the other is done in order to study how economic incentives affect the flow into disability, work, or combinations of these two. One necessary condition for this study is the ability predict what members of the group under study will earn if they work. To do this we have established a method using previous income to predict the future income if such income is observed, and if not the earning potential is estimated from a regression model. We have also simulated the uncertainty of the model predictions based on parametric bootstrap techniques.

Based on the results described in this article we conclude that changing economic incentives for the group described have a small- to moderate effect on the realized employment pattern. The simulations are done with increasing net labour income by 10 % and reducing net pension with 10 %, changes that would be dramatic in the present tax- and benefit system. If net labour income is increased and disability is reduced, the fraction working full-time is predicted to increase by 1.5 percentage points (about 5%). The corresponding numbers being 100% disabled is predicted to be reduced by 3 percentage points (about 9 %). The predicted confidence intervals show that there are statistical significant changes in labour market outcomes resulting from such changes in incentives. Factors that have the strongest effect on labour supply (diagnoses, and unemployment rate) are factors that are considered beyond control of the individual, and related to limitations in their choice set. We simulate the effect of business cycle fluctuations by increasing the local unemployment rate with 3 percentage points. As in the case of hypothetical income changes, such increase in unemployment would be a dramatic, but not completely unrealistic, recession for the Norwegian economy. In the bench mark model the simulation of such a recession would decrease the fraction working fulltime with about 5 percentage points (about 20 %). Corresponding numbers for the fraction becoming 100 % disabled is an increase of about 4.5 percentage points (about 12 %). The main results are not very sensitive to choice of model. However, we find that how the choice-limitation functions are specified is important.

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Appendix

A 1

Heckman selection model (Regression model with sample selection)

	Men		Women	
	Number of observations	7456	Number of observations	6547
	Censored observations	4188	Censored observations	4602
	Uncensored observations	3268	Uncensored observations	1945
	Coefficient	Std. Err.	Coefficient	Std. Err.
The wage equation				
Less than 2 years of experience	Reference		Reference	
2 years experience	-0,226	0,072	-0,054	0,069
3 years experience	-0,235	0,042	-0,161	0,042
4 years experience	-0,227	0,036	-0,178	0,035
5 years experience	-0,182	0,033	-0,095	0,032
6 years experience	-0,139	0,030	-0,052	0,031
7 years experience	-0,111	0,030	-0,095	0,027
8 years experience	-0,118	0,030	-0,081	0,028
9 years experience	-0,083	0,027	-0,059	0,025
10 years experience	-0,075	0,027	-0,058	0,027
11 years experience	-0,056	0,027	-0,044	0,024
12 years experience	-0,007	0,025	-0,044	0,023
13 years experience	0,008	0,025	-0,014	0,023
14 years experience	0,038	0,026	0,000	0,023
15 years experience	0,033	0,026	0,000	0,024
16 years experience	0,056	0,027	0,035	0,025
17 years experience	0,084	0,028	-0,008	0,024
18 years experience	0,116	0,028	0,058	0,025
19 years experience	0,146	0,028	0,062	0,025
20 years experience	0,180	0,027	0,067	0,023
age 21	-0,036	0,079	-0,055	0,181
age 22	0,013	0,053	0,024	0,073
age 23	-0,026	0,045	0,046	0,055
age 24	0,025	0,043	0,016	0,050
age 25	0,035	0,038	0,022	0,043
age 26	0,055	0,037	-0,069	0,038
age 27	0,073	0,036	-0,056	0,035
age 28	0,097	0,034	0,032	0,037
age 29	0,060	0,033	0,002	0,036
age 30	0,051	0,031	0,018	0,032
age 31	0,061	0,030	0,025	0,032
age 32	0,085	0,029	0,009	0,031
age 33	0,021	0,029	0,025	0,031
age 34	0,086	0,029	0,009	0,033
age 35	0,040	0,028	0,080	0,030

age 36	-0,002	0,028	-0,015	0,030
age 37	0,001	0,027	-0,005	0,031
age 38	-0,010	0,028	0,014	0,031
age 39	0,032	0,028	0,020	0,033
age 40	Reference		Reference	
age 41	-0,027	0,030	-0,006	0,030
age 42	-0,006	0,028	-0,027	0,029
age 43	-0,037	0,030	0,053	0,030
age 44	-0,029	0,028	0,043	0,031
age 45	-0,017	0,029	0,003	0,030
age 46	-0,007	0,030	0,037	0,031
age 47	-0,031	0,029	0,052	0,030
age 48	-0,008	0,031	-0,005	0,031
age 49	0,009	0,032	0,042	0,032
age 50	-0,038	0,031	0,014	0,033
age 51	0,006	0,032	0,030	0,034
age 52	-0,012	0,033	0,047	0,034
age 53	-0,014	0,032	0,041	0,034
age 54	-0,050	0,032	0,032	0,038
age 55	0,003	0,035	-0,014	0,035
Education info is missing	0,026	0,029	0,016	0,030
7 years education	-0,118	0,027	-0,064	0,040
8 years education	-0,089	0,023	-0,083	0,025
9 years education	-0,084	0,014	-0,065	0,018
10 years education	-0,088	0,011	-0,038	0,012
11 years education	-0,037	0,014	-0,020	0,015
12 years education	Reference		Reference	
13 years education	0,043	0,023	0,070	0,021
14 years education	0,006	0,028	0,101	0,027
15 years education	0,009	0,023	0,093	0,018
16 years education	0,013	0,029	0,102	0,018
17 years education	0,083	0,072	0,518	0,177
18+ years education	0,307	0,060	0,281	0,055
No-OECD immigrant	0,014	0,023	-0,043	0,024
Not unemployed last 3 years	Reference		Reference	
Unemployed 1-3 months	-0,023	0,010	-0,031	0,011
unemployed 4-11 months	-0,047	0,012	-0,031	0,013
unemployed more than 11 months	-0,113	0,023	-0,058	0,020
Not reported sick last 3 years	Reference		Reference	
Sick 1-3 months	0,011	0,018	-0,027	0,020
Sick 4-11 months	0,036	0,017	-0,018	0,016
Sick more than 11 months	0,073	0,020	0,000	0,015
Rehabilitation 3 months or less	-0,040	0,020	-0,026	0,024
Rehabilitation 4-11 months	Reference		Reference	
Rehabilitation more than 11 months	-0,012	0,011	-0,016	0,012
Not on labour market programs	Reference		Reference	

On labour marked programs 1-3 months	-0,010	0,012	0,013	0,016
On labour marked programs 4-11 months	-0,059	0,015	-0,052	0,018
On labour marked programs more than 11 months	-0,080	0,032	-0,015	0,042
Constant	12,504	0,045	12,459	0,039
The selection equation				
age21	0,331	0,249	-0,588	0,492
age22	0,838	0,195	0,122	0,267
age23	0,732	0,176	0,359	0,225
age24	0,864	0,168	0,343	0,206
age25	1,014	0,155	0,307	0,183
age26	0,870	0,151	0,586	0,170
age27	0,735	0,147	0,599	0,161
age28	0,800	0,142	0,262	0,163
age29	0,681	0,144	0,284	0,161
age30	0,575	0,134	0,412	0,147
age31	0,483	0,133	0,382	0,146
age32	0,434	0,134	0,651	0,151
age33	0,263	0,133	0,236	0,140
age34	0,281	0,134	0,154	0,148
age35	0,261	0,132	0,232	0,140
age36	0,202	0,135	0,235	0,141
age37	0,132	0,136	0,009	0,143
age38	-0,105	0,138	0,083	0,141
age39	-0,152	0,140	-0,189	0,142
age40	Reference		Reference	
age41	-0,161	0,147	-0,008	0,140
age42	-0,133	0,141	-0,041	0,136
age43	-0,260	0,142	-0,096	0,139
age44	-0,136	0,138	-0,230	0,145
age45	-0,190	0,147	-0,013	0,138
age46	-0,132	0,152	-0,297	0,144
age47	-0,048	0,149	-0,151	0,142
age48	-0,220	0,153	-0,117	0,150
age49	-0,209	0,165	-0,269	0,155
age50	-0,180	0,159	-0,299	0,157
age51	-0,170	0,165	-0,302	0,162
age52	-0,412	0,165	-0,284	0,163
age53	-0,400	0,164	-0,316	0,162
age54	-0,328	0,167	-0,232	0,188
age55	-0,140	0,177	0,094	0,182
Spouses income less than 50 000	-0,136	0,137	0,120	0,259
Spouses income 50-100 000	-0,217	0,157	0,368	0,318
Spouses income 100-150 000	-0,064	0,124	0,443	0,220

spouses income 150- 200 000	Reference		Reference	
Spouses income 200-250 000	0,004	0,105	0,193	0,153
spouses income 250- 300 000	0,075	0,109	-0,055	0,136
Spouses income 300-350 000	-0,098	0,133	0,031	0,132
spouses income above 350 000	-0,017	0,181	0,076	0,126
Married	0,247	0,082	-0,208	0,121
Less than 2 years of experience	Reference		Reference	
2 years experience	-2,317	0,148	-2,337	0,168
3 years experience	-1,183	0,131	-1,232	0,142
4 years experience	-1,016	0,129	-1,026	0,130
5 years experience	-0,694	0,128	-0,804	0,128
6 years experience	-0,486	0,125	-0,739	0,126
7 years experience	-0,528	0,126	-0,531	0,115
8 years experience	-0,552	0,128	-0,519	0,120
9 years experience	-0,292	0,121	-0,365	0,111
10 years experience	-0,288	0,118	-0,415	0,115
11 years experience	-0,259	0,120	-0,160	0,108
12 years experience	0,144	0,116	0,039	0,107
13 years experience	0,193	0,116	0,147	0,108
14 years experience	0,298	0,121	0,112	0,110
15 years experience	0,239	0,117	0,182	0,112
16 years experience	0,406	0,119	0,228	0,117
17 years experience	0,689	0,121	0,501	0,119
18 years experience	0,779	0,119	0,296	0,118
19 years experience	0,956	0,117	0,400	0,125
20 years experience	1,110	0,112	0,653	0,113
Education info is missing	-0,647	0,105	0,026	0,131
7 years education	-0,445	0,131	-0,215	0,188
8 years education	-0,173	0,130	-0,241	0,118
9 years education	-0,279	0,065	-0,053	0,080
10 years education	-0,340	0,048	-0,132	0,055
11 years education	-0,272	0,067	-0,194	0,068
12 years education	Reference		Reference	
13 years education	-0,176	0,109	0,018	0,101
14 years education	-0,072	0,124	-0,024	0,121
15 years education	-0,003	0,105	-0,050	0,080
16 years education	-0,198	0,140	0,216	0,089
17 years education	-0,331	0,282	-0,349	0,610
18+ years education	0,156	0,310	-0,005	0,268
No OECD-immigrant	0,716	0,086	0,528	0,103
Children below 3 years old	0,060	0,049	-0,209	0,057
Children 4-7 years	-0,008	0,050	-0,352	0,051
Children 8-11 years	-0,076	0,053	-0,325	0,050
Children 12-18 years	-0,027	0,055	-0,004	0,049
Not unemployed last 3 years	Reference		Reference	
Unemployed 1-3 months	-0,154	0,049	-0,085	0,052
unemployed 4-11 months	-0,446	0,051	-0,217	0,058
unemployed more than 11 months	-1,039	0,069	-0,493	0,080

Not reported sick last 3 years	Reference		Reference	
Sick 1-3 months	0,656	0,063	0,470	0,077
Sick 4-11 months	0,797	0,053	0,623	0,060
Sick more than 11 months	1,207	0,046	0,787	0,049
Rehabilitation 3 months or less	0,076	0,117	0,295	0,129
Rehabilitation 4-11 months	Reference		Reference	
Rehabilitation more than 11 months	-0,219	0,057	-0,221	0,060
Not on labour market programs	Reference		Reference	
On labour marked programs 1-3 months	-0,048	0,058	0,026	0,073
On labour marked programs 4-11 months	-0,091	0,062	-0,163	0,078
On labour marked programs more than 11 months	-0,012	0,127	-0,011	0,169
Constant	-0,499	0,145	-0,296	0,150
Heckman's lambda	-0,009	0,025	-0,081	0,017

A 2 Results OLS-regression

	Men		Women	
	Coefficients	std.error	Coefficients	std.error
age21	-0,005	0,080	-0,072	0,186
age22	0,036	0,053	0,038	0,074
age23	0,010	0,044	0,078	0,056
age24	0,057	0,042	0,045	0,050
age25	0,067	0,036	0,051	0,044
age26	0,080	0,036	-0,029	0,038
age27	0,093	0,035	-0,017	0,035
age28	0,117	0,032	0,055	0,038
age29	0,079	0,032	0,028	0,036
age30	0,064	0,030	0,053	0,032
age31	0,076	0,030	0,058	0,032
age32	0,096	0,029	0,053	0,031
age33	0,026	0,029	0,043	0,031
age34	0,091	0,029	0,026	0,033
age35	0,049	0,029	0,098	0,030
age36	0,003	0,029	0,008	0,030
age37	0,011	0,028	-0,004	0,031
age38	0,000	0,029	0,026	0,031
age39	0,032	0,029	0,005	0,032
age40	Reference		Reference	
age41	-0,025	0,030	-0,006	0,030
age42	0,003	0,029	-0,025	0,029
age43	-0,028	0,030	0,038	0,029

age44	-0,028	0,028	0,024	0,031
age45	-0,025	0,030	-0,002	0,030
age46	0,001	0,030	0,023	0,031
age47	-0,028	0,030	0,035	0,030
age48	-0,007	0,032	-0,010	0,031
age49	0,016	0,033	0,028	0,032
age50	-0,044	0,032	-0,003	0,033
age51	0,008	0,033	0,009	0,034
age52	-0,017	0,033	0,035	0,034
age53	-0,012	0,033	0,025	0,034
age54	-0,045	0,033	0,018	0,038
age55	0,005	0,036	-0,011	0,034
Spouses income less than 50 000	0,031	0,029	0,113	0,060
Spouses income 50-100 000	-0,033	0,031	0,058	0,073
Spouses income 100-150 000	0,029	0,023	0,151	0,048
spouses income 150- 200 000	Reference		Reference	
Spouses income 200-250 000	0,032	0,018	0,027	0,034
spouses income 250- 300 000	-0,018	0,019	-0,010	0,031
Spouses income 300-350 000	0,050	0,024	0,052	0,030
spouses income above 350 000	0,104	0,032	0,047	0,029
Married	0,014	0,015	-0,050	0,028
Less than 2 years of experience	Reference		Reference	
2 years experience	-0,232	0,057	-0,210	0,064
3 years experience	-0,244	0,037	-0,233	0,040
4 years experience	-0,232	0,034	-0,237	0,033
5 years experience	-0,182	0,032	-0,143	0,031
6 years experience	-0,137	0,030	-0,087	0,030
7 years experience	-0,106	0,030	-0,127	0,026
8 years experience	-0,110	0,030	-0,113	0,027
9 years experience	-0,084	0,028	-0,076	0,025
10 years experience	-0,073	0,027	-0,081	0,026
11 years experience	-0,055	0,027	-0,050	0,023
12 years experience	-0,005	0,025	-0,037	0,022
13 years experience	0,012	0,025	-0,004	0,022
14 years experience	0,041	0,026	0,014	0,023
15 years experience	0,032	0,026	0,016	0,024
16 years experience	0,062	0,027	0,049	0,025
17 years experience	0,091	0,027	0,022	0,024
18 years experience	0,114	0,026	0,080	0,024
19 years experience	0,151	0,025	0,089	0,025
20 years experience	0,182	0,024	0,105	0,022
Education info is missing	0,034	0,028	0,027	0,030
7 years education	-0,113	0,027	-0,072	0,040
8 years education	-0,094	0,023	-0,093	0,025
9 years education	-0,079	0,014	-0,066	0,017
10 years education	-0,090	0,010	-0,044	0,012
11 years education	-0,040	0,014	-0,033	0,015
12 years education	Reference		Reference	

13 years education	0,043	0,023	0,070	0,021
14 years education	0,017	0,028	0,100	0,026
15 years education	-0,002	0,024	0,085	0,017
16 years education	0,003	0,030	0,110	0,017
17 years education	0,090	0,073	0,528	0,179
18+ years education	0,303	0,061	0,283	0,055
No OECD-immigrant	0,022	0,021	-0,004	0,024
Children below 3 years old	0,007	0,010	-0,015	0,013
Children 4-7 years	0,018	0,010	-0,035	0,012
Children 8-11 years	0,002	0,011	-0,013	0,012
Children 12-18 years	0,003	0,011	0,006	0,011
Not unemployed last 3 years				
Unemployed 1-3 months	-0,026	0,010	-0,038	0,011
unemployed 4-11 months	-0,053	0,011	-0,044	0,013
unemployed more than 11 months	-0,122	0,018	-0,089	0,019
Not reported sick last 3 years	Reference		Reference	
Sick 1-3 months	0,016	0,016	0,004	0,019
Sick 4-11 months	0,041	0,013	0,020	0,014
Sick more than 11 months	0,081	0,011	0,046	0,012
Rehabilitation 3 months or less	0,015	0,013	0,037	0,015
Rehabilitation 4-11 months	Reference		Reference	
Rehabilitation more than 11 months	-0,036	0,021	-0,016	0,024
Not on labour market programs	-0,011	0,011	-0,025	0,012
On labour marked programs 1-3 months	-0,012	0,013	0,013	0,016
On labour marked programs 4-11 months	-0,061	0,015	-0,059	0,018
On labour marked programs more than 11 months	-0,075	0,032	-0,016	0,042
Constant	12,423	0,032	12,361	0,032

A3

Drop fraction of missing years

	Estimates	Std. Error
γ_2	1,270	0,218
γ_3	1,079	0,193
γ_4	1,000	
γ_5	0,328	0,067
γ_6	0,401	0,158
γ_7	-0,267	0,051
β_2	-0,548	0,152
β_3	1,423	0,265
β_4	-1,146	0,141

β_5	-4,314	0,439
g_0	0,953	0,105
g_1	-0,146	0,052
g_2	-0,003	0,039
g_3	-0,427	0,057
g_4	-0,009	0,057
g_5	0,121	0,073
g_6	0,029	0,017
g_7	0,355	0,043
g_8	0,776	0,047
g_9	0,708	0,094
α_0	0,823	0,070
α_1	-0,300	0,064
λ	0,882	0,142
θ_{023}	-0,469	0,159
θ_{123}	0,095	0,011
θ_{223}	-0,386	0,067
θ_{022}	-2,401	0,182
θ_{122}	-0,299	0,034
θ_{222}	-0,448	0,087
θ_{021}	-0,695	0,110
θ_{121}	-0,252	0,030
θ_{221}	-0,069	0,053
θ_{012}	-3,971	0,188
θ_{112}	-0,295	0,040
θ_{212}	-0,134	0,096
θ_{011}	-2,576	0,172
θ_{111}	-0,674	0,063
θ_{211}	0,424	0,077