Earnings Capacity and Labour Market Participation

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May 1996

Abstract

We analyze models for individuals' labour market state. We distinguish between full-time and part-time work, but also between various types of economic inactivity, i.e. unemployment, disability, early retirement and working in the household. We consider the impact on the state probabilities of individual attributes, with emphasis on earnings capacity. We take account of the problem that only earnings of workers are observed, and of the potential endogeneity of earnings. We generalize the multinomial logit model, allowing for unobserved heterogeneity. Moreover, we allow for non-linearities due to, for example, minimum wages. Using micro-data from the Dutch Socio-Economic Panel, we look at static models and compare results for various years. Finally, we also look at dynamic models, in which the transition probabilities from employment into various inactivity states are modelled, conditional on job characteristics.

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[1] We are grateful to an anonymous CentER DP referee for useful comments. Statistics Netherlands (CBS) is gratefully acknowledged for providing the data. Research of the first author has been made possible by a fellowship of the Netherlands Royal Academy of Arts and Sciences.

1. Introduction

During the past decades, labour market policy in industrialised countries has paid a vast amount of attention to the problem of unemployment. At least in The Netherlands, policy makers now realise that other types of economic inactivity may hinder the economy just as much (see WRR, 1990). For example, some people claim that elderly workers who lost their job, have been given easy access to disability benefits. This keeps unemployment low, but neither decreases the total benefits burden, nor increases total production. And apart from differences in benefit regulations, it does not make the workers involved better off. The example makes clear that the unemployment problem cannot be isolated from other, possibly related, types of economic inactivity. This paper aims at considering a number of economically active and economically inactive states (some clearly undesirable, some possibly less undesirable) simultaneously.

Compared to other industrialised countries, labour market participation in The Netherlands is low. According to the OECD Historical Statistics (1960-1989), net participation in persons (i.e. number of persons employed divided by total population of age 15-64) in 1960 was 61% in The Netherlands, and 67% for the OECD as a whole. In 1988, the respective numbers were 59% and 66%. The actual difference may still be larger: the Dutch figures may be biased upward because of definition and measurement problems (Van der Ploeg et al., 1991).

Moreover, working part-time is more common in The Netherlands than on average in the OECD, implying that the difference measured in terms of labour years would be even larger. The percentage of part-time workers in The Netherlands in 1987 was 24.9%, which is higher than in all other OECD countries except for Norway and Sweden (OECD, Economic Observer, May 1989). According to figures of WRR (1990), the net participation rate in 1987 in The Netherlands was 98.4% of the EC average if measured in persons, but only 87.8% if measured in labour years.

A closer look at some of the figures (tables 2.8 and 2.9 in WRR, 1990; primarily based on EUROSTAT figures) reveals substantial differences between The Netherlands and the EC average in 1987 concerning the importance of the various types of economic inactivity. For example, of Dutch males aged 55-64, 18% is on early retirement, vs. an EC average of 30%, and 24.4% is on disability schemes, vs. 7.2% in the EC as a whole. Although these figures may to some extent suffer from measurement and definition problems, they strongly suggest that it is worthwhile to analyze various types of economic activity and inactivity.

There is an extensive empirical literature on labour supply models, explaining whether or not people work, and, if so, the amount of time spent working (see, for example, Pencavel, 1986 and Killingsworth and Heckman, 1986). These models often focus on explaining hours worked, but usually do not distinguish many types of economic inactivity. The only distinction sometimes made is that between non-participating and unemployed (female) workers (cf. Blundell et al., 1987). The long term sick, disabled, or retired individuals in the sample are usually excluded a priori. A notable exception is Disney and Webb (1991), who focus on those receiving long term sickness benefits. In the micro-part of their analysis, they distinguish between recipients and non-recipients, but do not address other types of economic inactivity.

In this paper, we consider micro-econometric models which distinguish a number of economically active and inactive states. We focus on the age group 30-65, and thus do not consider full-time education. For males, we distinguish between full-time or part-time work, unemployment, early retirement, and disability. For females, we distinguish between full-time and part-time work, but do not consider early retirement. The small size of some of the categories motivates this asymmetric treatment. Moreover, working in the household ("housewife") is an important state for females, while negligibly small for males. In the static model, we analyze what determines the probability of being in each state, in the dynamic model we focus on the transition probability from (full-time or part-time) work into several types of economic inactivity. Emphasis is on the impact of earnings capacity, to shed some light on the extent to which an increase in labour market participation will affect average earnings capacity.

In contrast to earlier studies we do not analyze the impact of benefit levels. Both Woittiez et al. (1994) and Riphahn (1995) find a small and insignificant impact of financial incentives on disability. While they consider the labour market state as mainly supply determined, we choose the opposite point of departure and look at demand factors. Potential benefit levels at one point in time will be strongly correlated with potential earnings. Given the short panel we have, and the lack of systematic variation in benefit levels over that period, we cannot separately identify demand and supply effects.

The remainder of this paper is organized as follows. In section 2, we describe the data: several waves of the Socio-Economic Panel drawn by The Netherlands Central Bureau of Statistics (CBS), 1984-1989. Each wave contains data on about 4,000 households, with information on household composition, individual characteristics such as age and education, all types of income of household members of at least 16 years old, some job characteristics for workers, search behaviour of individuals who are looking for a job, etc. We discuss the definitions of the various labour market states, and the survey information used to identify these, and provide some descriptive statistics for our sample.

In section 3, we discuss the static model and the way to estimate it. The model is of multinomial logit nature, but the presence of potential hourly earnings (F), reflecting productivity or earnings capacity among the variables determining an individual's labour market state, poses some problems: first, these earnings are unobserved for non-workers. Second, we want to allow them to be endogenous. Third, we allow earnings to enter in a non-linear way, accounting for the fact that it may matter whether or not potential earnings exceed some threshold value (e.g. some relevant minimum wage). Fourth, we allow for unobserved heterogeneity. We extend the multinomial model to allow for these features and then briefly explain how the extended model can be estimated with smooth simulated maximum likelihood. Estimation results are discussed in section 4.

A more direct test of whether earnings capacity affects the probability of economic inactivity or not, is to consider transition probabilities of workers, whose wages are observed. This is the issue of section 5: We explain transitions of employment to various types of economic inactivity between two sequential panel waves, conditional on earnings and other job characteristics. The model is similar to the static model. Due to the relatively small number of transitions in the data, we combine some of the states and pool the various pairs of panel waves. Finally, conclusions are drawn in section 6.

2. Data

The data are drawn from the Dutch Socio-Economic Panel. This is a rotating panel which originally started semi-annually in 1984, with interviews in April and October. For this study, we only use the October waves since most of the April waves do not contain information on earnings or income. Furthermore, as the set up of the questionnaire went through a major revision in 1990, we only used the waves 1984-1989. The static model was estimated for each wave separately. We will focus on 1988, and briefly discuss the deviations for other years. For the dynamic model we combined the six October waves.

Several questions in the survey can be used to identify someone’s labour market state. Information is available on whether or not someone has a paid job, and on the number of hours worked. Detailed information is available on earnings and all types of benefits income, such as disability and unemployment benefits, and on pensions. If people receive disability benefits, it is also known whether this replaces their full-time income, or serves as an addition to earnings in a part-time job. In the latter case, disability benefits are referred to as partial.[2]

For people without a paid job, we know whether or not they are seriously looking for a job, and, if they are, whether that is a full-time or a part-time job. Finally, the survey also contains the subjective question: "What do you consider your major activity?" with ten possible answers, including working full-time and part-time, unemployed, disabled, retired, at school, working in the household, etc. (see table 1). We used this information only in case the other information was incomplete or inconsistent.

In most cases, there is no ambiguity in defining someone’s labour market state, and it makes no difference which survey questions are used. Problematic cases however do exist. For example, some people work part-time and also receive some benefits. For these people, identifying the main activity requires some arbitrary choice. We used the following criteria, ordered from highest to lowest priority: once a criterion is satisfied, the others are no longer considered. We use the abbreviations for the various states throughout the paper.

1: Those working at least 32 hours per week are classified as full-time workers (FTW).
2: People who receive full disability benefits or partial disability benefits for at least 50%, are categorized as disabled (DIS).
3: Those who work between 20 and 32 hours per week are classified as part-time workers (PTW).
4: Individuals receiving some pension (including early retirement benefits) and no unemployment benefits, are classified as retired (RET). They are also classified as retired if they receive both a pension and unemployment benefits, and claim that their major activity is ’retired’.
5: Persons receiving unemployment compensation or claiming to be seriously looking for a job, are classified as unemployed (UNE). The same applies to males receiving social security benefits. The unemployed thus include discouraged workers, particularly males.
6: Those with major activity ’working in the own household’ or ’other’ are categorized as part-time employed if they work a positive number of hours per week. If they don’t work and receive one type of benefits, they are classified in the corresponding state: disabled, retired, or unemployed. In case of more than one type of benefits, they are left unclassified.

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[2] Full-time disability benefits amount to 70 or 80 percent of earnings in the last job. See Aarts and de Jong (1990) or Van der Ploeg et al. (1991) for institutional details. More than 80 percent of persons receiving disability benefits receive full-time benefits or partial benefits for at least 80 percent.

7: Females with major activity ’working in the household’ are classified as housewives (HSW). This category may include discouraged female workers without unemployment benefits.
8: Those who are not yet classified are deleted from the sample.

We have tried to minimize the number of people who cannot be classified. Differences with alternative classifications are limited. In table 1, we compare our classification with the one exclusively based on the "major activity" survey question.

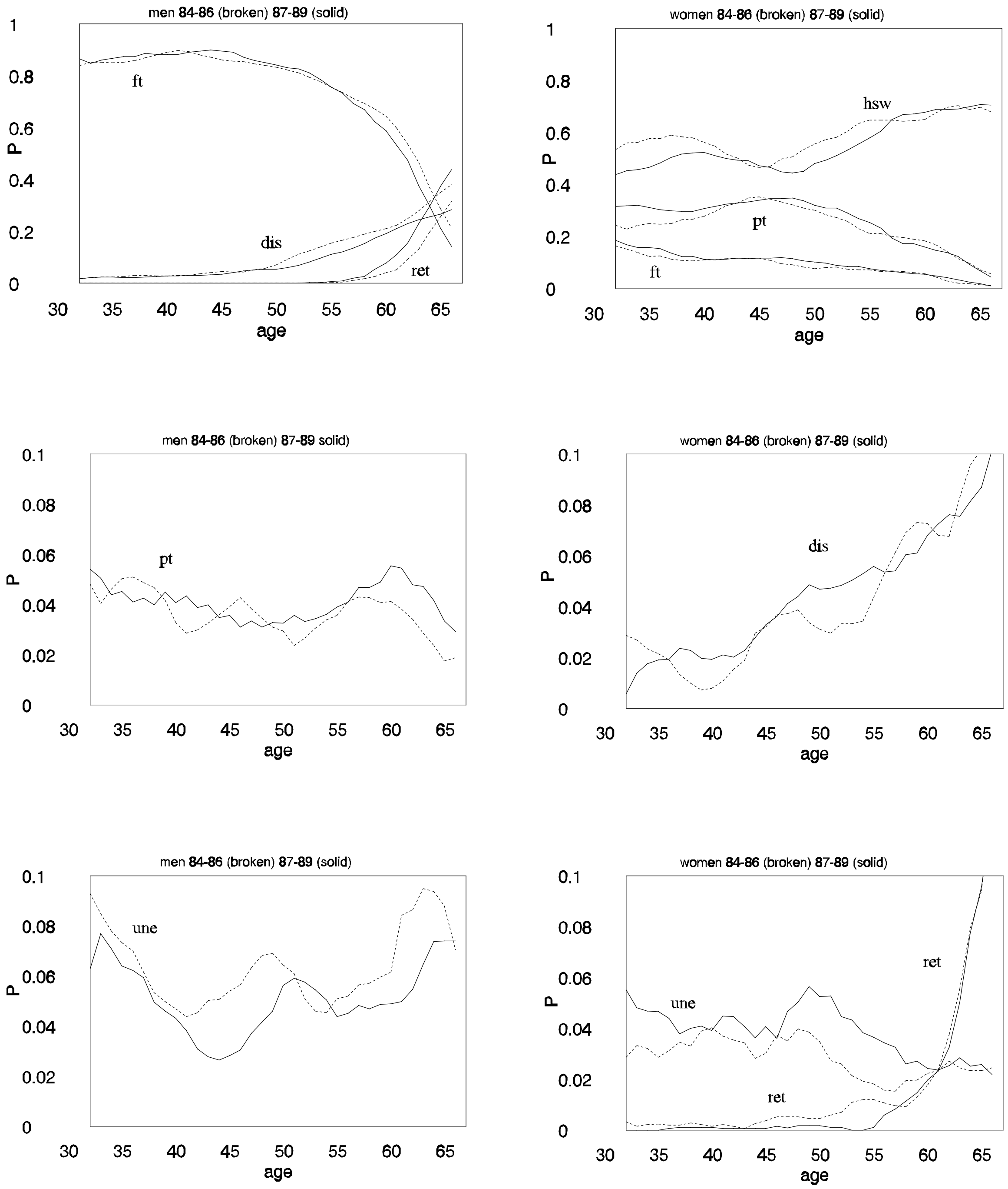
An apparent difference is the distinction between part-time and full-time employment. The "major activity" question does not specify which number of hours should be used to distinguish between the two, leading to subjective answers. Another difference is the classification of females with major activity "working in the own household". This state seems more ’active’ than receiving disability or retirement benefits, and is therefore often chosen as the major activity. Our objective definition of the states implies that many of these are classified differently.

Table 1: Classification based on "Major Activity" question in survey (MA) and final classification (FC); October 1988; age group 30-64.

Males FC:	PTW	FTW	UNE	DIS	RET	HSW
MA						
education	0	2	6	0	0	0
military service	0	2	0	0	0	0
full-time work	48	2112	2	1	3	0
part-time work	54	17	11	4	5	0
work in own hh	1	2	7	1	2	0
unemployed	0	3	93	0	0	0
search first job	0	0	6	1	0	0
disabled	3	0	3	272	0	0
retired	0	0	0	4	158	0
other	0	3	18	2	2	0
total	106	2141	146	285	170	0

Females FC:	PTW	FTW	UNE	DIS	RET	HSW
MA						
education	1	2	6	1	0	0
full-time work	37	247	1	0	0	0
part-time work	471	42	21	5	0	0
work in own hh	270	4	75	50	29	1590
unemployed	1	0	22	0	0	0
search first job	0	0	1	0	0	0
disabled	0	1	0	75	0	0
retired	0	0	0	1	19	0
other	10	0	5	2	1	0
total	790	296	131	134	49	1590

Figure 1: Labour market state probabilities for men and women of age 30 to 64



Labour market state probabilities by age are depicted in Figure 1 for men and women separately. As fluctuations over both age and time in the data of the labour market state probabilities are such that they would obscure the general tendencies, we pooled the data of 1984 until 1986 and those of 1987 until 1989. We then calculated an average over 5 ages to smooth out random fluctuations. For all states we find clear cohort effects. For example, the age pattern for men in the state unemployed is more or less shifted over 3 years of age if one compares the situation for 1984-1986 to the one for 1987-1989.

For men, full-time work is the most important state for all ages and its probability slightly increases up to the age of 40. After the age of 40 the probability to be full-time employed decreases, and the slope increases with age. The probability to be unemployed decreases until the age of 40-45, shows a hump around the age 45-50 and a sudden increase after the age of 58-60. The latter is accompanied by a rapidly rising probability of being retired. The reason for this increase is that early retirement schemes start at about this age and that more supple unemployment benefit conditions occur at higher ages. For women the state housewife is dominant for all ages. For those women who work, part-time work is the most likely state, with a maximum probability at an age around 45. This maximum causes a dip in the probability to be a housewife at this age. The probability of working full-time decreases with age, that of being retired increases with age. The probability of being in the state of disability tends to increase with age.

In table 2, means of explanatory variables other than potential earnings are presented for each labour market state. Compared to table 1, the numbers of observations are reduced, because some observations with missing information on the explanatory variables have been deleted. Table 2 is based on the same observations that will be used for estimating the (1988) static model, 2707 males and 2829 females. The number of females in retirement is too small to treat them as a separate category in estimations. This group is deleted from the sample used to estimate the model for females.

The explanatory variables refer to individual characteristics (level and type of education, nationality, age, marital status), household composition, and characteristics of the place of residence (unemployment rate at provincial aggregation level, degree of urbanisation). Job characteristics are not included, since these are only available for workers. What is obviously missing and will be quite relevant, is information on someone's health.[3] This is not contained in the data. Moreover, we cannot distinguish people on temporary sickness leave from workers. Only those eligible for disability benefits (WAO etc.) are categorised as disabled. Before becoming eligible, these people have not worked because of health reasons for at least one year. The nature of the data we use and of our analysis is thus quite different from that of Aarts and de Jong (1990), who specifically analyze long-term sickness and disability in The Netherlands.

The data used for the analysis of transition probabilities are described in tables 3 and 4. The number of observations is limited because we only consider those with a full-time or part-time job during the first of the two succeeding interviews.

The number of transitions between two successive waves is small. This will make it infeasible to estimate the transition model in section 5 for each separate pair of waves. Instead, we will pool the different pairs of waves and include time dummies. In the pooled data set, individuals taking part in (at least) two pairs of waves are treated as independent observations. Someone who has been in the panel during the whole period from '84 to '89 and has always been employed, thus counts for five observations ('84-'85, '85-'86, '86-'87, '87-'88 and '88-'89).

Tables 3 and 4 refer to these pooled data. Still, the numbers of transitions out of employment are quite small. Transitions from part-time work to full-time work are not shown. Because only transitions out of employment are considered, we can include some job characteristics as explanatory variables. Descriptive statistics of these are mentioned in table 4. Required education and required experience are indications of job level. The ratio

[3] See for example Stern (1996) for the impact of health on participation.

Table 2: Sample fractions (in%) and means by state; October 1988; Age group 30-64

Males	PTW	FTW	UNE	DIS	RET
divorced	8.7%	2.8%	12.9%	8.6%	3.0%
widower	1.0%	0.5%	2.1%	2.2%	6.5%
single	11.7%	7.4%	26.4%	9.7%	3.6%
EDUCL	3.2	2.9	2.2	2.1	2.6
tech	20.3%	41.3%	27.1%	3.4%	8.7%
adm	14.6%	22.8%	14.3%	4.7%	2.0%
serv	8.7%	4.8%	3.6%	3.2%	3.6%
CHILDREN	0.7	1.3	0.7	0.3	0.0
child<6	18.4%	26.6%	15.7%	4.7%	0.0%
not Dutch	4.9%	3.6%	11.4%	5.4%	8.3%
UNEMPRT	6.5%	6.3%	6.7%	6.4%	6.3%
URB	3.7	3.5	3.9	3.5	3.5
AGE	44.2	41.7	44.5	53.2	61.0
Total (2707)	103	2018	140	278	168

Females	PTW	FTW	UNE	DIS	RET	HSW
divorced	4.1%	13.3%	22.6%	9.9%	4.3%	5.5%
widow	4.3%	1.9%	2.8%	1.5%	5.6%	5.3%
single	3.2%	29.7%	18.9%	9.8%	0.8%	0.6%
EDUCL	2.5	2.9	2.7	2.2	2.1	2.1
tech	3.1%	3.4%	5.7%	7.6%	6.5%	6.1%
adm	17.7%	28.5%	11.3%	3.0%	19.6%	13.7%
serv	34.4%	24.7%	24.5%	4.4%	3.0%	28.8%
CHILDREN	1.3	0.4	0.7	0.4	0.0	1.1
child<6	19.4%	5.3%	10.4%	9.1%	0.0%	21.8%
not Dutch	4.8%	6.8%	8.5%	6.1%	4.3%	5.6%
UNEMPLRT	6.3%	6.2%	6.5%	6.3%	6.4%	6.3%
URB	3.6	3.9	3.8	3.9	3.7	3.4
AGE	41.3	39.9	42.3	49.3	60.6	45.7
Total (2829)	748	263	106	131	46	1535

Explanation: All variables are dummies, except those in capitals. Divorced, widow(er), single, refer to civil status (reference group: married). EDUC(ation) L(evel) ranges from 1 (primary school) to 5 (university level), tech(nical), adm(inistrative) and serv(ices) refer to the type of education (reference group: General). CHILDREN is the number of children living at home, child<6 is a dummy for the presence of a child younger than six. not Dutch refers to nationality, UNEMPRT is the regional unemployment rate (in%), URB the degree of urbanisation ranging from 1 (country) to 6 (big city). AGE is in years.

Table 3: Labour market state of workers, one year later: October waves 1984-1989.

New state	Males		Females	
Working (PTW+FTW)	8472	(96.6%)	3414	(89.5%)
Unemployed	75	(0.9%)	87	(2.3%)
Disabled	88	(1.0%)	31	(0.8%)
Retired	139	(1.6%)	26	(0.7%)
Housewife	0	(0.0%)	260	(6.8%)
Total	8774		3816	

Table 4: Job characteristics of full-time and part-time workers; October waves 1984-1989.

	Males		Females	
	mean	std devv	mean	std dev
EDREQ	4.07	1.15	3.58	1.22
EXPREQ	2.81	0.79	2.34	0.82
Construction	0.102		0.013	
Trade	0.114		0.141	
Transport	0.088		0.032	
Manufacturing	0.218		0.071	

Explanation: EDREQ: required education level, ranging from 1 (lowest) to 7 (highest). EXPREQ: required experience; 1: no, 2: little, 3: much, 4: very much. Construction, ..., manufacturing: dummies pertaining to various sectors (reference group: service sector).

between education level required and actual education level indicates how demanding the job is for a given individual, and may affect the probability of becoming disabled. We also include sector dummies, distinguishing five different sectors of the economy.

It is needless to say that the information on job characteristics is far from complete. Partly, this is because of the limited information available in the data. One might think of adding dummies pertaining to occupational groups, on which the data contain some information. This, however, strongly correlates with the sector dummies.

3. Static model

In this section we formulate a static model to explain in which labour market state an individual can be found. The possible states are: full-time working (1), part-time working (2), unemployed (3), disabled (4), retired (5; males only) and working in own household (5; females only). For the definition of the states, see the previous section. As explanatory variables we include variables like age and family characteristics, but also the earnings capacity per hour worked (before tax). We assume that this is fixed, i.e. it does not depend on the labour market state. It does not, for example, incorporate a negative effect of temporary sickness, which might be related to the probability of becoming disabled. Moreover, we assume that it does not depend on hours worked. For workers, earnings capacity is equal to the before tax hourly wage rate. It can be thought of as a proxy for the individual’s productivity, which is not observed in the data. We incorporate productivity in the model by assuming that it is strongly related to earnings capacity. The first part of the model is therefore as follows.

$$\log F_i = x_i'\beta + \varepsilon_i^F \tag{1}$$

Here F denotes productivity, i is the individual, and x is a vector of explanatory variables. We assume that the error term ε^F is independent of explanatory variables and normally distributed with mean zero and variance σ_F^2. Since productivity is not observed, we need an identifying assumption to distinguish it from the wages. We assume that the before tax hourly wage rate W is a weighted average of productivity and a reference wage rate R:

$$\log W_i = b \log F_i + (1-b) \log R_i \qquad (0 \le b \le 1) \tag{2}$$

R can, for example, be the minimum wage or the starting wage in the public sector at a given education level. Several choices of R will be used in the empirical implementation. The weight b indicates to what extent the wage is determined by productivity. If b=1, the wage is exclusively determined by productivity. In most cases, F is expected to be larger than R, and (2) can be interpreted as the result of a Nash bargaining process between employers (with threat point F) and employees (with threat point R). See, for example, MaCurdy and Pencavel (1986). If b<1, an increase in R leads to a wage increase, also for those earning more than R. This may reflect the fact that minimum wages or public sector wages push up other (higher) wages.

Equation (2) may be attractive from a theoretical point of view, but is hard to estimate, since neither F nor R are observed. For R we choose something which is observed, but it is not clear whether the choice is appropriate. The same problem occurs in some labour demand models, where it is not clear what to choose empirically for "the alternative wage" (cf., for example, Machin et al., 1993). It is at least doubtful whether reliable estimates of b can be expected, also because R and x will be strongly correlated. (For example, if R is the legal minimum wage, it is constant across the sample). We do not estimate b, but compare the results for b=1 and b=0.8, to see whether or not the assumption that earnings equal productivity (b=1) makes a difference.

The second part of the model explains the individual’s labour market state S. We formulate a multinomial choice model, with K=5 alternatives:

$$U_{ki} = z_i'\alpha_k + \delta_k \log F_i + \mu_k\, g(\log(F_i/R_i)) + \gamma_k \varepsilon_i \qquad (k=1,\ldots,K) \tag{3}$$

$$\varepsilon_i = \lambda \varepsilon_i^F + \sigma_0 \varepsilon_i^0 \tag{4}$$

The function g is a smoothed version of a dummy variable indicating whether or not productivity is lower than the reference wage.[4] It can be interpreted as a threshold value.

[4] For g(t) we choose g(t)= 1 if t≤0, 0.25[{2t/ub-1}^{3}-3{2t/ub-1}]+0.5 if 0≤t≤ub and 0 if t≥ub. The function is monotonically decreasing with g(t)→0 if t→∞ and g(t)→1 if t→-∞. Different values of the smoothness parameter ub led to similar results. Results presented are those with ub=0.1398=log(1.15).

The reason for smoothing is twofold. First, R is probably not measured perfectly, and we think it might be somewhat low. Second, continuity and differentiability of g is necessary to make the approximation of the likelihood we use (see below) continuous and differentiable. Experiments with other smoothing functions suggest that the results are robust with respect to the choice of g.

A positive value of μ_3 implies, for example, that, ceteris paribus, the probability of unemployment compared to that of full-time employment is lower if productivity exceeds the reference wage (g(log(F/R)=0) than if productivity is smaller than the reference wage (g(log(F/R)=1). This reflects a possible positive impact of the reference wage on unemployment (cf, for example, Meyer and Wise, 1983, for the case that R is a minimum wage): higher reference wages make low productivity workers more costly, so that the probability that firms are not willing to hire them increases. We allow for this type of effect on all state probabilities, but do not impose the sign of the effect a priori. Note however that this effect (μ_k) can only be distinguished from a direct productivity effect (δ_k), either if there is enough independent variation in R, or due to the functional form assumption that the direct effect enters log-linearly in (3). Conclusions about the separate impact of minimum or reference wages should thus be interpreted with care. Our main interest is the total impact of F on the state probabilities, through $\delta_k$log F and μ_kg(log(F/R)), with R remaining constant. The sign of this total effect is unambiguously determined if δ_k and μ_k have opposite signs.

The error term ε reflects unobserved heterogeneity in the state equations. We assume that ε^0 is standard normally distributed and independent of explanatory variables and ε^F. The vector $(\varepsilon,\varepsilon^F)$ is then bivariate normal, so that any correlation is allowed for between unobserved heterogeneity in the state and productivity equations.

Some normalizations are needed for identification. As in the multinomial logit model, only differences are identified. Therefore, we set U_{1i} equal to zero: $\alpha_1=\delta_1=\mu_1=\gamma_1=0$. Since γ_k and ε only enter through $\gamma_k\varepsilon$, we also have to normalize the scale of ε, for example by choosing $\sigma_\varepsilon^2=\sigma_0^2+\lambda^2\sigma_F^2=1$. This excludes the case $\sigma_\varepsilon^2=0$, the model with no unobserved heterogeneity in the state equations. Alternative normalizations would be $\lambda=1$ or $\sigma_0=1$, but these are somewhat more restrictive in the sense that they exclude more cases. Finally we add alternative specific random error terms in the same way as in the multinomial logit model:

$$u_{ki} = U_{ki} + v_{ki} \qquad (k=1,...,K) \tag{5}$$

We assume that the random errors v_k are iid type I extreme value distributed, independent of explanatory variables (z,x) and other errors $(\varepsilon^0,\varepsilon^F)$ in the model.

An individual chooses alternative k if u_k is larger than the utilities of all other alternatives. This leads to the multinomial logit model. The structure of the complete error terms $\zeta_k=\gamma_k\varepsilon+v_k$ generalizes the error structure of the multinomial logit model. The assumption of independence of irrelevant alternatives (IIA, see, for example, Train, 1986), is relaxed, since $\zeta_1,....\zeta_K$ are not independent. It is easy to check that

$$E\{\zeta_k\} = 0;$$

$$E\{\zeta_k\varepsilon^F\} = \lambda\gamma_k\sigma_F^2;$$

$$E\{\zeta_k\zeta_j\} = \gamma_k\gamma_j\sigma_\varepsilon^2 = \gamma_k\gamma_j(\lambda^2\sigma_F^2 + \sigma_0^2) \quad (k\neq j);$$

$$V\{\zeta_k\} = \pi^2/6 + \gamma_k^2\sigma_\varepsilon^2.$$

This way of introducing correlation between errors in the productivity equation and the errors in the state equations is an alternative for the procedure introduced by Lee (1982). Our approach is intuitively more attractive and easier to understand, since it builds on the distribution of the original errors in the model, and it is clear which simultaneous distribution of all the errors it implies. It will also appear to yield tractable estimators, even though log F enters non-linearly in the state equations.

In absence of unobserved heterogeneity in the state equations and for given productivity F_i, the probability that individual i chooses alternative k would reduce to a standard multinomial logit:

$$P[\ S=k_i \mid x_i,z_i,R_i,W_i\ ] = \frac{\exp(U_{ki})}{\sum_{j=1}^{K}\exp(U_{ji})} \tag{6}$$

Estimation of this model with maximum likelihood would be straightforward. The fact that productivity is not observed and the introduction of the unobserved heterogeneity complicate the estimation procedure. In case the wage is observed, the likelihood contribution of individual i is as follows:

$$L_i = (b\sigma_F)^{-1}\phi(\varepsilon_i^F/\sigma_F)\ E_{\varepsilon^0}\ P[\ S=k_i \mid x_i,z_i,R_i,W_i,\varepsilon^0\ ] \tag{7}$$

where ϕ is the standard normal density. The expectation is taken with respect to the unobserved error term ε^0. For given ε^0, the probability for S=k is given by (6). To calculate the expectation, we have to integrate out the unobserved error term.

If the wage is not observed, the likelihood contribution is given by:

$$L_i = E_{\varepsilon^0,W}\ P[\ S=k_i \mid x_i,z_i,R_i,W,\varepsilon^0\ ] \tag{8}$$

In this case we take the expectation with respect to ε^0 and the unobserved wage rate W. Computation would require numerical integration over two dimensions. Reduction to a one dimensional integral is not possible, since the wage rate W enters nonlinearly.

Instead of numerical integration, we use simulated maximum likelihood to estimate the model. This means that we replace the expectation by an average of M independent drawings. If the wage rate is not observed, the simulated likelihood is given by:

$$SL_i = \frac{1}{M}\sum_{m=1}^{M}\ P[\ S=k_i \mid x_i,z_i,R_i,W_{im},\varepsilon_{im}^0\ ] \tag{9}$$

Here $\varepsilon^0_{i1},..,\varepsilon^0_{iM}$ are independent draws from the standard normal distribution, while $W_{i1},..,W_{iM}$ are independent draws of W_i conditional upon x_i, z_i and R_i, with $\varepsilon^F_{i1},..,\varepsilon^F_{iM}$ also independent draws from the standard normal distribution, independent of $\varepsilon^0_{i1},..,\varepsilon^0_{iM}$. Instead of maximizing the exact likelihood, we maximize the approximate likelihood obtained by replacing L_i by SL_i. Gourieroux and Monfort (1993) show that under appropriate regularity conditions simulated maximum likelihood is asymptotically equivalent to maximum likelihood. Results of Boersch-Supan and Hajivassilijou (1993) suggest that already for small M, the estimation methods yield similar results.

4. Estimation results static model

We have estimated various versions of the model introduced above, for several years, and for males and females separately. We present the results of one model (Model I) for each year (1984-1989). Our discussion, however, focuses on the results for 1988. For this year we also present two alternative models for males, to get some idea about the robustness of the results. The base model (Model I) is characterised as follows:

- R is the estimated wage rate in the public sector for someone with little or no (potential) experience and given education level. This is constructed using wage regressions of public sector employees in the data. See appendix B for details.
- b=1, so hourly wage and productivity are equal.
- Z, the vector of exogenous variables in the state equations (3), contains no education variables.

The other models differ from the base model in one of these respects. In model II we set b equal to 0.8, so that the wage is for 80% determined by productivity and for 20% by the reference wage. In model III we add education variables (EDUCL, EDUCL squared, and EDUCL*AGE) to the state equations.

Full tables with estimation results are included in appendix C. Tables C1 and C2 relate to model I for males and females, respectively. Table C3 compares the three models for males in 1988. The impact of exogenous variables on productivity and state probabilities largely corresponds to our expectations. There are some substantial differences between the various specifications as well as the various years. Productivity increases with age, with a concave age pattern of log productivity. The importance of age increases with education level, but this is only significant for males. Not being of Dutch nationality has no significant effect on earnings capacity. The type of education plays an important role, possibly also because it is an indicator of occupation. The reference group is those with general education. People with technical training are not very well paid, probably since most of them are blue collar workers. Those with an economic or administrative training appear to be significantly better off than others. The 'services' type of education refers to nurses, social workers, etc.. Their potential earnings are smaller than on average. The unemployment rate in the region has the expected significant negative effect for males, except in 1989, where it is positive but insignificant. For females it is mostly insignificant.[5]

[5] Theoretically, it seems better to let the unemployment rate enter through the bargaining power coefficient b instead of through the systematic part of productivity, but this would imply estimating b.

The slope parameters in the state equations can be interpreted using (6). They relate to relative probabilities, compared to the probability of full-time work (state 1). According to table C3, results of models I and II are very similar. There are, however, many differences, in terms of signs and significance levels, between models I and III and, according to tables C1 and C2, also between the results for the various years.

We first discuss the exogenous variables, focusing on those which are significant. In the probability of working part-time working, the only finding which is significant (at a 5% level) for all years is that single females have a lower probability of being part-time employed than married females. Also for females, having children strongly increases the probability of working part-time compared to that of working full-time, in particular if there are children younger than six. The year 1984 is an exception in this respect. For divorced females, part-time work is less common than for married women.

The state "housewife" includes more than 50% of all females. Its probability (compared to that of working full-time) is significantly affected in the same way by marital status and family composition as the probability of part-time work.

There is some similarity between the impact of exogenous variables on the probability of unemployment and that of disability. For males who are divorced or never married, both probabilities are larger than for others. For females, being divorced increases the unemployment probability. A high level of urbanisation tends to increase the probability of unemployment, but this is only significant for men in 1984 and 1986. Not being of Dutch nationality tends to increase the unemployment probability, but is only significant in 1984 for males. The regional unemployment rate has no significant impact on either the unemployment probability or the probability of disability, except for men in 1989. Having children and having children younger than six increases the probabilities of unemployment and disability for females. For males, we see the opposite effect of children on unemployment.

The probability of early retirement is set to zero for people younger than 49. The impact of variables other than age is not strong. For males, living in a city seems to increase this probability in 1984 and 1989. In 1988, it surprisingly appears that not being of Dutch nationality increases the retirement probability.

As we have seen in the previous section, the effect of productivity on the state probabilities comes through both $\delta_k \log(F)$ and $\mu_k g(\log(F/R))$. There is not much difference between the estimates of δ_k and μ_k from 1984 till 1989. There are some sign changes, but never significant. Most significance levels hardly change. We confine ourselves to a discussion of the results for 1988. Again, table C3 shows that estimates for models I and II are virtually identical, but substantial differences exist between these two and model III.

For males, the model I and model II estimates of δ_k and μ_k imply a significantly negative impact of productivity on the probabilities of unemployment and disability. The parameters for working part-time are also significant, but imply opposite effects: higher productivity leads to a higher probability of part-time work, but if productivity exceeds the reference wage, the probability falls. The parameters δ_5 and μ_5 (retirement) are insignificant.

Model III differs from models I and II. For disability, δ_k is positive but insignificant. Furthermore, the direct effect of productivity is never significant. Since in model III education is included among the regressors, the direct effect through education and the effect of productivity are hard to disentangle, also because the wage, the index for productivity, is observed only for workers. On the other hand, the effect of having a productivity below the reference wage on the probabilities of part-time work, unemployment, and disability, remains significant and has the same sign as in models I and II. For retirement, this effect remains insignificant.

For females, we also find a negative impact of productivity on all state probabilities (relative to the probability of working full-time). In most cases, at least one of the two effects (through log(F) or through g(log(F/R))) is significant.

The final panels of tables C1-C3 contain the estimates which determine whether or not productivity is endogenous in the state equations. Some of the correlations are indeed significantly different from zero. According to likelihood ratio tests, the five correlation coefficients are jointly significant in all cases at any reasonable significance level. Similar tests also suggest that the most general model, model III, performs significantly better than model I. Likelihood differences between the nonnested models I and II are quite small.

Simulations

The estimates can be used to predict the productivity or earnings capacity of non-workers, whose wage is not observed. As has been noted before, earnings capacity is defined as an individual characteristic, not depending on someone's actual labour market state, and should thus be interpreted as earnings capacity in normal circumstances. In tables 5 and 6, we present the predicted mean earnings capacity by labour market state for model I. Table 5 is based upon the estimates of equation (1) only. For each individual, the estimated systematic part is used to predict log productivity, and then the average is taken by observed labour market state. This way of computing the average by state thus ignores the rest of the model and the correlations between the error terms. Differences between average productivities of various states reflect differences in the distribution of the exogenous variables across states: average productivity of unemployed people is, for example, lower than that of full-time workers, because on average the unemployed have lower education level or (potential) experience than the full-time employed.

Table 6 is based upon the whole model: we have drawn the error terms in (1) and (4), and computed the state probabilities conditional on these and on the exogenous variables, thus taking full account of the correlations between the error in the productivity equation and the errors in the state equations. This has been repeated fifty times for each individual, with independent drawings per individual and across individuals. We then computed the weighted average of log productivity per labour market state, using the state probabilities as weights. We present estimated state probabilities for the whole sample and estimates of average productivity per labour market state.

The main finding in table 5 is that average productivity of retired, unemployed or disabled persons, and housewives is always lower than that of full-time workers. For males, we find high earnings capacities of part-time workers. For females, productivity of part-time workers is lower and similar to that of unemployed females. These results are quite robust across models and years, except for retired males.

The average estimated state probabilities in table 6 can be compared to the sample probabilities in table 5. They should be similar if the model captures the data. This is indeed the case. The main conclusion from table 5 is confirmed by table 6: average productivity of the unemployed, disabled, and housewives, is lower than that of full-time workers. The differences in table 6 are larger than those in table 5, indicating that, apart from observed characteristics such as age and education, unobserved characteristics also explain part of the productivity gap.

Table 5: Estimated mean systematic part of F (Model I; October 1988)

	Males		Females	
	prob.(%)	F	prob.(%)	F
FTW	74.5	23.0	9.5	19.1
PTW	3.8	24.5	26.9	18.1
UNE	5.2	20.0	3.8	18.6
DIS	10.3	18.9	4.7	16.9
RET(m)/HSW(f)	6.2	20.5	55.2	16.8

Table 6: Simulated state probabilities and earnings capacity (Model I; October 1988)

	Males		Females	
	prob.(%)	F	prob.(%)	F
FTW	70.1	24.3	9.0	20.4
PTW	3.4	24.6	26.0	16.4
UNE	7.0	17.2	4.0	13.6
DIS	13.8	15.6	4.5	12.4
RET(m)/HSW(f)	5.7	23.0	56.5	18.2

In the appendix, we provide some more detailed simulation results. The two tables there (tables A1 and A2) are constructed in the same way as tables 5 and 6, but with the sample has been partitioned according to age and education. We only present results for model I and 1988. Three age categories and three education levels are distinguished. Comparison of simulated state probabilities in table A2 with sample probabilities in table A1 again shows how the model fits the data. According to table A1, there is not much difference between average productivity in the various states, for given education level. This implies that the other observed exogenous variables hardly contribute to the differences. If, however, unobserved variables are included, we find notable differences between average state productivities (table A2). This reveals once more that unobserved variables play an important role in the model. The conclusion thus is that, for most specifications, for both sexes and for both years considered, we find a negative correlation between earnings capacity and the most important types of economic inactivity, i.e. unemployment, disability, and, for females, working in the household. Only part of this correlation can be explained by differences in education level and age.

5. Transitions

In the previous sections, we considered static models, estimated with cross-section data. This has the drawback that no wages of non-workers are observed. In this section, we exploit the panel nature of the data and analyze the probability that someone who works (part-time or full-time) at one point in time (year t, say), no longer works one year later (year t+1). Transition probabilities are modelled as functions of observed characteristics in year t, including job characteristics such as wage, job level, and sector of industry. To define the transition probabilities, we use the same expressions as in section 3 (equations (1)-(6)). For example, we again include log F as well as the 'smoothed dummy' g(log(F/R)). The interpretation is different: we are now estimating the probability that someone is, for example, unemployed or disabled at t+1, conditional upon the fact that he was working at time t, and given individual and job characteristics at time t. The reference state is working at time t+1. Part-time and full-time work at time t+1 are not distinguished. A dummy for part-time work at time t is included among the explanatory variables.[6]

As we saw in section 2, the number of transitions in the data is rather small. We therefore consider fewer states than in the static model: working (full-time or part-time), unemployed, disabled, retired (males only) and working in the own household (females only). Moreover, we link observations from the various couples of years and include time dummies. The small number of transitions is also the reason why we only look at transitions out of employment, and not from other states into employment.

Estimation results are mentioned in tables 7 and 8. Some of the parameters of the dummies could not be estimated, due to absence of transitions in the corresponding

Table 7: Transition probabilities males

age group 30-64; October waves 84-89; absolute t-values in parentheses						
	Unemployment		Disability		Early retirement	
const	1.85	(0.56)	0.47	(0.12)	-137.26	(4.43)
single	0.85	(2.42)	0.56	(1.71)	0.30	(0.93)
not Dutch	0.62	(1.33)	-0.13	(0.19)	0.40	(0.88)
URB	0.05	(0.76)	-0.11	(1.59)	0.07	(1.24)
AGE	-0.19	(1.26)	0.07	(0.49)	4.27	(3.96)
$AGE^2/100$	0.25	(1.52)	0.02	(0.12)	-3.37	(3.59)
part-time	1.26	(3.16)	1.34	(2.97)	0.45	(1.10)
req.educ.	-0.02	(0.16)	-0.14	(1.30)	-0.02	(0.22)
req.exp.	-0.38	(2.32)	0.03	(0.20)	-0.12	(0.88)
industry	0.37	(1.06)	0.32	(0.99)	-0.07	(0.25)
construct.	0.32	(0.67)	0.95	(2.55)	0.45	(1.05)
trade	0.55	(1.48)	0.22	(0.50)	-0.46	(1.22)
transport	-9.00	(-.--)	0.83	(2.25)	0.19	(0.47)
log(F)	-1.09	(1.85)	-2.74	(4.87)	0.44	(1.64)
g(log(F/R))	0.61	(1.28)	-1.20	(1.92)	-1.09	(1.29)
85/86	0.79	(1.66)	-0.66	(1.41)	-0.30	(0.84)
86/87	0.51	(1.03)	0.39	(1.15)	0.05	(0.15)
87/88	0.59	(1.22)	-0.13	(0.32)	0.46	(1.46)
88/89	0.10	(0.19)	0.33	(0.89)	0.01	(0.04)

[6] The questionnaire is organised such that the number of working hours is only asked the first time that someone joins the panel, unless the individual has changed employer. Transitions from part-time to full-time work or vice versa will therefore often remain unobserved.

category. We tested whether the correlation between the productivity and the state equation is significant using likelihood ratio tests. It appeared to be insignificant for males (realization of the test statistic is 5.8, with four degrees of freedom), but significant for females (test statistic of 20.7). We therefore present the results without correlation for males (table 7) and with correlation for females (table 8). Table 8 shows that the rejection on the restriction for the correlation for the females is caused by a significant correlation between the wage and the utility of becoming housewife. An interpretation is that certain unobserved characteristics have a positive effect on both the wage and the probability of becoming housewife, but have no effect on the probability of becoming unemployed or disabled. For both males and females several of the individual characteristics are significant. Being single gives for males a higher probability of becoming unemployed, while for females it gives a lower probability of working in the household. As expected, age is strongly significant for the transition into retirement, while children are important for the transition to working in the own household. For females, very few parameters are significant for becoming unemployed or disabled. This could be due to the small number of transitions into these states.

Table 8: Transition probabilities females

age group 30-64; October waves 84-89; absolute t-values in parentheses
σ_0 = 0.54 (2.14)

	Unemployment		Disability		Housewife	
const	-1.44	(0.36)	-3.72	(0.31)	8.97	(3.62)
single	0.58	(1.83)	0.80	(1.11)	-1.20	(3.81)
# children	0.12	(0.84)	0.02	(0.05)	0.14	(1.78)
child<6	-0.77	(1.58)	-0.86	(0.41)	0.66	(3.05)
not Dutch	0.66	(1.50)	1.13	(1.06)	0.85	(2.87)
URB	-0.01	(0.20)	-0.04	(0.25)	-0.04	(1.09)
AGE	-0.15	(0.92)	-0.01	(0.03)	-0.23	(2.27)
$AGE^2/100$	0.17	(0.91)	0.07	(0.14)	0.27	(2.40)
part-time	0.81	(2.21)	0.09	(0.12)	0.28	(1.31)
req.educ.	0.02	(0.11)	-0.04	(0.12)	0.24	(3.10)
req.exp.	-0.10	(0.63)	-0.05	(0.13)	-0.26	(2.60)
industry	0.58	(1.46)	0.76	(0.84)	0.21	(0.77)
trade	0.18	(0.47)	-0.08	(0.11)	-0.04	(0.20)
log(F)	-0.05	(0.05)	-0.97	(0.50)	-2.73	(4.50)
g(log(F/R))	-0.85	(1.88)	1.38	(1.12)	0.49	(1.71)
85/86	0.22	(0.42)	0.74	(0.75)	-0.36	(1.36)
86/87	0.94	(2.05)	0.21	(0.17)	0.03	(0.11)
87/88	0.72	(1.48)	0.95	(0.82)	-0.33	(1.32)
88/89	0.42	(0.84)	-0.20	(0.13)	-0.46	(1.90)
γ_k (in (3))	0.02	(0.04)	0.63	(0.76)	1.12	(3.41)

We used a Wald test to determine whether the parameters with respect to the productivity, log(F) and g(log(F/R)), are jointly significant (controlling for the observed individual and job characteristics). They are significant for both males and females, with realizations of the test statistic of 41.7 and 30.5, with four degrees of freedom. For males, productivity has a negative impact on the probability of becoming disabled, although the opposite effect induced by the parameter for g(log(F/R)) weakens this result. For becoming unemployed both parameters have the expected sign: males with low productivity have a relatively high probability of becoming unemployed. It turns out however that for early retirement this effect is opposite: male workers with low productivity have a lower probability of early retirement. For females we get the result that a low productivity results in a high probability of becoming a housewife.

We now turn to the effects of job characteristics. Working in a part-time job gives a significantly lower probability of staying employed. For males, a high required experience level in the job gives a lower probability of becoming unemployed, while for females it gives a lower probability of a transition to working in the own household. On the other hand, a high required education level gives females a higher probability of this same transition. Most dummies for the sectors of industry are insignificant. The exception is that males in the construction and transport sector have a significantly higher probability of becoming disabled than others.

6. Conclusions

This paper builds on the literature on micro-models to explain whether people work, are unemployed, or do not participate in the labour market. We explicitly distinguish between several types of so-called ’non-participation’. In particular, some emphasis is put on the state of ’disability’, i.e. receiving disability benefits and, for females, the ’housewife’ state, i.e. working in the own household. The methodological contribution of the paper is that we generalize the multinomial logit model to allow for unobserved heterogeneity and endogeneity of one of its righthand side variables. We show that this generalized model can easily be estimated, and our static model estimates show that taking endogeneity into account makes a big difference. This is illustrated by the differences between simulations with and without taking account of the error structure.

One of the main findings is that the probability of unemployment and the probability of disability follow a similar pattern as a function of potential hourly earnings, particularly for males. These probabilities decrease with earnings capacity and are significantly larger for those with earnings capacity below some reference wage level. This corresponds to the theory that disability and unemployment are substitutes: low productivity workers often end up in disability before they would be fired. For females, the housewife state makes the rest of the picture less clear. The probability of becoming a housewife is clearly negatively related to earnings capacity. It might be the case that females with low productivity often leave the labour market and become a housewife if their unemployment or disability risk increases. The negative relation between the probability of economic inactivity and earnings capacity or productivity is revealed by static and dynamic models. In the dynamic models which explain transitions out of employment, earnings are more important than other job characteristics.

On a macro-level, our results imply the following. If labour market participation increases, average productivity per worker will decrease. This is because people with relatively low earnings capacity will be added to the employed workforce. This may explain why, for example, Van Schaik (1992) finds a negative correlation between participation rate and labour productivity, using aggregate cross-section data on 95 countries. Of course, alternative explanations may also exist (cf. Van der Ploeg et al., 1991). For example, increasing average labour productivity leads to pressure on average wages, which, through collective bargaining agreements, leads to high minimum wage costs, and thus to high exit probabilities of low productivity workers, leading to lower participation rates. Such explanations are far beyond the aim of this paper.

The main motivation for this paper is the fact that it is now realised that unemployment and other types of economic inactivity are features of the same problem: labour market participation is low, and the burden on those who work in terms of the benefit premiums to be paid, becomes too large. Our analysis aims at locating the most vulnerable groups, i.e. the groups for whom the probability of unemployment, disability, etc. is largest. This may be useful to determine the groups at which policy measures should be directed, but of course does not indicate which policy measures could be used. For that purpose, our analysis lacks structure. If someone is unemployed, it is not clear whether this is demand or supply related. Our reduced form approach does not tell us whether disability probabilities go down if corresponding benefits go down. The only explanatory variable incorporated which could be thought of as a policy instrument, is the reference wage level, i.e. the starting wage in the public sector. It should be realised however, that the effect of reference wages and the effect of earnings capacity itself can only be disentangled because of functional form assumptions. Explicitly aiming at the impact of specific policy measures thus remains a topic of future research.

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Appendix A: Detailed simulation results

Table A1: Estimated mean systematic part of F by labour market state, education level and age; Model I; October 1988

	education level						age group					
	<=2		3		>=4		<=40		41-50		>=51	
	prob	F	prob	F	prob	F	prob	F	prob	F	prob	F
Males												
FTW	64.5	18.1	80.5	23.1	79.9	32.4	87.9	22.5	85.4	24.1	44.6	22.7
PTW	2.8	17.1	2.3	22.9	8.5	31.5	3.9	24.0	3.4	25.6	4.1	24.5
UNE	8.7	17.1	2.9	22.8	3.6	31.6	5.2	20.1	4.9	21.5	5.4	18.7
DIS	17.2	16.2	8.1	22.9	2.7	33.1	3.0	20.0	6.2	19.8	24.8	18.5
RET	6.8	15.0	6.1	22.1	5.3	34.9	0	----	0.1	23.6	21.1	20.5
Females												
FTW	5.4	16.3	12.7	19.0	20.1	23.3	12.6	18.9	9.7	19.5	4.4	18.6
PTW	22.9	16.3	31.0	18.7	34.7	22.6	31.3	18.4	33.7	18.2	13.6	16.7
HSW	64.0	15.7	49.0	18.5	30.0	22.4	49.5	17.6	47.2	17.6	71.5	15.5
UNE	3.0	16.2	2.7	18.6	10.2	22.7	4.3	19.0	4.5	19.4	2.5	16.5
DIS	4.7	15.5	4.7	18.0	5.0	21.6	2.4	18.1	5.0	17.3	8.0	16.2

Table A2: Simulated state probabilities and earnings capacity by state, education level and age group; Model I; October 1988

	education level						age group					
	<=2		3		>=4		<=40		41-50		>=51	
	prob	F	prob	F	prob	F	prob	F	prob	F	prob	F
Males												
FTW	60.2	19.7	73.8	24.2	80.4	32.7	84.4	23.5	81.1	25.4	38.9	25.4
PTW	2.4	17.7	3.4	23.0	5.3	35.5	4.0	22.5	2.9	26.3	3.1	28.1
UNE	9.8	14.7	6.2	18.7	3.7	27.1	7.3	16.3	5.7	17.9	7.6	18.0
DIS	22.1	13.3	10.9	18.1	5.2	28.2	4.3	14.5	10.2	15.9	30.9	15.8
RET	5.6	18.0	5.7	23.8	5.5	34.6	0	----	0.1	24.4	19.5	23.0
Females												
FTW	5.5	17.3	10.2	20.5	21.8	24.7	11.8	20.7	9.7	20.1	3.9	19.9
PTW	22.4	14.7	29.5	17.2	33.4	21.3	30.9	16.7	31.2	16.8	13.3	15.1
HSW	64.8	16.9	51.3	20.2	32.1	25.4	49.8	19.3	51.2	19.4	72.1	16.5
UNE	2.8	11.6	4.6	13.7	8.2	17.3	4.7	13.8	3.9	13.9	3.0	13.0
DIS	4.6	11.1	4.4	13.5	4.5	17.0	2.7	13.1	4.0	13.0	7.8	11.9

Appendix B: Reference Wages

For the reference wage R, we have used the estimated starting wage in the public sector, for a given education level. Five education levels are distinguished in the data. To construct R, we have run a regression of the log wage rate on functions of education level and potential experience, for public sector employees of each separate education level (males and females aged 16-64; no selectivity bias corrections; separate regressions for the two years). Potential experience is defined as age minus six minus number of years required to obtain the given education level. The latter is, rather roughly, estimated under the constraint that potential experience is negative for no one in the sample. As a consequence, our measure for potential experience may on average be somewhat high. Regression results are summarized in table B1. The choice of regressors is based upon some specification analysis. For example, gender dummies (or cross products with these) appeared not to be significant.

Table B1: Regression results

Dependent variable: log before tax hourly wage rate; t-values in parentheses		
	1984	1988
constant	2.35 (30)	2.56 (37)
dummy EDUCL=2 /10 (D2)	-0.59 (0.7)	-1.82 (2.3)
dummy EDUCL=3 /10 (D3)	1.34 (1.7)	0.28 (0.4)
dummy EDUCL=4 /10 (D4)	3.14 (3.8)	0.26 (0.3)
dummy EDUCL=5 /10 (D5)	4.80 (4.9)	3.56 (3.6)
POT EXPERIENCE /100 (PE)	0.97 (3.5)	1.08 (4.7)
PE^2-a*PE°	-6.48 (8.2)	-7.82 (7.9)
D2 * PE	5.58 (1.7)	2.30 (0.7)
D3 * PE	4.22 (1.4)	0.71 (0.2)
D4 * PE	6.74 (2.0)	11.50 (3.5)
D5 * PE	13.81 (3.2)	6.67 (1.5)

° 1984: a=38.32, 1988: a=42.82; a is nonzero to orthogonalize regressors.

In table B2, we present wage predictions in the public sector as a function of potential experience and education level. The result that, for low PE, the prediction for EDUCL=2 is below that for EDUCL=1, is a bit strange. There are not many young public sector employees with EDUCL=1. Because our measurement of PE may be somewhat high, we used the predictions for PE=2 instead of PE=0 in the ultimate analysis. A sensitivity analysis however showed that choosing PE=0 hardly alters the results. We also estimated a version of the model in which R is the predicted wage in the public sector, taking full account of actual potential experience (i.e. using all the predictions in table B2). The empirical results of that however were clearly less successful than the results of the models we present in the text. Table B.3 gives the wage predictions as we use them in the analysis.

Table B2: wage rate predictions public sector

PE	EDUCL 1	2	3	4	5
1984					
0	10.45	9.85	11.95	14.30	16.88
1	10.81	10.24	12.41	14.89	17.71
2	11.16	10.64	12.88	15.49	18.55
5	12.21	11.84	14.27	17.29	21.15
10	13.83	13.78	16.50	20.25	25.65
20	16.07	16.94	20.00	25.18	34.23
1988					
0	12.90	10.73	13.27	13.24	18.47
1	13.47	11.23	13.87	13.98	19.42
2	14.05	11.74	14.47	14.75	20.39
5	15.78	13.27	16.29	17.15	23.36
10	18.57	15.80	19.24	21.37	28.42
20	22.86	19.90	23.85	29.52	37.40

Table B3: wage rate predictions public sector, two years of potential experience

PE=2	EDUCL 1	2	3	4	5
1984	11.16	10.64	12.88	15.49	18.55
1985	12.31	11.89	14.21	16.45	20.15
1986	12.65	12.00	13.79	15.85	22.01
1987	13.91	14.73	14.92	16.76	22.39
1988	14.05	11.73	14.47	14.75	20.39

Appendix C: Estimations results static model

Table C1: Men, model 1

	1984		1985		1986		1987		1988		1989	
LOGLIK:	-629.50		-455.65		-577.67		-526.67		-751.62		-588.589	
	parm	t-val	parm	t-val	parm	t-val	parm	t-val	parm	t-val	parm	t-val
PTW												
interc	-3.2824	-0.84	-9.1283	-2.27	-8.3391	-2.52	-4.8273	-1.40	-2.1262	-0.62	-4.0909	-1.33
divorced	0.4431	0.63	0.6187	0.94	0.5172	0.97	0.4415	0.96	0.8833	1.86	0.4835	1.03
widow(er)	0.2443	0.22	-10.0000	0.00	0.8108	0.76	0.4934	0.35	0.2523	0.21	0.6049	0.42
single	0.3697	0.79	0.4624	1.08	1.0872	3.01	0.0158	0.04	0.1509	0.37	0.1394	0.35
CHILDREN	-0.3158	-1.83	-0.2248	-1.49	0.0156	0.12	-0.1914	-1.36	-0.3828	-2.55	-0.2772	-1.93
not Dutch	-0.2305	-0.35	-1.7166	-1.21	-0.3227	-0.65	-0.6166	-0.80	0.1806	0.29	-0.5705	-0.84
URB	0.0922	1.84	0.0906	1.15	0.0561	0.84	0.1038	1.61	0.0316	0.46	0.0758	1.17
UNEMPR	0.0816	1.49	0.0788	1.13	0.0816	1.54	0.1392	2.46	0.1369	1.34	0.1134	1.90
AGE	-0.2362	-1.47	-0.1777	-1.09	-0.1304	-0.91	-0.3364	-2.41	-0.3327	-2.25	-0.2830	-1.95
AGE*AGE	0.0027	1.54	0.0017	0.96	0.0015	0.92	0.0037	2.41	0.0038	2.43	0.0033	2.13
child<6	0.0780	0.17	0.1381	0.37	0.0186	0.05	-0.1962	-0.57	0.1970	0.47	0.3609	1.02
log(F)	0.9866	1.61	2.6718	4.58	1.9808	4.62	2.0402	4.22	1.5352	3.54	1.6975	3.90
g(log(F/R))	2.2991	3.66	2.0796	3.21	1.8959	3.32	1.6584	2.98	2.3601	4.73	2.2650	3.60
RET												
interc	-73.1942	-0.59	-21.5867	-0.49	-107.2282	-1.63	29.7177	0.33	-20.8153	-0.62	-45.7890	-1.14
divorced	-10.0000	0.00	-0.4708	-0.36	0.6422	0.95	-1.2918	-1.05	-0.3179	-0.48	0.2540	0.48
widow(er)	0.0855	0.08	0.7858	0.57	0.5871	0.66	2.1473	1.22	1.5564	1.48	1.1114	0.91
single	0.6528	0.77	-0.4166	-0.63	0.6702	1.10	0.5819	0.61	-0.3189	-0.42	0.4520	0.88
CHILDREN	-0.8399	-1.06	0.0318	0.08	-0.4679	-0.87	-0.9788	-1.30	-0.7594	-1.65	-0.5633	-1.55
not Dutch	0.3939	0.31	1.0231	1.49	0.3415	0.51	0.8473	0.85	1.5851	2.39	0.4547	0.71
URB	0.1589	2.25	0.0726	0.81	0.1035	1.24	0.0960	0.81	0.0837	1.08	0.1505	2.08
UNEMPR	0.1187	1.27	0.0432	0.43	-0.0305	-0.38	0.0210	0.21	0.0823	0.79	0.0114	0.16
AGE	1.7514	0.42	0.1844	0.12	3.0328	1.38	-1.7954	-0.56	0.1591	0.13	0.9602	0.70
AGE*AGE	-0.0095	-0.27	0.0029	0.22	-0.0206	-1.12	0.0219	0.78	0.0033	0.33	-0.0036	-0.31
child<6	-10.0000	0.00	-10.0000	0.00	-10.0000	0.00	-10.0000	0.00	-10.0000	0.00	-10.0000	0.00
log(F)	-0.5109	-0.60	-0.4962	-0.81	-0.2692	-0.45	-0.6099	-0.71	-0.3753	-0.70	0.1929	0.46
g(log(F/R))	-5.2411	-0.15	-4.9640	-0.25	-3.2645	-0.21	-55.2406	-0.75	-0.8519	-0.57	0.0256	0.00
UNE												
interc	5.3312	1.33	3.1615	0.58	6.8690	1.76	5.3986	0.96	2.2768	0.58	8.8040	2.68
divorced	2.5682	5.21	1.7593	3.14	1.5342	3.47	2.4671	2.74	2.3580	4.60	1.8910	4.94
widow(er)	0.5512	0.69	0.9545	0.76	1.1587	1.40	1.1108	0.68	1.8852	1.62	0.1841	0.14
single	1.6988	4.28	2.4327	3.76	1.7084	4.23	3.0103	3.13	2.1919	4.61	1.8889	5.55
CHILDREN	0.1371	0.96	-0.0749	-0.40	-0.2589	-1.63	-0.3281	-1.09	-0.1481	-0.90	0.0139	0.09
not Dutch	1.1039	2.36	0.6162	1.01	0.4447	0.91	0.3080	0.42	0.7320	1.45	0.4893	1.16
URB	0.0792	2.08	0.0916	1.17	0.1728	2.68	0.1399	1.58	0.1065	1.61	0.0447	0.77
UNEMPR	0.0089	0.16	0.0311	0.45	0.0261	0.44	-0.0019	-0.02	0.2053	1.94	0.0891	1.83
AGE	-0.1729	-1.20	-0.0803	-0.45	-0.2330	-1.72	-0.2965	-1.62	-0.2304	-1.55	-0.3318	-2.67
AGE*AGE	0.0027	1.73	0.0022	1.18	0.0035	2.30	0.0049	2.36	0.0035	2.14	0.0045	3.38
child<6	0.0982	0.25	0.1050	0.19	0.6183	1.38	0.4593	0.72	0.2854	0.66	-0.2606	-0.60
log(F)	-2.5691	-3.71	-3.2077	-2.84	-2.8860	-3.69	-2.9147	-1.99	-1.7538	-2.57	-2.5118	-5.08
g(log(F/R))	4.4488	3.63	6.0634	3.05	5.1818	3.82	6.4543	2.53	4.4301	3.99	1.1106	1.29
DIS												
interc	1.2184	0.29	2.6984	0.54	2.1196	0.52	1.1523	0.17	-2.9592	-0.71	-0.9791	-0.26
divorced	1.5592	2.84	0.6205	0.98	0.5911	1.25	1.9079	1.90	1.6053	3.28	0.8243	2.02
widow(er)	-0.1606	-0.20	-0.3864	-0.25	0.7485	0.96	0.8287	0.54	0.9410	0.86	0.6895	0.57
single	1.2961	3.17	1.5824	2.48	0.8897	2.18	2.0753	2.02	1.1600	2.60	0.6660	2.01
CHILDREN	-0.1045	-0.75	-0.3742	-1.81	-0.4164	-2.37	-0.7600	-2.09	-0.4550	-2.67	-0.3617	-2.36
not Dutch	0.6540	1.23	0.3421	0.55	-0.3581	-0.59	-0.2069	-0.23	0.0985	0.18	-0.7790	-1.34
URB	0.0548	1.48	0.0523	0.69	0.0044	0.07	-0.0190	-0.18	0.0337	0.52	-0.0233	-0.40
UNEMPR	0.0004	0.00	-0.0088	-0.12	-0.0173	-0.28	-0.1408	-1.41	0.0193	0.20	-0.1269	-2.31
AGE	0.0473	0.31	-0.0139	-0.07	-0.0928	-0.64	0.0069	0.03	0.0232	0.14	0.1291	0.87
AGE*AGE	0.0012	0.76	0.0023	1.22	0.0028	1.86	0.0026	1.08	0.0015	0.88	0.0005	0.30
child<6	0.2042	0.44	0.3542	0.62	0.5529	1.10	0.2701	0.36	0.1997	0.38	0.4412	0.92
log(F)	-3.2439	-4.39	-3.7304	-3.12	-2.4211	-2.96	-3.6249	-2.27	-1.6755	-2.42	-2.3862	-4.57
g(log(F/R))	4.5815	4.11	6.5412	3.22	5.8628	4.78	7.6784	2.65	5.0056	5.00	4.7200	6.10
PROD EQ												
interc	2.4672	8.19	2.7905	10.79	2.9033	12.28	2.7680	12.17	2.3904	9.34	2.1929	7.40
not Dutch	0.0198	0.40	-0.0652	-1.78	0.0121	0.37	-0.0382	-1.04	-0.0410	-1.02	-0.0336	-0.79
UNEMPR	-0.0213	-4.92	-0.0206	-5.18	-0.0168	-3.89	-0.0170	-4.19	-0.0188	-2.16	0.0024	0.44
AGE	0.0322	2.46	0.0201	1.84	0.0115	1.17	0.0202	2.20	0.0345	3.23	0.0390	3.28
AGE*AGE	-0.0004	-2.62	-0.0003	-2.33	-0.0002	-1.83	-0.0003	-3.13	-0.0005	-3.92	-0.0005	-4.07
tech	-0.0220	-0.87	-0.0408	-2.00	-0.0441	-2.17	-0.0428	-2.07	-0.0335	-1.43	-0.0256	-1.20
adm	0.1233	4.29	0.0858	3.60	0.1021	4.31	0.1129	4.96	0.1546	6.05	0.1248	4.98
serv	-0.1624	-3.46	-0.0240	-0.57	-0.0440	-1.38	-0.0494	-1.34	-0.0245	-0.54	-0.0655	-1.49
EDUCL	-0.0772	-1.44	-0.1314	-2.71	-0.1214	-2.78	-0.1310	-2.91	-0.1832	-3.88	-0.2194	-3.94
EDUCL*EDUCL	0.0252	3.95	0.0253	4.29	0.0237	4.28	0.0252	4.62	0.0349	6.34	0.0295	4.90
EDUCL*AGE	0.0029	3.61	0.0044	5.50	0.0043	6.39	0.0043	6.41	0.0043	5.84	0.0058	6.14
sigma prod	0.3858	69.15	0.3345	70.48	0.3497	80.58	0.3456	78.81	0.3861	108.32	0.3761	113.18
CORREL												
gamma PTW	0.3928	1.18	-0.5014	-1.48	-0.0776	-0.34	-0.5417	-1.25	-0.3439	-0.97	-0.1787	-0.86
gamma RET	-0.5609	-0.70	-0.7160	-0.86	-0.3143	-0.55	-1.2801	-1.01	-0.3111	-0.53	0.0324	0.08
gamma UNE	1.7024	2.53	2.4918	2.36	2.1407	2.79	2.9945	1.88	1.9967	2.75	-0.0447	-0.11
gamma DIS	2.2046	3.59	3.0660	2.79	2.0681	2.82	4.0243	2.34	1.8779	2.82	1.4010	3.29
sig0	0.5192	1.01	0.7535	1.04	0.6349	1.04	0.9142	1.02	0.8606	1.04	0.5100	1.01

Table C2: Women, Model 1

	1984		1985		1986		1987		1988		1989	
LOGLIK:	-1656.84		-1879.91		-2276.06		-2057.01		-2442.08		-2266.97	
PTW	parm	t-val	parm	t-val	parm	t-val	parm	t-val	parm	t-val	parm	t-val
interc	-66.2139	-1.81	-0.1065	-0.03	2.6817	0.93	0.9649	0.29	2.2979	0.72	6.7381	2.13
divorced	-10.0000	0.00	-1.1741	-3.25	-1.1663	-3.77	-1.1426	-3.74	-1.3889	-4.90	-1.6128	-5.93
widow(er)	-10.0000	0.00	-0.1701	-0.29	-0.2124	-0.39	-0.4969	-0.90	0.2927	0.53	0.5958	0.99
single	-25.7894	-3.60	-1.4336	-4.45	-1.6690	-5.94	-1.6497	-5.88	-1.6410	-5.88	-1.8155	-7.01
CHILDREN	0.0870	0.07	0.8138	5.60	0.9822	8.33	0.8135	7.18	0.8562	8.00	0.6256	6.47
not Dutch	-10.7139	-2.19	-0.3669	-0.85	-0.1124	-0.28	-0.5833	-1.46	-0.5561	-1.25	-0.5475	-1.45
URB	-0.0921	-0.31	0.0248	0.44	0.0581	1.13	0.1167	2.31	0.0729	1.42	0.1016	2.27
UNEMPR	-0.8002	-1.87	-0.0550	-1.16	0.0078	0.16	-0.0360	-0.70	0.1019	1.00	-0.0091	-0.17
AGE	2.9955	1.93	0.1363	1.05	-0.0128	-0.10	0.0757	0.58	0.1332	0.96	-0.0094	-0.08
AGE*AGE	-0.0369	-1.96	-0.0009	-0.61	0.0009	0.60	0.0000	0.02	-0.0009	-0.55	0.0006	0.44
child<6	-1.7659	-0.54	0.6197	1.52	0.5494	1.50	1.0891	3.03	0.7886	2.23	0.1130	0.39
log(F)	8.8095	1.79	-0.9136	-1.39	-1.3024	-2.45	-1.2975	-2.08	-2.3322	-3.17	-2.2734	-3.37
g(log(F/R))	-1.5332	-0.35	1.2491	2.68	1.0919	2.83	1.1927	3.14	1.2724	3.58	0.8443	2.23
HSW												
interc	16.0626	1.66	13.0292	2.45	12.1766	3.36	16.1438	3.79	11.2967	2.38	24.6672	3.77
divorced	-2.8485	-2.73	-0.8895	-2.29	-0.8852	-3.10	-0.8221	-2.94	-1.0196	-3.92	-1.0319	-3.87
widow(er)	-1.8457	-1.36	-0.3608	-0.62	-0.7597	-1.43	-0.6429	-1.25	-0.2989	-0.55	-0.2446	-0.39
single	-10.2157	-6.42	-3.4934	-5.25	-2.8802	-7.43	-2.4367	-7.22	-3.1673	-7.43	-3.1798	-6.77
CHILDREN	1.7397	5.60	1.1662	6.44	1.2592	10.69	1.1248	9.86	1.1281	10.36	1.0167	9.44
not Dutch	-0.9017	-0.97	0.1424	0.23	0.4783	1.06	0.1310	0.27	-0.4192	-0.62	0.3930	0.62
URB	-0.1177	-1.31	-0.0398	-0.68	0.0339	0.66	0.0320	0.64	0.0148	0.28	-0.0019	-0.04
UNEMPR	-0.0661	-0.64	0.0018	0.02	0.0298	0.50	0.0018	0.02	0.1884	1.43	0.0145	0.15
AGE	-0.4308	-1.20	-0.1477	-0.81	-0.1519	-1.01	-0.1646	-1.09	0.0582	0.30	-0.2411	-1.24
AGE*AGE	0.0067	1.68	0.0030	1.40	0.0031	1.78	0.0037	2.11	0.0008	0.36	0.0045	2.01
child<6	2.6286	2.79	1.5928	3.48	1.4719	4.05	1.6906	4.76	1.5102	4.24	0.6406	2.13
log(F)	-2.0757	-1.58	-3.9778	-3.80	-3.9881	-5.64	-5.3033	-5.93	-5.5775	-4.54	-7.2952	-4.82
g(log(F/R))	3.9866	2.72	1.3357	2.31	0.8474	1.89	0.5671	1.26	1.8358	4.55	1.4780	2.76
UNE												
interc	8.8898	0.81	3.8556	0.61	3.2449	0.64	2.4102	0.40	-2.1311	-0.47	6.0579	1.30
divorced	2.5502	1.94	2.6590	3.64	2.1537	5.61	1.3492	3.51	0.7954	2.16	1.1415	3.69
widow(er)	0.5993	0.34	-10.0000	0.00	0.9967	1.29	0.1811	0.23	-0.0804	-0.09	0.1830	0.19
single	-0.1908	-0.09	0.8297	1.17	0.9818	2.17	0.5365	1.21	0.1043	0.27	0.3224	0.88
CHILDREN	0.2970	0.55	0.6668	2.91	0.8521	4.21	0.5076	2.94	0.3549	2.27	0.2862	1.86
not Dutch	-0.6408	-0.85	0.8042	1.04	0.8691	1.63	-0.1236	-0.20	-0.0383	-0.07	0.7180	1.42
URB	0.1624	1.77	0.1045	0.98	0.0691	0.80	0.0578	0.69	0.0502	0.63	0.0784	1.15
UNEMPR	-0.1813	-1.91	-0.0200	-0.22	-0.0729	-0.93	0.0105	0.15	0.2384	2.12	0.0668	0.91
AGE	-0.3882	-1.02	-0.1211	-0.52	-0.1953	-1.08	-0.1452	-0.75	-0.1534	-0.88	-0.0465	-0.28
AGE*AGE	0.0053	1.23	0.0018	0.69	0.0028	1.36	0.0024	1.12	0.0022	1.13	0.0012	0.68
child<6	2.4228	2.40	1.2601	2.04	0.7093	1.29	0.2829	0.42	0.5445	1.06	0.6740	1.65
log(F)	-1.1733	-1.08	-2.3279	-2.06	-0.9499	-1.04	-1.3415	-1.14	0.1674	0.17	-2.9600	-2.92
g(log(F/R))	0.8527	0.45	3.4596	3.17	3.1146	4.04	2.9856	2.94	2.9381	3.90	2.1002	3.17
DIS												
interc	14.2255	1.53	3.9696	0.51	6.3434	1.16	5.8643	0.97	1.6445	0.33	14.5898	2.35
divorced	0.1966	0.15	1.2453	2.20	0.7388	1.68	0.5151	1.22	-0.0608	-0.14	-0.3775	-0.89
widow(er)	0.4070	0.30	1.0263	1.45	0.3018	0.46	-0.5340	-0.81	0.6729	1.08	0.7257	1.05
single	-3.2641	-1.48	0.5479	0.86	0.6267	1.30	0.4271	1.02	0.5973	1.45	0.0738	0.18
CHILDREN	0.8138	1.67	0.4235	1.47	0.6031	2.78	0.3577	1.41	0.4518	2.48	0.0317	0.13
not Dutch	-0.9183	-1.04	-0.5557	-0.59	0.4364	0.70	-0.2248	-0.35	-0.3958	-0.60	0.0215	0.03
URB	0.0547	0.58	0.1691	1.95	0.1952	2.48	0.2123	2.74	0.1444	2.00	0.0408	0.55
UNEMPR	-0.0559	-0.55	0.0331	0.37	0.0855	1.10	0.0660	0.81	0.1610	1.15	-0.0420	-0.43
AGE	-0.6531	-2.05	-0.0194	-0.07	-0.2206	-1.17	-0.2262	-1.22	0.0637	0.32	-0.1923	-0.97
AGE*AGE	0.0090	2.50	0.0015	0.51	0.0038	1.83	0.0044	2.14	0.0006	0.30	0.0038	1.76
child<6	1.7025	1.51	1.5237	2.00	1.3641	1.99	1.7358	2.25	1.5971	2.55	-100.0000	0.00
log(F)	-1.4631	-1.05	-3.4972	-2.23	-3.0860	-2.66	-2.9571	-2.28	-3.2816	-2.81	-4.8553	-3.50
g(log(F/R))	4.0353	1.43	3.6378	2.38	1.7720	1.37	2.0209	1.55	2.7287	3.80	-23.4863	-0.02
PROD EQ												
interc	3.0510	5.28	2.3578	3.74	2.3952	5.21	2.5796	6.49	1.9865	4.29	2.8020	6.58
not Dutch	0.1322	1.70	0.0824	0.88	0.1774	2.96	0.0753	1.42	-0.0134	-0.16	0.0632	1.07
UNEMPR	-0.0232	-3.05	-0.0075	-0.84	-0.0003	-0.03	-0.0025	-0.32	0.0252	1.95	0.0015	0.16
AGE	-0.0169	-0.69	0.0178	0.64	0.0190	0.94	0.0053	0.31	0.0319	1.53	0.0005	0.02
AGE*AGE	0.0001	0.55	-0.0002	-0.57	-0.0003	-1.38	-0.0001	-0.27	-0.0004	-1.68	0.0000	-0.06
tech	-0.0234	-0.32	-0.1787	-3.03	-0.0872	-1.66	-0.1578	-3.01	-0.0998	-2.15	-0.0631	-1.85
adm	0.0375	0.69	0.0179	0.47	0.0238	0.68	0.0193	0.69	0.0504	1.82	0.0451	2.11
serv	-0.0759	-1.65	-0.0657	-2.02	-0.0703	-2.47	-0.0595	-2.40	-0.0494	-1.99	-0.0238	-1.27
EDUCL	0.0689	0.57	0.1215	1.32	-0.0321	-0.41	0.0368	0.57	-0.0465	-0.72	-0.0219	-0.40
EDUCL*EDUCL	0.0381	2.52	0.0259	2.36	0.0199	1.81	0.0128	1.46	0.0253	2.85	0.0108	1.63
EDUCL*AGE	-0.0011	-0.59	-0.0024	-1.70	0.0021	1.74	0.0008	0.81	0.0008	0.80	0.0021	2.45
sigma prod	0.4391	29.84	0.4236	28.19	0.4094	45.89	0.3583	49.18	0.4725	45.92	0.3917	29.20
CORREL												
gamma PTW	25.1744	3.42	0.8932	2.10	0.9157	3.65	0.4417	1.66	1.2535	3.45	0.8467	2.64
gamma RET	4.6996	7.25	2.7299	3.26	2.0438	5.11	2.0462	4.14	3.4470	4.67	4.1145	4.63
gamma UNE	-0.2577	-0.13	0.5059	0.62	1.4022	3.43	0.9061	1.88	0.1154	0.23	1.2928	2.83
gamma DIS	2.1302	1.31	2.4911	1.94	1.0575	1.40	0.9458	1.36	1.6999	2.16	3.4394	4.05
sig0	0.9829	1.0570	0.4120	0.95	0.0477	0.09	0.1226	0.27	0.0613	0.13	0.0779	0.16

Table C3: Men, 1988, Models 1-3

	Model 1		Model 2		Model 3	
LOGLIK:	-751.62		-756.11		-735.79	
PTW	parm	t-val	parm	t-val	parm	t-val
interc	-2.1262	-0.63	-1.5301	-0.46	-1.5268	-0.27
divorced	0.8833	1.87	0.8776	1.85	1.4523	2.26
widow(er)	0.2523	0.21	0.2451	0.20	0.7421	0.50
single	0.1509	0.37	0.1644	0.41	0.4674	0.86
CHILDREN	-0.3828	-2.56	-0.3822	-2.55	-0.4695	-2.62
not Dutch	0.1806	0.29	0.1804	0.29	0.3440	0.48
URB	0.0316	0.47	0.0324	0.48	0.0310	0.40
UNEMPR	0.1369	1.34	0.1372	1.34	0.1712	1.33
AGE	-0.3327	-2.26	-0.3329	-2.26	-0.2233	-1.20
AGE*AGE	0.0038	2.43	0.0038	2.43	0.0028	1.36
child<6	0.1970	0.47	0.1940	0.46	0.2558	0.52
EDUCL					-0.5852	-0.72
EDUCL*EDUCL					0.1607	1.56
EDUCL*AGE					-0.0006	-0.04
log(F)	1.5352	3.55	1.2990	3.40	0.1567	0.11
g(log(F/R))	2.3601	4.74	2.4760	4.98	3.6171	4.36
RET						
interc	-20.8153	-0.63	-19.0449	-0.57	-18.3065	-0.46
divorced	-0.3179	-0.48	-0.2907	-0.44	-0.4051	-0.46
widow(er)	1.5564	1.49	1.5814	1.52	1.4594	1.31
single	-0.3189	-0.42	-0.3206	-0.48	-0.7203	-0.78
CHILDREN	-0.7594	-1.65	-0.7627	-1.63	-0.9081	-1.63
not Dutch	1.5851	2.39	1.6080	2.38	1.6659	2.08
URB	0.0837	1.09	0.0806	1.03	0.0562	0.62
UNEMPR	0.0823	0.79	0.0859	0.81	0.0747	0.64
AGE	0.1591	0.14	0.0910	0.08	-0.0358	-0.03
AGE*AGE	0.0033	0.33	0.0039	0.39	0.0067	0.57
child<6	-10.0000	0.00	-10.0000	0.00	-10.0000	0.00
EDUCL					3.5100	1.03
EDUCL*EDUCL					-0.0160	-0.13
EDUCL*AGE					-0.0523	-0.95
log(F)	-0.3753	-0.70	-0.3381	-0.74	-1.6623	-1.44
g(log(F/R))	-0.8519	-0.58	-1.5423	-0.99	-1.5125	-0.79
UNE						
interc	2.2768	0.59	1.9099	0.51	3.1351	0.62
divorced	2.3580	4.61	2.3313	4.63	2.3209	4.20
widow(er)	1.8852	1.62	1.8663	1.63	1.8090	1.56
single	2.1919	4.61	2.1821	4.66	2.1283	4.75
CHILDREN	-0.1481	-0.91	-0.1505	-0.93	-0.1620	-1.01
not Dutch	0.7320	1.45	0.7062	1.40	0.9114	1.85
URB	0.1065	1.61	0.1027	1.57	0.1013	1.55
UNEMPR	0.2053	1.94	0.2027	1.93	0.2497	2.36
AGE	-0.2304	-1.55	-0.2285	-1.56	-0.2903	-1.91
AGE*AGE	0.0035	2.15	0.0034	2.18	0.0035	2.04
child<6	0.2854	0.66	0.2849	0.66	0.2701	0.64
EDUCL					-1.5285	-1.95
EDUCL*EDUCL					0.1441	1.51
EDUCL*AGE					0.0122	0.88
log(F)	-1.7538	-2.58	-1.5643	-2.70	-0.7491	-0.54
g(log(F/R))	4.4301	3.99	4.4985	4.11	3.3891	3.17
DIS						
interc	-2.9592	-0.71	-3.3776	-0.84	-5.4148	-1.22
divorced	1.6053	3.29	1.5826	3.29	1.4974	3.27
widow(er)	0.9410	0.87	0.9114	0.85	0.8012	0.75
single	1.1600	2.60	1.1579	2.62	0.9746	2.52
CHILDREN	-0.4550	-2.67	-0.4576	-2.69	-0.4526	-2.80
not Dutch	0.0985	0.18	0.0758	0.14	0.1532	0.31
URB	0.0337	0.52	0.0297	0.46	0.0387	0.63
UNEMPR	0.0193	0.20	0.0198	0.21	0.0298	0.34
AGE	0.0232	0.14	0.0225	0.14	-0.0573	-0.38
AGE*AGE	0.0015	0.89	0.0015	0.92	0.0016	0.98
child<6	0.1997	0.39	0.1963	0.38	0.1005	0.20
EDUCL					-0.2855	-0.43
EDUCL*EDUCL					-0.1919	-1.78
EDUCL*AGE					0.0184	1.41
log(F)	-1.6755	-2.42	-1.4641	-2.47	0.2714	0.30
g(log(F/R))	5.0056	5.00	5.0948	5.06	5.0565	6.02
PROD EQ						
interc	2.3904	9.34	2.3425	7.48	2.2961	8.84
not Dutch	-0.0410	-1.03	-0.0545	-1.11	-0.0266	-0.65
UNEMPR	-0.0188	-2.16	-0.0232	-2.17	-0.0187	-2.15
AGE	0.0345	3.23	0.0404	3.09	0.0453	4.26
AGE*AGE	-0.0005	-3.93	-0.0005	-3.72	-0.0006	-5.65
tech	-0.0335	-1.44	-0.0401	-1.40	-0.0218	-0.88
adm	0.1546	6.06	0.1975	6.20	0.1848	6.80
serv	-0.0245	-0.55	-0.0326	-0.60	-0.0106	-0.23
EDUCL	-0.1832	-3.88	-0.1777	-3.07	-0.2644	-5.11
EDUCL*EDUCL	0.0349	6.35	0.0328	4.81	0.0391	6.60
EDUCL*AGE	0.0043	5.85	0.0051	5.59	0.0056	7.08
sigma prod	0.3861	108.33	0.4826	108.94	0.3902	100.34
CORREL						
gamma PTW	-0.3439	-0.98	-0.3554	-1.02	1.9353	2.95
gamma RET	-0.3111	-0.54	-0.3506	-0.63	-0.8864	-0.87
gamma UNE	1.9967	2.75	2.0289	2.82	1.7706	2.41
gamma DIS	1.8779	2.82	1.9263	2.90	1.0865	1.88
sig0	0.8606	1.04	0.8286	1.04	0.9712	1.92