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ABSTRACT

Self-Employment and Labour Market Transitions: A Multiple State Model*

We use the British Household Panel Survey (BHPS) to estimate a multiple state transition model with three possible labour market states: self-employment, employment, and unemployment. This enables us to assess the effects of changes in demographic characteristics and economic conditions on the probabilities of exiting and entering these states. We allow for unobservable individual heterogeneity, duration dependence, lagged duration dependence and state dependence. Three main results are obtained. First, the aggregated unemployment rate is found to have a positive effect on the probability of becoming self-employed (push effect). Second, unemployed individuals are found to be more likely to become self-employed but the duration of their unemployment drastically reduces this probability. Third, the government policies undertaken during the 1980s are found to have been successful in promoting the entrance into self-employment, but not in preventing the exit from self-employment.

JEL Classification: J23 and J64
Keywords: duration, self-employment, transitions and unemployment

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1. Introduction

During the late 1970's and the 1980's many OECD countries were experiencing an increase in the ratio of self-employed to employed individuals. Except for Portugal, the UK showed the biggest increase in this ratio. In particular, according to OECD data from the Labour Force Statistics (see Table 1), in 1975 8.1% of all employed individuals in the UK were self-employed whereas by 1995 this number had risen to 13.2%. In the 1980´s unemployment peaked too in the UK (see Figure 1). The UK government introduced several programs to alleviate unemployment by supporting the start-up and expansion of small businesses.[1] Examples are the Enterprise Allowance Scheme (EAS) and its successor, the Business Start-up Scheme (BSUS), which give transfer payments to the unemployed when they start their own business.

The purpose of this paper is to provide empirical evidence on the individual characteristics and the economic factors that determined self-employment decisions in the UK. We focus on the effects that the individual unemployment experience and the aggregate unemployment rate have on the probability of becoming and remaining self-employed. This will allow us to answer the question whether self-employment is a way to escape unemployment.

We employ a semi-parametric, reduced-form, multiple-state transition model. Three states are considered: self-employment, employment, and unemployment. The main advantage of this empirical specification is its flexibility, which allows us to take account of the following determinants of the self-employment decision: state dependence, duration dependence, lagged duration dependence, and unobservable heterogeneity. State dependence accounts for the possibility that the transition probabilities depend on the origin and destination states. This allows us to test whether the probabilities of transition into self-employment are different for unemployed and employed individuals. Duration dependence and lagged duration dependence account for the possibility that the time during which the current state has been occupied and the length of previous visits to the different states ("experience") affect the transition probabilities. Unobservable heterogeneity is likely to matter in this context due to

[1] Other OCDE countries such as the US or Spain implemented similar programs during this period.

differences in tastes, ability, or "entrepreneurial spirit" that cannot be observed by the econometrician.[2]

The data used is a sample of males between 16 and 55 years of age that is drawn from the second wave of the British Household Panel Survey (BHPS). This wave includes a retrospective work history questionnaire, which records all employment, unemployment, and self-employment spells for all members of a household since they left school. Using this information, we estimate the transitions between the states with the maximum likelihood estimator of Heckman and Singer (1984), which approximates the distribution function of the unobservables by a finite mixture distribution. We concentrate on males no older than 55, thus we can ignore inactivity as an additional labour market state because they have high participation rates in the labour market. Note that males from this age group also constituted 67% of all the self-employed workers in 1992 in the UK (2nd Wave BHPS).

We obtain three main results. First, we find that the aggregate unemployment rate has a positive effect on the transition probability to self-employment, especially for unemployed individuals. Second, we find that the transition probability to self-employment is much higher for unemployed individuals than for employed individuals. However, we also find that the transition probability from unemployment to self-employment drastically decreases with the number of periods spent unemployed and with the previous unemployment experience. Third, we find that the probabilities of both entering and exiting self-employment are positively correlated with two time dummies for the two periods in which the UK government introduced the Enterprise Allowance Scheme (EAS) and the Business Start-up Scheme (BSUS).

Our first result that the aggregate unemployment rate has a positive effect on the transition probability to self-employment is consistent with the interpretation that the deterioration in economic conditions generates an increase in the self-employment rates ("push" factors). This finding is in line with the evidence reported by Acs *et al.* (1994) and Schuetze (2000), who obtain a positive correlation between the unemployment rate and the self-employment rate for a panel of OECD countries and for micro-data for

[2] Only few empirical applications analyse the flows between self-employment and other labour market states. Among them are Magnac and Robin (1994), Carrasco (1999) and Burdett and Taylor (1994). They estimate less flexible models for France, Spain, and the UK, respectively.

Canada and the US, respectively. Our first result contradicts the evidence of Blanchflower and Oswald (1990, 1998) and Taylor (1996), who find a negative relationship between the unemployment rate and the probability of becoming self-employed using micro-data for the UK.

Our second result has two aspects. The first one is that the transition probability to self-employment is much higher for unemployed individuals than for employed individuals. This suggests that unemployed individuals consider self-employment as a possibility of escaping unemployment. This finding is as in Evans and Leighton (1989), who used US data, and in Carrasco (1999), who used Spanish data. The second aspect is that the transition probability from unemployment to self-employment decreases with the duration of unemployment. This is consistent with the hypothesis that the duration of unemployment has detrimental effects on the unemployed individuals' stocks of human and physical capital and therefore reduces the probability of self-employment. This finding is novel in the literature.

Our third result that the probabilities of entering and exiting self-employment are positively correlated with the two time dummies for the policy changes suggests that the introduction of the EAS and the BSUS had a positive effect on both the inflows to and the outflows from self-employment. Interestingly the effect on the outflows was stronger than that on the inflows. Therefore, the effect on the stock of self-employment is ambiguous and will depend on the evolution of the initial stocks in unemployment, employment and self-employment.

Our empirical specification has several appealing features that are novel in the literature. First, it allows for the analysis of the effects of both the general economic conditions and the individual unemployment experience on the transitions to and from self-employment. Second, our empirical specification considers separately the effects of all explanatory variables on the entry to and the exit from self-employment. This is different from binary choice models that only analyse the net effect of explanatory variables on the stock of self-employed individuals. This difference may be responsible for the difference between our first result and the results of Blanchflower and Oswald (1990,1998) and Taylor (1996), who estimate binary choice models using a stock sample. Third, our empirical specification does not constrain us to consider only the transition of employed individuals to self-employment, as is the case in Evans and

Leighton (1989) and Alba-Ramírez (1994). Rather it allows us to estimate the transition probabilities between all three states (employment, self-employment, unemployment). Consequently, the working decision is endogeneous and we avoid possible sample selection bias. Finally, unlike previous studies on self-employment transitions, our empirical specification allows for state dependence, duration dependence, lagged duration dependence, and unobservable heterogeneity. These factors turn out to be significant determinants of the self-employment decisions.

The outline of the paper is as follows. Section 2 describes the model specification and discusses the estimation of the transition probabilities. Section 3 presents the data used for the analysis. Section 4 presents and discusses the estimation results. Section 5 concludes. Tables and figures are at the end of the paper.

2. The model

In Section 2.1, the main features of the proposed empirical specification are presented and discussed. Section 2.2 deals with some identification issues relating the empirical specification. In Section 2.3 we describe the estimation method used.

2.1 Empirical specification

The specification of the model is guided by the standard theory of on-the-job search. Specifically it is assumed that unemployed individuals devote some of their time searching for jobs, but also that once an individual has accepted a job and starts working, it could continue searching for a better job. Two types of jobs are considered here: employment and self-employment. In other words self-employment is considered as an alternative to employment[3]. Thus we distinguish between three possible states: unemployment, employment, and self-employment[4]. An individual can move from any of these states to any of the others at any point in time. We call these states the origin state, which is represented by the first subscript, and the destination state, which is

[3] Self-employment is also considered as an alternative to employment by, among others, Ress and Shah (1985), Blanchflower and Oswald (1990, 1998), Burdett and Taylor (1994), Blundell et al. (1995), and Taylor (1996), who all used UK data, by Evans and Leighton (1989), who used US data, and by Alba (1994) and Carrasco (1999), who used Spanish data.

[4] We neglect the possible state inactivity. As we will see in Section 3, this is innocuous for the sample considered here.

represented by the second subscript. Therefore we have six possible transitions in Table 2.

In order to derive the likelihood function, consider a sample of N individuals. Each individual spends time in at least one of the three states. The number of months spent in state k before changing to state l is called elapsed duration. For each individual we observe a sequence $t_i = \{t_i^c\}_{c \in \{1,\dots,C_i\}}$ of contiguous periods of time (spells) spent in different states. t denotes the elapsed duration in a particular state, the subscript i denotes the individual and the superscript, c denotes the cth spell of individual i. For each individual, these spells can be complete or incomplete (right censored) at the interview date. The derivation of the likelihood function requires that we distinguish between complete and incomplete spells. The contribution to the likelihood function of an incomplete spell is the probability of surviving in a state to the time of the interview, which is called the survivor function. The contribution to the likelihood function of a complete spell is the probability of surviving in state k until time t (survivor function) times the probability of moving from state k to state l in the infinitesimally short subsequent interval $(t, t+\partial t)$ (transition intensity).

We assume that individual labour market transitions are governed by intensity functions of the mixed proportional hazard (MPH) type. Specifically, for each spell, c, the transition intensity from state k to state l for the individual i, θ_{kl}, is assumed to have the following functional form:

$$\theta_{kl}\left(t_i^c \mid X_{ikl}, v_{ikl}; \beta\right) = h_{kl}(t_i^c) \exp(\beta'_{kl} X_{ikl}) v_{ikl}, \qquad (1)$$

where the elapsed duration enters the transition intensities (duration dependence) through the baseline function $h_{kl}(t_i^c)$. In equation (1), X_{ikl} is a vector of observable variables describing demand conditions and demographic characteristics. They include the time that individual i has spent previously in any of the three states (lagged duration dependence)[5]. These variables are assumed to affect a move from state k to state l through a vector of unknown parameters, β_{kl}, which can vary depending on the origin and destination states (state dependence). Finally, v_{ikl} is a positive random individual effect (unobservable heterogeneity), which can be due to differences in the individual's preference for leisure or to differences in the individual's ability to start-up a business. The unobserved heterogeneity term is different for different origin and destination states.

In sum, the specification of the transition intensities proposed in equation (1) allows for state dependence (through the estimation of parameters specific to every state) along with duration dependence, lagged duration dependence, and unobservable heterogeneity. Note that the model is in continuous time and that the explanatory variables X_i are not time-varying; in practice all the explanatory variables will be fixed to their values at the beginning of each spell as explained in Section 3.

Given the form of the transition intensities in (1), individual i's contribution to the likelihood function of a completed spell of duration t_i^c in state k that ends in state l is,

$$P_{kl}\left(t_i^c \mid Z_i ; W\right) = exp\left\{-Q_k\left(t_i^c \mid Z_i ; W\right)\right\} q_{kl}\left(t_i^c \mid Z_i ; b\right). \tag{2}$$

The contribution to the likelihood function of a right censored spell, that is, the probability of surviving in state k until time t or the survivor function in state k, can be expressed as follows:

$$\overline{F}_k\left(t_i^c \mid Z_i ; W\right) = exp\left\{-Q_k\left(t_i^c \mid Z_i ; W\right)\right\}, \tag{3}$$

where Q_k is the corresponding integrated hazard function, $Q_k = \int_0^{t_i} \sum_{l \neq k} q_{kl}\left(s \mid Z_i ; W\right) \partial s$, $Z_i = \left\{X_{ikl}, v_{ikl}\right\}_{l \neq k}$ is the vector of all observed and unobserved variables, and O is the vector of all unknown parameters that enter equation (1).

To see how the model works suppose first that there is no unobserved heterogeneity, that is, v_{kl} is zero for all individuals. The contribution to the log-likelihood function of an individual with a sequence of spells $\left\{t_i^1, t_i^2, ..., t_i^{C_i}\right\}$ then is[6]

[5] The model is identified given standard regularity conditions. See Honore (1993) for more details.
[6] The derivation of the likelihood function with and without unobserved heterogeneity can be found in Flinn and Heckman (1982) or Lancaster (1990).

$$ln\left(L_i\left(W \mid t_i^1, t_i^2, ..., t_i^{C_i}; X_i\right)\right) = \sum_{c=1}^{C_i}\sum_{k=1}^{3}\left[\left(\sum_{l \neq k} d_{kl}^c \, ln\left(P_{kl}\left(t_i^c \mid X_i; W\right)\right)\right) + s_k^c \, ln\left(\overline{F}_k\left(t_i^c \mid X_i; W\right)\right)\right], \quad (4)$$

where d_{kl}^c is an indicator variable which equals 1 if the individual changed from state k to state l in the cth spell and zero otherwise and s_k^c is a dummy variable which equals one if the cth spell is incomplete and zero otherwise. The log-likelihood function for the whole sample is the summation of equation (4) over the N individuals. This log-likelihood function breaks up into separate contributions from each type of transition. Therefore, given that the transition intensities depend upon disjoint sets of parameters, the sub-likelihood functions can be maximised separately and the parameters of each transition can be estimated independently.

When there is unobservable heterogeneity among the individuals the model becomes more complicated. The unobservable individual effects, v_{ikl} $(\forall k, l, k \neq l)$, then vary over the population. Note that we cannot condition the individual probabilities on v_{ikl} since they are unobservable. Instead, it is necessary to integrate v_{ikl} over all possible values to get the unconditional probabilities.

Lets assume that the individual effects are identically and independently distributed for all individuals with a joint distribution function $G(v_{iEU}, v_{iESE}, v_{iUE}, v_{iUSE}, v_{iSEE}, v_{iSEU})$. This specification allows the unobservable heterogeneity terms to be correlated across different transitions (see Van den Berg, 2000). In that case, the individual contribution to the likelihood function takes the form:

$$L_i(W \mid t_{i1}, ..., t_{iC_i}, X_i) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\left(\prod_{c=1}^{C_i}\prod_{k}\prod_{l \neq k} P_{kl}(t_c \mid X_{ikl}, v_{ikl}; W)^{d_{kl}^c}\right) \times \left(\prod_{c=1}^{C_i}\prod_{l} \overline{F}_k(t_c \mid X_{ikl}, v_{ikl}; W)^{s_k^c}\right) \times dG(v_{iEU}, v_{iESE}, v_{iUE}, v_{iUSE}, v_{iSEE}, v_{iSEU}) \quad (5)$$

The log-likelihood function for the whole sample is the summation of the log of equation (5) over the N individuals.

2.2. Identification issues

Two issues remain that have to be fully specified before we can estimate the model just presented: the baseline rates of transition and the unobserved heterogeneity terms.

The baseline rates of transition, $h_{kl}(t_i^c)$, are assumed to be linear functions of the elapsed duration in state k before transiting to state l with splines at 6, 9 and 12 months:

$$h_{kl}(t) =$$

$$exp(a_{1kl}\, ln(t) + a_{2kl} I(t > 6)(ln(t) - ln(6)) + \qquad (6)$$

$$a_{3kl} I(t > 9)(ln(t) - ln(9)) + a_{4kl} I(t > 12)(ln(t) - ln(12))),$$

where I(.) is an indicator function that equals one if the condition in brackets is fulfilled and zero otherwise. This specification generalises the traditional Weibull proportional hazard, which is the special case where α_{2kl}=0, α_{3kl}=0 and α_{4kl}=0 for all k and l[7]. Note that specification (6) allows for a non-monotonic relationship between the elapsed duration and the transition intensities.

With respect to unobserved heterogeneity, a completely flexible specification of the joint distribution function *G(.)* would require the evaluation of a complicated integral like in (5). To avoid the implied computational burden we reduce the dimensionality of *G(.)* from six to two by assuming a two-factor loading specification[8]. Specifically, we assume that the unobservable terms $\{v_{kl}\}_{k?l}$ are generated by two common factors: $v_{ikl} = exp(d_{kl} v_{1i} + l_{kl} v_{2i})$, where v_{1i} and v_{2i} are the common factors, which are independently and identically distributed across individuals with a distribution function $H(v_{1i}, v_{2i})$, and d_{kl} and $?_{kl}$ are the corresponding loading parameters for different type of transitions that become parameters to estimate jointly with the rest of parameters of the model. This specification is tested against a more restrictive one, in which each factor affects only the transitions with the same origin or the same destination $(v_{ikl} = d_k v_{1i} + l_l v_{2i})$[9]. The two-factor loading specification nests a one-

[7] Several alternative specifications were tried but this fitted best the data. The splines do not mimic the unemployment legislation since there have been several changes through the years. A means tested subsidy can be perceived in the UK for an unlimited period of time. The selection of the splines is motivated by the fact that 75% of all unemployed transit towards other state in less than 1 year.

[8] See Van den Berg (2000) for a detailed exposition of this type of models.

[9] See Bonnal, Fougère and Sérandon (1997) for a similar specification of the two-factor loading

factor loading specification that is also tested in the estimation. From an economic point of view, one of the factors underlying the unobserved heterogeneity could represent heterogeneous tastes for leisure while the other could relate to risk preferences.

2.3. Estimation method

The joint distribution for the unobserved heterogeneity factors, $H(v_{1i},v_{2i})$, could be fully specified (for example as a bivariant normal) and equation (5) could then be estimated using maximum likelihood. However, Heckman and Singer (1984) pointed out that the results of this procedure are misleading when the chosen distribution for the unobservable term is not the true one. They show that this problem can be avoided by using the Non-Parametric Maximum Likelihood Estimator (NPMLE), which does not make a distributional assumption. This procedure approximates the distribution function of unobservables with a finite mixture distribution, in our case bivariant. Denote by $v_i=(v_{1i},v_{2i})$ the vector containing the two unobserved factors, each of which can take two different values, v_m^a and v_m^b ($m=1,2$). We define the probabilities attached to the different possible combinations as follows:

$$prob(v_i = v^1) = prob(v = (v_1^a, v_2^a)) = p_1$$

$$prob(v_i = v^2) = prob(v = (v_1^b, v_2^a)) = p_2$$

$$prob(v_i = v^3) = prob(v = (v_1^a, v_2^b)) = p_3$$

$$prob(v_i = v^4) = prob(v_i = (v_1^b, v_2^b)) = p_4 = 1 - p_1 - p_2 - p_3 .$$

The points of support of the finite mixture distribution are the unknown vectors v^1, v^2, v^3, v^4 to which the four unknown probabilities p_1,p_2,p_3,p_4, are attached.

The contribution to the likelihood of an individual then becomes:

$$L_i(W,v,p \mid t_i^1, t_i^2, \ldots, t_i^{C_i}; X_i) = \sum_{m=1}^{4} \left\{ \left(\prod_{c=1}^{C_i} \prod_{k=1}^{3} \prod_{l \neq k} P_{kl}(t_c \mid X_i, v^m; W)^{d_{kl}^c} \right) \left(\prod_{c=1}^{C_i} \prod_{k=1}^{3} \overline{F}_k \left(t_i^c \mid X_i, v^m; W \right)^{s_k^c} \right) \right\} p_m , \quad (7)$$

where m denotes the number of support points.

model.

The log-likelihood function is the summation of the log of equation (7) over all individuals. The points of support as well as the probabilities assigned to each of them are estimated jointly with the rest of the *O*'s. The estimation is implemented, as proposed by Heckman and Singer (1984), by an EM-algorithm (see the Appendix A for details). Note that we choose the number of points of support to be two for each factor. Therefore the method becomes a flexible parametric way to model unobserved heterogeneity[10].

3. Data Description

The data used in this analysis are obtained from the British Household Panel Survey (BHPS). This is an annual survey that the ESRC Research Centre on Micro-social Change has been carrying out since 1991. The survey is conducted over a nationally representative sample of at least 5000 UK households, resulting in a total of approximately 10000 individual interviews per year. The data are collected at the individual and the household level and include information about household organisation, labour status, income and wealth, housing, health, and socio-economic variables.

The Second Wave was carried out in 1992 with 5225 households (9845 individuals). This wave contains an additional questionnaire with information about the individuals' past history of marriage, cohabitation, children, and employment status. In particular, it collects information about employment status spells since the respondent first left full time education. The dates at which the different spells began and ended as well as their length are recorded. This information enables us to estimate the model proposed in Section 2.

We select working age males who at the first of December of 1992 were between 16 and 55 years of age who constitutes the majority of the self-employed[11]. This yields an initial sample of 3445 individuals. We made several modifications to the initial sample. First, males who were not directly interviewed (somebody else in the household answered the questionnaire on their behalf) were dropped because for them

[10] The number of support points can be estimated but in that case the standard errors of the estimates are unknown (see Heckman and Singer, 1985, for further discussion).
[11] From the Second Wave of the BHPS, 67% of all self-employed individuals were males between 16 and 55 years old; 10% were males older than 55, and 22% were females.

no answers are available for the additional questionnaire (220 individuals). Second, we only considered job histories after the individual is 16 years old and has left definitively full time education or military services. This implies that further 295 individuals were dropped from the original sample. Third, there was a reduced number of spells in which individuals declare to be in some other type of inactivity. We considered these spells as unemployment spells[12]. Fourth, we moreover dropped individuals that are retired or long-term sick (125 individuals) and individuals with invalid values for the relevant variables (183 individuals). We make no differences between full-time and part-time work: both are considered employment. Also, job-to-job transitions are ignored, i.e. the individual concerned is considered employed throughout. More details about the selection process and the description of the data can be found in the Appendix B.1.

The selection conditions described above are fulfilled by 2401 individuals providing 5811 complete and incomplete spells[13]. Table 3 reports the number of observations for each of the transitions considered. The last spell for every individual is incomplete since it is censored on the right by the interview date. Note that for the group of males considered here it is innocuous to ignore inactivity as an additional state. As shown in the Appendix B, 125 individuals (364 spells) out of the 2526 valid (6175) were dropped since they corresponded to individuals out of the labour force (retired and, mostly, sick for the long term) at some point in their job histories.

The retrospective data we use has two main advantages. First, it allows us to study the transitions to self-employment from the 1970's until the 1990's. There is no alternative way of studying the transitions during that period accounting for individual unobserved heterogeneity, because there does not exits a panel data set that covers this period. The second advantage of the retrospective data is that it avoids initial-condition problems because it considers the complete individual job histories, so the sample

[12] Of the reduced number of spells in other-type-of-inactivity spells (the individual declares itself doing family care or doing "something else") 70% lasted less than a year. They usually occurred between unemployment spells.

[13] That sample constitutes 69.7% of all men between 16 and 55 in the 2nd Wave of the BHPS and 75.6% of all men between 16 and 55 that have already left school. The average and standard deviation of variables as age, education or job status are similar for the selected sample and this subgroup of males between 16 and 55 that already left school.

looks like a flow sample[14]. The retrospective data that we use may suffer from recall bias, implying that shorter or more distant spells could be underreported. Using data from the BHPS, Paull (1996) finds that unemployment spells are more likely than other types to fail to be recalled and that this likelihood increases with the period of recall. With the same data set, Elias (1996) and Dex and McCulloch (1997) conclude that the recall problems are particularly severe for women and older workers. Therefore, the fact that we considered a sample of males younger than 56 years is likely to reduce the possibility of this type of bias[15]. In addition, we will check the robustness of our results (Section 4.4) by estimating the full model for two subgroups of individuals for which the probability of recall bias is expected to be small: individuals that were between 16 and 35 at the interview date and individuals that in Wave 3 declared that the job history that they provided in Wave 2 was completely correct.

The variables used in the estimation can be classified in two groups: demographic variables relating to the individuals' characteristics and demand-side variables relating to the general economic conditions. In the first group, we include age, education, race, three cohort dummy variables, and two dummy variables reflecting whether the father and the mother of the individual were self-employment when the individual was 14 years old. In the second group, we include the national unemployment rate and two time dummy variables for the times at which the EAS and its continuation, the BSUS, were introduced[16]. Other variables related to the business cycle (such as the GDP growth, the number of vacancies, or the change in the unemployment rate) were dropped from the final specification since they were insignificant. Note that a dummy for the spells starting after 1981 (when the Loan Guarantee Scheme was introduced) too turned out to be insignificant. Assets and job

[14] Education is in labour market studies generally taken as being exogenous. However, the exit from education or the nature of the first spell could also be correlated with the unobserved individual term. In that case the first spell of education should be modelled.

[15] Selecting a sample with a shorter period of recall is a common way of dealing with the recall bias. It can be found, for example, in Meghir and Whitehouse (1997) or Mealli and Pudney (1996), that use the UK Retirement Survey (1988/89) to study retirement.

[16] Note that we consider observable aggregate variables that vary with time but not accross individuals. However we do not allow for the presence of unobservable time random shocks. According to Moulton (1986) this omission could bias downwards the standard errors of the estimates. Robust standard errors are easily computed in a linear regression model but not in our highly non linear model. Any attempt to get efficient standard errors in our context is too demanding in terms of the number of parameters.

status specific variables, like wages, earnings, benefits, and occupation, are not considered[17]. The reason is that we lack the relevant lifetime information and therefore cannot estimate a structural version of our model, which would be appropriate because these variables are likely to be endogenous. Our model should therefore be interpreted as a reduced form. Table 4 reports the means and standard deviations for the relevant variables and the Appendix B.2 reports their precise definition.

In order to understand better the data we use, a non-parametric description of the survivor function, which is presented in Figure 2. This figure shows Kaplan-Meier estimates of the probabilities of survival for each possible origin state conditioned on the destination state (first column) and for each destination state conditioned on the origin state (second column). Although Figure 2 does not take into account either personal or demand side characteristics it brings out several important properties of the data. First, the probability of survival in a state depends not only on the origin state but also on the destination state. Therefore a satisfactory model has to account for state dependence. Second, the probability of survival depends on the time spent in a particular state. Therefore a satisfactory model has to allow for a flexible form of duration dependence. The model proposed here meets these two requirements.

Some interesting differences and similarities among the probabilities of survival in the different states can be observed in Figure 2. First, the probability of survival in unemployment is lower than in any other state, independent whether the transitions are to employment or to self-employment. Second, given that an individual moves out of employment, the probability of survival in employment is higher for those individuals that become self-employed than for those that become unemployed. This is consistent with the hypothesis that employed individuals become unemployed early in their carriers while starting a business requires human or physical capital which is typically accumulated while being employed. Third, there are no substantial differences between the survival probabilities for transitions from any origin to unemployment, for transitions from self-employment to any destination, and for transitions from unemployment to any destination. The fact that the probability of survival in

[17] For an analysis of self-employment decisions with liquidity constraints, see Evans and Jovanovic (1989) and Holtz-Eakin et al. (1994a, 1994b) for the US and Blanchflower and Oswald (1990, 1998) for the UK.

unemployment is similar for transitions to employment and to self-employment suggests that it is not the case that the individuals with the lowest probability of finding a job are the ones that become self-employed. The question whether the differences and similarities in individual characteristics can explain the differences and similarities stated above is addressed by the econometric analysis of the next section.

4. Results

Here we discuss the estimation results. In Section 4.1, some tests for the specification of our model are presented and discussed. Section 4.2 discusses the results relating to the demographic variables included in the analysis. In Section 4.3 we present the results relating to the key variables of our paper: the duration variables, the unemployment rate and the policy variables. Section 4.4 contains a discussion of the robustness of the results to the presence of recall bias.

4.1. Specification tests

Table 5 shows the results for the estimation of the full model and Table 6 presents some specification tests. In the final specification we approximate the bivariate distribution of the unobserved heterogeneity by a finite mixture distribution with two points of support for each factor. The estimates of the parameters of interest are similar to the ones obtained without unobservable heterogeneity[18], with the biggest differences in the duration parameters. In general, the parameters are overestimated when unobservable heterogeneity is ignored. A Wald test of the joint hypothesis that all the parameters related to heterogeneity are zero gives us a value of 245.15, distributed as χ^2 with 12 d.o.f. Therefore the null hypothesis of no unobservable heterogeneity is clearly rejected and we will only refer to the results of the estimation with unobservable heterogeneity

With respect to the rest of the specification of the model, a one-factor loading specification is clearly rejected at any conventional significance level against the two-factor loading according to the Wald tests in Table 6. An alternative specification of the two-factor loading model, in which the loading parameters for the first factor are common for transitions from common origins and the loading parameters for the second

[18] The results without unobservable heterogeneity are available from the author on request.

factor are common for transitions to common destinations, is also rejected at a level of significance of 5%. Finally, the null hypotheses of no duration dependence and of a monotone specification for the hazard rate are clearly rejected (at 1% significance level) by the Wald tests in Table 6.

4.2. Demographic variables

Here we discuss the estimates that relate to the demographic variables, such as education, age, family background, cohort, and race. They are reported in Table 5.

Our results suggest that education plays an important role in determining the transitions between states. In particular we find that the more educated an individual is the lower is its probability of becoming unemployed while being employed. However, to have some type of education reduces the probability of exiting self-employment towards unemployment, and medium level educated individuals are the less likely to become unemployed when self-employed. Moreover, we find that education influences positively the probability of entering employment, whichever the origin state is. This effect is not found for the probability of entering self-employment: people with a medium level of education (A-levels and O-levels) are more likely to enter self-employment. This contradicts the previous findings of Rees and Shah (1985) and Evans and Leighton (1989), which suggest that self-employed individuals are low wage earners (low educated) and misfit for paid work. Nevertheless, note that the positive effect of having a higher degree on the probability of becoming self-employed is significant only when the individual is initially unemployed. This effect may reflect the lower opportunity cost (in terms of wages) that self-employment has for this group of individuals.

For most of the transitions age has a significant non-linear effect. In particular, it positively affects (at a decreasing rate) the probability of becoming self-employed. This concave effect has a maximum at a latter age for those individuals that come from unemployment. This is coherent with the theory that human capital (contacts, experience) and physical capital (wealth) are required for self-employment and that these types of capital are harder to accumulate when unemployed.

Cohort variables have a significant effect on the probability of transiting from one state to another. In particular, the younger cohorts are more likely to enter unemployment (from employment or from self-employment) and less likely to leave it.

They also are more likely to enter self-employment when employed and more likely to enter employment when self-employed.

Family background variables have the expected sign. The probability of becoming self-employed is higher if one of the parents was self-employed (especially the father). Whether this happens because the offspring run the family business or because there is a transfer of knowledge from parents to children cannot be identified given the characteristics of the data[19]. Once the individual is self-employed, the job status of the parents does not have any effect on the probability of becoming unemployed although it will be less likely to become employed.

The effect of the race variable (a dummy for non-white individuals) shows that non-white individuals are slightly more likely to lose their jobs when employed and less likely to become employed when initially unemployed. They are also slightly less likely to enter self-employment, especially from unemployment. This is evidence in favour of the hypothesis that job opportunities for non-white individuals are poorer than for white individuals. Rees and Shah (1986) also find this result for the UK[20]. Once self-employed, non-white individuals have the same probability of success as white individuals, everything else constant. Note that “non-white” is a wide classification that picks up rather different minority groups. Unfortunately, the nature of the data makes it impossible to refine the race variable more.

4.3. Duration, unemployment and policy variables

Next, we turn to the discussion of the elapsed duration variables, the lagged duration variables, the rate of unemployment, and the policy dummies. Based on the estimates presented in Table 5, Figures 3 and 4 plot the predicted transition probabilities against elapsed duration for a reference individual and allow some of its characteristics to change (the unemployment rate in Figures 3a and 3b and the time

[19] In a recent paper Dunn and Holtz-Eakin (2000) provide evidence for the US on the intergenerational links and the transitions to self-employment and conclude that the parent’s strongest effect runs through their own self-employment experience and business success.

[20] Le (1999), in a revision of the empirical self-employment literature, points out that the evidence about the effect of race on the entrance in self-employment differs across countries.

dummies in Figures 4a to 4b) [21]. These figures are used for a clearer interpretation of the estimates in Table 5.

Figure 3a presents the reference individual's transition probabilities to self-employment from employment and unemployment given different values of the national unemployment rate. Before discussing the effect of the unemployment variable we focus on the elapsed duration effect. The first feature is that for any rate of unemployment the transition probabilities to self-employment are different for employed and unemployed individuals. Unemployed individuals have initially a higher probability of becoming self-employed than employed individuals. Evans and Leighton (1989) and Carrasco (1999) find the same result for the US and Spain, respectively. This finding supports the idea that individuals escape from unemployment by becoming self-employed. However, the probability of becoming self-employed falls drastically with the elapsed duration for unemployed individuals. This probability rises again more moderately from the 9th month that the individual is unemployed to the 12th month. In contrast, it steadily increases with the elapsed duration of employment to a point in which the employed individuals are more likely than the unemployed individuals to become self-employed. This finding is novel in the literature and is coherent with the following hypothesis. On the one side, the individual needs to cumulate some human and physical capital to become self-employed. This can best be achieved when employed. The positive effect of age on the probability of becoming self-employment is also consistent with this hypothesis. On the other side, the longer unemployment lasts the more individual human and physical capital depreciates. This reduces the individual's job opportunities, including self-employment opportunities. Therefore, we observe that individuals either switch to self-employment shortly after becoming unemployed or that they do not switch at all. Finally, as in previous studies for the US (Evans and Leighton, 1989, and Bates, 1990) we find that the longer the time in self-employment the less likely individuals are to leave that state, especially towards employment.

The effect of the lagged duration is captured by three variables: previous experience in self-employment, previous experience in employment, and previous

[21] The reference individual is a white, 30 years old male, born between 1957 and 1967, with O-levels, no previous employment, self-employment or unemployment experience, and parents that were not

experience in unemployment. Previous self-employment experience increases marginally the probability of becoming self-employed. This effect is stronger and significant at 10% significance level when the individual is employed. Moreover, previous self-employment experience makes it less likely for unemployed and self-employed individuals to transit to employment. This variable does not have any effect on the probability of surviving in self-employment. A hypothesis coherent with this zero effect is as follows. If there is a learning process that makes individuals with longer self-employment experience more likely to remain self-employed, this process is business specific, which means that this experience can not be transferred to increase the survival probabilities in other business.

Previous employment experience does not have any effect on any of the transitions. It is the elapsed duration of employment, instead of the previous experience, that matters for the transition probabilities among states.

The effect of previous unemployment experience is more important. Previous unemployment affects negatively the entry into self-employment, in particular when the origin state is unemployment. This negative effect is in line with the negative effect of the elapsed unemployment duration, and suggests that unemployment experiences make transitions to self-employment more difficult[22]. As expected, the previous unemployment experience has a negative effect on the probability of re-employment for unemployed individuals and a positive effect on the probability of losing their job for employed individuals. However, the previous unemployment experience does not have any effect on the probability of leaving self-employment.

The effect of the national unemployment rate is illustrated in Figures 3a and 3b. The figures are plotted for the reference individual and allow the national unemployment rate to vary from 3%, which was the lowest figure during the period under consideration, to 13%, which was the highest figure. Figure 3a shows a positive and significant effect of the national unemployment rate on the probability of going from unemployment to self-employment. The effect is smaller and less precise for employed

self-employed. He is in a spell that started before 1983 and the national unemployment rate at the beginning of the spell is set to 8%.

[22] Evans and Leighton (1989) in their study on the US found that the effect of previous unemployment experience varies drastically across different years.

individuals[23]. This suggests that bad economic conditions act as "push" factors towards self-employment: lower probabilities of finding a job when unemployed or poorer career perspectives when employed make individuals more likely to opt for self-employment. Figure 3b shows the effect of the unemployment rate on the probability of exiting self-employment. An increase in the national unemployment rate (marginally) reduces the probability of switching to employment and has no effect on the probability of switching to unemployment. Although similar evidence concerning the push effect has been found for other countries[24], our findings seem to contradict most of the previous evidence for the UK. For example, Blanchflower and Oswald (1990, 1991, and 1998) and Taylor (1996) find that good economic conditions, which imply a lower risk of a business failure or a higher probability of finding a job in the event of failure, "pull" individuals out of other states into self-employment. An explanation for this difference between their and our results is that these studies are carried out using data on the stock of self-employed individuals. Our findings are that the aggregated unemployment rate has a positive effect on the inflow to self-employment but also on the outflow from self-employment. The negative effect of unemployment on the probability of being self-employed follows because the difference between the inflow and the outflow rates turns out to be negative.

Finally, Figures 4a to 4d show the effect of the time dummy variables that act as proxies for policy changes. Specifically the dummy for the introduction of the BSUS is found to have a positive effect on the probability of becoming self-employed for employed and unemployed individuals (Figures 4a and 4b). The effect of the 1984 dummy is small and not precise. Interestingly, it can also be seen that the probability of exiting self-employment (Figures 4c and 4d) was increased by these two policies. Especially the exit towards unemployment is much bigger for spells that started in 1991 or afterwards[25]. These findings are consistent with the hypothesis that the policies were successful in promoting self-employment but not in preserving it[26]. This hypothesis

[23] The null hypothesis of no effect can not be rejected at the usual significance levels.
[24] See Schuetze (2000) for the US and Canada, Carrasco (1999) for Spain, or Acs *et al* (1994), for a panel of OECD countries.
[25] Note that we are controlling for the unemployment rate at the beginning of the spell, and therefore for the possible negative business cycle effects of the recession period that started precisely in 1991.
[26] This hypothesis has been suggested by Blanchflower and Freeman (1994).

however has to be taken with some caution since the time dummies could be picking up some other macroeconomic changes that we were unable to control.

4.4. Robustness of the results

In Section 3 we mentioned that the data could suffer from recall bias. There is no straightforward procedure to correct this problem. However, we can conduct some robustness checks that investigate whether this bias is not very important here. Tables 7 and 8 show the results of the estimation for two subsamples of individuals for which the probability of recall bias is expected to be smaller. In particular, Table 7 presents the results of the estimation using a group of individuals whose age was between 16 and 35 at the interview date (1367 individuals and 3333 spells). The length of recall for these individuals is shorter than for the whole sample and there is empirical evidence that reporting errors and incompleteness increase with the length of recall (see, Beckett et al, 2001). Therefore this group of younger individuals is expected to suffer less from recall bias. In general, the results found in the previous section, namely the effect of the aggregate unemployment rate, the unemployment experience and the time dummies on the transitions towards self-employment, still hold for the subgroup of younger individuals, at least qualitatively. The main difference is that some variables are no longer significant, which may be due to the loss of observations. For example the parameters of the transitions from self-employment to employment, from self-employment to unemployment, and from unemployment to self-employment are estimated with only 64, 65, and 67 observations respectively.

Table 8 presents the results for the subgroup of individuals that in Wave 3 declare that the job history that they reported in Wave 2 was correct (1001 individuals and 2365 spells). This information is available because in Wave 3 all individuals still in the sample were ask whether the information about the job history that they provided in Wave 2 was correct, partially correct or incorrect[27]. Again, the main results from previous section hold for this subsample of individuals although the significance of many parameters disappear, which again is probably due to the reduced sample size of some of the transitions.

[27] Note that the question in Wave 3 relates to spells in full time employment, part time employment and self-employment. The question does not clarify why answers in Wave 2 were partially incorrect

These two robustness checks suggest that the main results of Section 4 are not likely to be originated by recall bias.

5. Conclusions

In this paper we estimate transitions from and to three possible labour market states: employment, self-employment, and unemployment. We use a flexible specification of a multiple state transition model that allows for the presence of state dependence, duration and lagged duration dependence, and unobservable heterogeneity. The distribution of the unobservable heterogeneity is approximated with a finite mixture distribution. The support points of this distribution as well as the probabilities associated with them are estimated jointly with the rest of the parameters of interest using the non-parametric maximum likelihood estimator proposed by Heckman and Singer (1982).

The main purpose of the paper is to determine the effects of the individual unemployment experiences and the aggregate unemployment rate on the probability of becoming and remaining self-employed. We find three main results. First, the aggregate unemployment rate has a positive effect on the transition probability to self-employment, especially for unemployed individuals. Second, the finding that the transition probability to self-employment is much higher for unemployed individuals than for employed individuals. However, the transition probability from unemployment to self-employment drastically decreases with the periods spent in unemployment and with the previous unemployment experience. Third, we find that the probabilities of entering and exiting self-employment are positively correlated with two time dummies for the two periods in which the UK government introduced the Enterprise Allowance Scheme (EAS) and the Business Start-up Scheme (BSUS), respectively.

Therefore, our results suggest that bad economic conditions (high unemployment) "push" individuals to become self-employed and unemployed individuals are more likely than employed individuals to become self-employed. However, the probability of becoming self-employed falls drastically for unemployed individuals as their elapsed duration increases.

or completely incorrect. In addition is conditional to survival in the panel until Wave 3.

With respect to the policies implemented during the 80’s in order to promote self-employment, our results suggest that they were effective in increasing the inflows to self-employment, but that they also increased the outflows from self-employment during the same period. Therefore, we do not find support for the hypothesis that the rising rates of self-employment during the 80’s can be attributed to the effectiveness of those policies. This result might be taken with some caution since the effect of the policies on the stock of self-employment is ambiguous and depends on the evolution of the initial stocks in unemployment, employment and self-employment.

Our results also suggest that human and physical capital accumulation are necessary to become self-employed. While this is consistent with the presence of liquidity constraints, the simplicity of the model and the nature of the data make it impossible to test this hypothesis. An interesting extension would be to allow for an explicit test of this hypothesis within a structural model. This is left for future research.

Table 1: Self-employment across selected OECD countries[1]

Self-employment as a proportion of total employment[2]
(Percentage point changes)

	1975-1980	1980-1985	1985-1990	1990-1995	1975-1995	1975 Level	1995 Level
Austria	-2.41	-6.07	-0.11	3.37	-5.22	19.51	14.29
Belgium	-0.08	1.19	0.07	0.79	1.96	13.70	15.66
Denmark	-1.63[a]	-2.74[a]	-0.37	-1.31	-6.05	14.54	8.48
Finland	-3.02	-0.35	0.32	0.22	-2.83	16.96	14.13
France	-1.44	-0.84	-2.69	-1.75	-6.72	18.23	11.51
Germany	-5.44	0.41	-0.17	0.47	-4.72	14.24	9.52
Greece	-2.09[b]	-8.14	-2.25	-1.40	-13.88[b]	52.40[b]	38.51
Ireland	-3.25	-0.06	1.12	-2.14	-4.33	25.44	21.12
Italy	-4.96	1.12	-0.11	0.20	-3.75	29.53	25.78
Japan	-1.16	-1.80	-2.15	-2.40	-7.51	20.48	12.97
Luxembourg	-2.29	-1.72	-2.37	-1.75	-8.13	15.75	7.62
Netherlands	-0.85	-0.65	-1.75	1.48	-1.77	13.08	11.32
Norway	-1.38	-0.55	-0.49	-0.93	-3.36	11.86	8.50
Portugal	9.71	-0.10	-5.37	-0.49	3.75	22.71	26.45
Spain	1.10	1.25	-3.38	0.56	-0.47	23.13	22.66
Sweden	0.22	-0.46	1.92	1.85	3.52	7.26	10.79
UK	-0.02	3.61	1.90	-0.36	5.13	8.07	13.20
US	0.03	-0.08	-0.16	-0.12	-0.34	8.74	8.40

Self-employment as a proportion of total non-agricultural employment
(Percentage point changes)

	1975-1980	1980-1985	1985-1990	1990-1995	1975-1995	1975 Level	1995 Level
Austria	-0.79	-2.72	0.61	1.83	-1.07	9.60	8.53
Belgium	0.27	1.34	0.43	1.05	3.10	11.35	14.44
Denmark	-0.47[a]	-2.09[a]	-0.01	-0.37	-2.95	9.86	6.91
Finland	0.48	0.38	2.32	0.94	4.12	5.63	9.75
France	-0.52	-0.03	-1.19	-0.86	-2.60	11.06	8.46
Germany	-1.95	0.63	0.11	0.90	-0.30	9.00	8.70
Greece	-0.05[b]	-2.27	0.22	0.59	-1.51[b]	30.90[b]	29.43
Ireland	-0.29	1.73	1.50	0.11	3.06	10.54	13.60
Italy	-2.65	2.33	0.77	0.57	1.02	22.61	23.62
Japan	0.07	-1.03	-1.54	-1.84	-4.34	14.71	10.37
Luxembourg	-1.07	-0.71	-1.37	-1.11[c]	-4.25[c]	10.26	6.01[c]
Netherlands	-0.15	-0.69	-0.42	1.79	0.53	9.21	9.74
Norway	-0.83	-0.13	-0.36	-0.27	-1.59	7.50	5.90
Portugal	2.83	1.68	0.40	2.63	7.53	12.07	19.60
Spain	1.78	1.97	-1.21	1.40	3.95	15.28	19.23
Sweden	0.08	-0.03	2.82	1.99	4.86	4.43	9.29
UK	-0.04	3.65	1.88	-0.37	5.11	7.16	12.26
US	0.35	0.21	0.02	-0.23	0.36	6.94	7.30

Source: OECD, Labour Force Statistics, 1975-1995.

(1) Excludes unpaid family workers.
(2) Total employment=employment+self-employment.
(a) Data corresponds to 1979 instead of 1980.
(b) Data corresponds to 1977 instead of 1975.
(c) Data corresponds to 1993 instead of 1995.

Table 2: Transition intensities.

	Destination State		
Origin State	Self-employment	Employment	Unemployment
Self-employment	------	$q_{see}(t \mid Z; b)$	$q_{seu}(t \mid Z; b)$
Employment	$q_{ese}(t \mid Z; b)$	------	$q_{eu}(t \mid Z; b)$
Unemployment	$q_{use}(t \mid Z; b)$	$q_{ue}(t \mid Z; b)$	------

Note: U stands for unemployment, E for employment and SE for self-employment.

Table 3: Number of observations for each transition.

	Destination State			
Origin State	Self-employment	Employment	Unemployment	Censored
Self-employment	------	176	127	382
Employment	362	------	1205	1692
Unemployment	162	1378	------	327

Table 4: Sample statistics (2401 individuals, 5811 spells)

	Observations	Mean (Std.dev.)
DURATION		
Self-employment: all spells	**685**	**78.57**
		(81.44)
SE→E	176	46.79
SE→U	127	47.43
SE→SE	382	103.56
Employment: all spells	**3259**	**105.24**
		(106.16)
E→U	1205	62.32
E→SE	362	98.69
E→E	1692	137.21
Unemployment: all spells	**1867**	**12.03**
		(21.74)
U→E	1378	9.93
U→SE	162	12.58
U→U	327	20.59
Total number of spells	**2401**	**2.42**
		(2.02)
Number of spells for individuals with at least one spell of:		
E	2189	2.53
		(2.07)
U	1180	3.60
		(2.48)
SE	581	3.35
		(2.90)
NON WHITE: all individuals	2401	0.04
		(0.19)
AGE beginning spell	5811	24.38
		(8.51)
Spells SE	685	29.15
		(8.50)
Spells E	3259	22.30
		(7.54)
Spells U	1867	26.27
		(8.96)
Higher Degree		0.39
A levels	2401	0.15
O levels		0.28

Table 4: Sample statistics (2401 individuals, 5811 spells) (continued)

Mother SE: all individuals	**2401**	**0.04**
Spells SE	685	0.06
Spells E	3259	0.04
Spells U	1867	0.04
Father SE: all individuals	**2401**	**0.15**
Spells SE	685	0.22
Spells E	3259	0.14
Spells U	1867	0.14
Cohort 67-76	**5811**	**0.19**
Spells SE	685	0.10
Spells E	3259	0.20
Spells U	1867	0.22
Cohort 57-66	**5811**	**0.38**
Spells SE	685	0.30
Spells E	3259	0.38
Spells U	1867	0.39
Cohort 47-56	**5811**	**0.26**
Spells SE	685	0.35
Spells E	3259	0.26
Spells U	1867	0.24
NUR beginning spell	5811	8.73
		(3.99)

Notes: Duration is measured in months. Age is age at the interview date (around 12/92). NUR is national unemployment rate

Table 5. Maximum likelihood estimates for the transition equations controlling for unobserved heterogeneity (NPMLE)

	E ® U		E ® SE		U ® E		U ® SE		SE ® E		SE ® U	
	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio
Intercept	-3.037	-6.748	-7.502	-6.279	0.856	2.238	-6.323	-3.597	0.661	0.393	-3.959	-1.572
Higher Degree	-0.662	-6.681	0.024	0.119	0.591	6.774	0.472	1.591	0.636	2.045	-0.478	-1.438
A-levels	-0.473	-3.932	0.230	1.001	0.546	5.354	0.671	1.968	0.414	1.136	-0.672	-1.566
O-levels	-0.250	-2.645	0.250	1.197	0.409	4.700	0.334	1.094	0.044	0.141	-0.887	-2.313
Age	0.494	1.760	1.608	2.373	0.162	0.642	1.885	1.948	-2.391	-2.545	0.410	0.300
Age Square	-0.048	-1.031	-0.251	-2.054	-0.067	-1.632	-0.233	-1.734	0.366	2.454	-0.053	-0.243
Mother SE	0.233	1.461	0.410	1.284	-0.224	-1.319	0.261	0.649	0.578	1.411	0.431	0.826
Father SE	0.166	1.879	0.447	2.683	-0.077	-0.767	0.391	1.452	-0.454	-1.487	-0.050	-0.163
Non White	0.178	1.107	-0.431	-0.954	-0.525	-2.938	-1.048	-1.437	0.307	0.463	0.538	0.627
Cohort67-76	1.807	8.624	0.723	1.807	-0.520	-2.834	-0.137	-0.166	1.033	1.380	2.228	2.443
Cohort57-66	1.236	7.570	0.272	0.993	-0.432	-3.031	-0.067	-0.112	0.584	1.137	1.002	1.447
Cohort47-56	0.527	3.993	0.265	1.423	-0.130	-1.168	0.012	0.028	0.597	1.747	0.682	1.452
Ln(duration/12)	0.442	4.597	0.537	1.035	0.308	5.907	0.350	2.001	1.662	1.888	1.018	1.598
Spline durat=6	-3.492	-6.179	-0.092	-0.048	-2.536	-7.514	-4.088	-3.157	-2.751	-1.361	-2.423	-1.215
Spline durat=9	4.384	3.742	-0.658	-0.212	3.363	4.641	7.591	2.555	3.110	1.162	1.909	0.561
Spline durat=12	-1.442	-2.001	0.309	0.175	-2.021	-3.884	-4.266	-2.113	-2.475	-1.608	-0.508	-0.236
SE Experience	-0.001	-0.036	0.053	1.245	-0.105	-3.436	0.040	1.214	-0.169	-1.603	-0.029	-0.377
E Experience	0.014	1.461	-0.020	-0.843	-0.003	-0.486	0.011	0.668	0.009	0.416	-0.003	-0.106
U Experience	0.138	6.559	-0.041	-0.514	-0.152	-5.158	-0.145	-1.793	0.063	0.543	0.112	1.195
NUR	-0.024	-1.489	0.022	0.570	-0.001	-0.071	0.098	1.912	-0.059	-1.247	0.050	0.868
D83	0.332	2.886	0.002	0.007	0.115	1.132	0.028	0.077	0.160	0.471	0.533	1.168
D91	0.718	5.467	1.024	2.317	0.013	0.140	0.461	1.762	0.536	1.159	1.995	4.774
d	1.000	---	1.002	2.339	0.492	2.809	1.614	4.136	1.429	2.733	1.630	2.971
l	1.000	---	-0.320	-1.337	0.403	3.529	0.361	1.370	-0.308	-1.046	1.356	2.739
	$v_1^a = 0$ $v_1^b = 1.189(5.830)$ $v_2^a = 0$ $v_2^b = -1.961(-6.661)$ P_1=0.644 P_2=0.018 P_3=0.234 P_4=0.104											
Log-likelihood	-8841.67											
Observations	5811											

Notes: SE denotes self-employment, E employment and U unemployment. NUR is the national unemployment rate. Age and NUR are measured at the beginning of the spell. The heterogeneity coefficients, δ and ?, for the transition from E to U are normalised to one for identification as well as the first point of support for each heterogeneity factor is set to zero.

Table 6: Specification tests

	Wald Test	Degrees of freedom	p-value
Duration dependence	351.99	24	4.95×10^{-60}
Monotone duration dependence	261.30	18	1.37×10^{-45}
Unobserved heterogeneity (both factors)	245.15	12	4.07×10^{-45}
Unobserved heterogeneity: factor 1	117.95	6	4.39×10^{-23}
Unobserved heterogeneity: factor 2	100.28	6	2.19×10^{-19}
Alternative unobserved heterogeneity*	15.64	6	0.016

(*)The alternative heterogeneity specification imposes that the loading parameters for Factor 1 are equal for equal destination states and the loading parameters for Factor 2 are equal for equal origin states.

Table 7. Maximum likelihood estimates (NPML): Sample of younger individuals

	E ® U		**E ® SE**		**U ® E**		**U ® SE**		**SE ® E**		**SE ® U**	
	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio
Intercept	-1,429	-1,337	-9,502	-1,962	0,149	0,123	-13,733	-2,438	-0,216	-0,036	-2,708	-0,309
Higher Degree	-0,867	-5,934	-0,574	-1,223	0,646	4,304	0,390	0,541	0,630	1,070	-0,233	-0,240
A-levels	-0,575	-3,621	-0,015	-0,035	0,548	3,117	0,694	0,987	-0,029	-0,044	-0,655	-0,702
O-levels	-0,361	-3,001	-0,411	-1,002	0,476	3,468	0,370	0,694	-0,285	-0,530	-0,960	-1,131
Age	0,057	0,058	2,839	0,700	0,791	0,758	8,365	1,791	-0,162	-0,034	1,619	0,241
Age Square	0,035	0,165	-0,374	-0,401	-0,250	-1,121	-1,639	-1,770	-0,077	-0,077	-0,616	-0,484
Mother SE	-0,053	-0,203	0,248	0,387	-0,222	-0,835	-0,212	-0,165	0,381	0,464	0,926	0,682
Father SE	0,109	0,905	0,588	1,657	-0,203	-1,267	-0,007	-0,011	-0,420	-0,860	-0,652	-0,795
Non White												
Cohort67-76	0,441	2,924	1,004	2,164	-0,250	-1,562	0,421	0,634	0,456	0,782	0,683	0,688
Cohort57-66												
Cohort47-56												
Ln(duration/12)	0,382	3,323	0,735	0,886	0,368	5,055	0,436	1,454	1,994	0,578	1,308	1,178
Spline durat=6	-3,828	-5,417	-1,048	-0,335	-2,119	-4,595	-8,376	-2,576	-1,024	-0,177	-2,723	-0,927
Spline durat=9	5,750	3,799	0,853	0,152	2,368	2,469	18,216	2,223	-0,385	-0,081	3,078	0,640
Spline durat=12	-2,545	-2,668	-0,151	-0,046	-1,207	-1,735	-10,648	-1,955	-1,293	-0,504	-2,005	-0,591
SE Experience	-0,180	-1,504	-0,024	-0,095	-0,234	-1,882	0,268	1,616	-0,111	-0,291	-0,340	-0,585
E Experience	-0,003	-0,142	-0,020	-0,232	-0,020	-1,067	0,088	1,089	0,024	0,329	0,073	0,711
U Experience	0,174	4,286	-0,209	-0,909	-0,034	-0,645	0,030	0,155	-0,114	-0,341	0,078	0,254
NUR	-0,029	-1,422	0,041	0,655	-0,001	-0,029	0,194	1,855	-0,095	-1,101	-0,047	-0,267
D83	0,404	2,450	-0,415	-0,929	0,275	1,665	-1,079	-1,698	0,294	0,503	1,116	1,003
D91	0,715	4,637	1,030	1,454	0,025	0,196	0,783	1,676	0,704	0,852	2,557	3,106
d	1.000	---	1,241	2,213	0,347	2,094	1,320	2,713	0,586	0,819	2,297	2,624
l	1.000	---	-7,807	-0,793	4,998	0,944	7,629	0,915	-0,208	-0,059	9,451	0,937
					$v_1^a = 0$		$v_1^b = 1.490 (6.525)$					
					$v_2^a = 0$		$v_2^b = -0.235 (-0.970)$					
					P_1=0.647	P_2=0.014	P_3=0.275	P_4=0.064				
Log-likelihood						-4294.14						
Observations						3333						

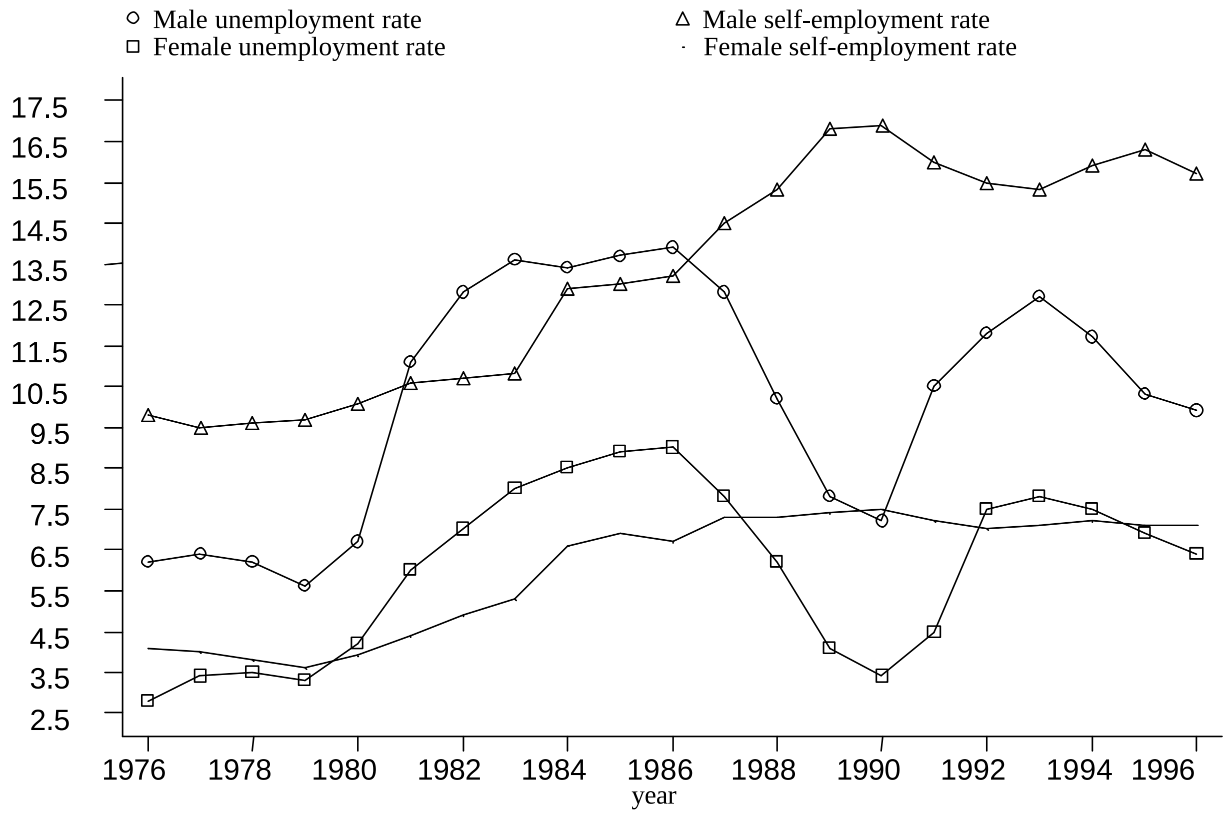
Notes: SE denotes self-employment, E employment and U unemployment. NUR is the national unemployment rate. Age and NUR are measured at the beginning of the spell. The heterogeneity coefficients, δ and ?, for the transition from E to U are normalised to one for identification as well as the first point of support for each heterogeneity factor is set to zero.

Table 8. Maximum likelihood estimates (NPML): Sample of individuals declaring no errors in the reported data

	E ® U		E ® SE		U ® E		U ® SE		SE ® E		SE ® U	
	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio
Intercept	-3,228	-3,554	-8,224	-3,572	2,515	3,397	-5,461	-1,101	0,019	0,005	-3,240	-0,266
Higher Degree	-0,343	-1,797	0,073	0,181	0,701	4,198	1,405	1,440	0,963	1,898	0,003	0,003
A-levels	-0,176	-0,781	0,577	1,268	0,577	2,729	0,919	0,775	1,170	1,881	0,444	0,434
O-levels	-0,107	-0,575	0,451	1,093	0,482	2,747	1,042	1,139	0,429	0,771	-1,417	-0,958
Age	-0,145	-0,240	1,646	1,281	-0,760	-1,686	0,087	0,029	-3,395	-1,845	-1,667	-0,342
Age Square	0,065	0,676	-0,216	-0,944	0,060	0,837	-0,010	-0,025	0,608	2,208	0,095	0,137
Mother SE	0,232	0,690	0,961	1,475	-0,280	-0,918	0,475	0,414	0,592	0,630	0,592	0,428
Father SE	0,068	0,413	0,384	1,116	-0,058	-0,324	0,953	1,143	-0,301	-0,588	0,590	0,562
Non White	0,576	2,449	-0,506	-0,732	-0,334	-1,159	-0,424	-0,199	0,398	0,355	0,313	0,144
Cohort67-76	2,048	5,398	0,720	0,814	-0,915	-2,548	-1,545	-0,800	1,087	0,693	3,290	1,122
Cohort57-66	1,536	5,249	0,043	0,081	-0,593	-2,136	-1,772	-1,404	1,068	1,151	1,239	0,574
Cohort47-56	0,638	2,419	0,154	0,445	-0,122	-0,541	-0,478	-0,487	0,510	0,920	1,482	0,920
Ln(duration/12)	0,241	0,999	0,459	0,450	0,375	4,209	0,543	1,183	1,025	0,514	1,338	0,185
Spline durat=6	-3,623	-2,682	-1,543	-0,321	-2,533	-4,510	-0,708	-0,280	-0,663	-0,139	1,353	0,088
Spline durat=9	5,804	2,263	3,532	0,369	3,033	2,379	4,102	0,827	0,419	0,071	-4,158	-0,356
Spline durat=12	-2,482	-1,683	-2,454	-0,441	-1,644	-1,667	-5,552	-1,489	-1,163	-0,341	1,635	0,301
SE Experience	-0,106	-0,719	0,009	0,120	-0,106	-1,389	-0,080	-0,334	-0,148	-0,958	-1,258	-0,593
E Experience	-0,010	-0,449	-0,004	-0,099	-0,013	-1,112	0,025	0,612	-0,039	-0,992	0,112	1,207
U Experience	0,138	2,577	-0,016	-0,047	-0,124	-2,174	0,186	0,646	0,180	0,297	0,433	0,952
NUR	-0,024	-0,826	0,008	0,108	-0,028	-1,063	0,241	1,731	-0,002	-0,024	0,170	1,009
D83	0,606	2,667	-0,435	-0,828	0,406	2,023	0,271	0,262	-0,608	-0,918	-0,654	-0,490
D91	0,839	3,835	1,534	1,462	0,082	0,492	0,404	0,560	0,812	0,511	2,169	1,336
d	1.000	---	0,877	0,797	1,192	1,589	3,021	1,435	1,154	0,926	2,933	1,351
l	1.000	---	-1,112	-1,479	0,421	1,318	-0,786	-0,947	-0,865	-1,198	1,418	0,990
	$v_1^a = 0$ $\quad v_1^b = 0.902(2.174)$ $v_2^a = 0$ $\quad v_2^b = -1.644(-2.638)$ P_1=0.644 P_2=0.018 P_3=0.234 P_4=0.104											
Log-likelihood	-3396.05											
Observations	2365											

Notes: SE denotes self-employment, E employment and U unemployment. NUR is the national unemployment rate. Age and NUR are measured at the beginning of the spell. The heterogeneity coefficients, δ and ?, for the transition from E to U are normalised to one for identification as well as the first point of support for each heterogeneity factor is set to zero.

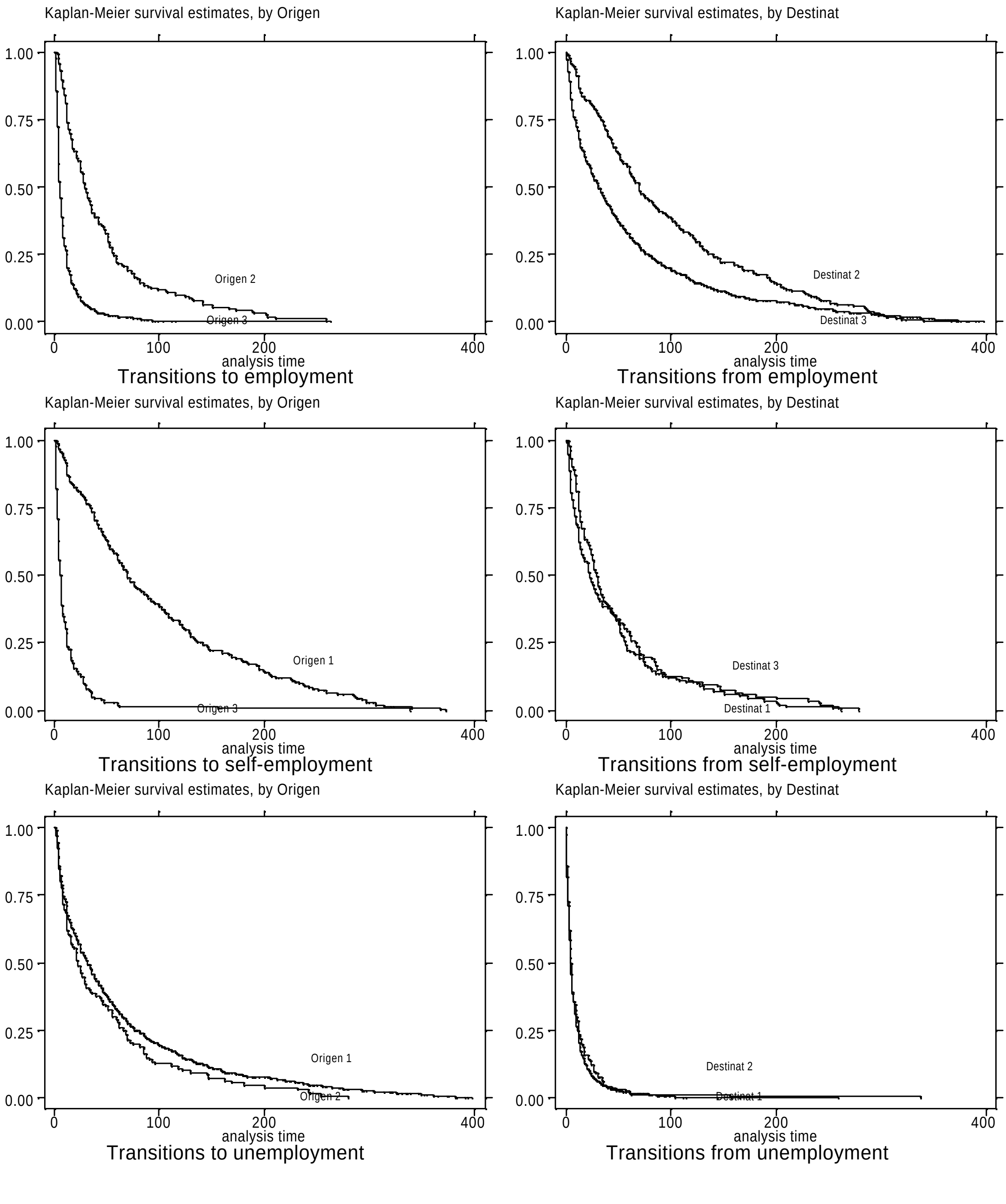
Figure 1: Self-employment* and Unemployment Rates for the UK by Sex.



(*) Self-employment as a percentage of the labour force
Source: OECD, Labour Force Statistics.

Figure 2. Kaplan-Meier survivor function estimates

(Origin/Destination=1 Employment; Origin/Destination=2 Self-employment; Origin/Destination=3 Unemployment)



Note: The Kaplan-Meier survivor function estimator has the following form: $\hat{\hat{F}}(t) = \prod_{t_{(j)}<t} (1-\hat{J}_j)$ with $\hat{J}_j = \frac{n_j}{r_j}$,

where n_j is the number of people observed to leave at $t_{(j)}$ and r_j is the number of people in the risk set the instant before $t_{(j)}$. The subscript j runs over the M distinct times at which exits are observed.

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Figure 3a

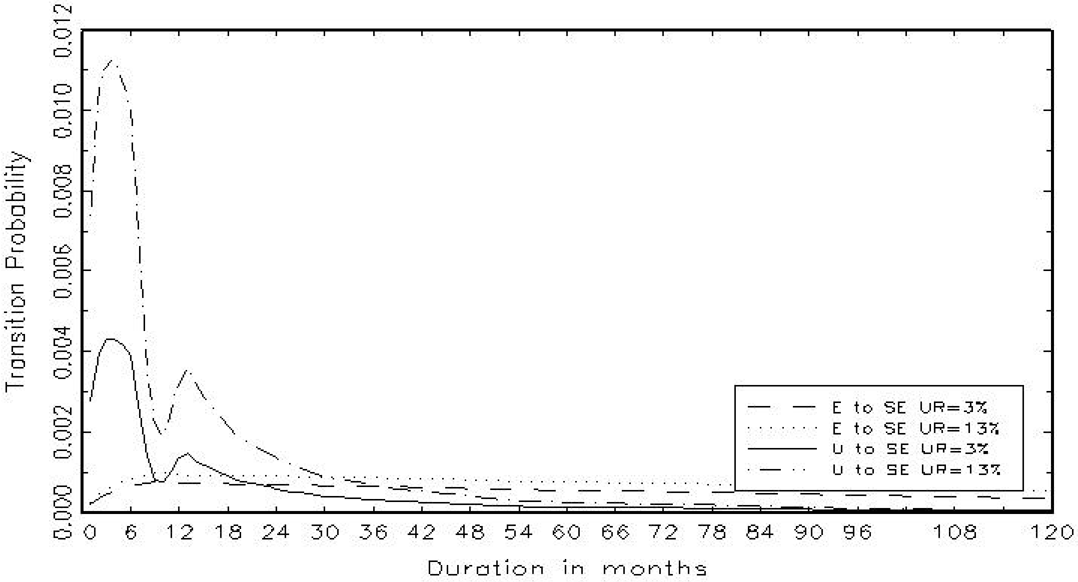

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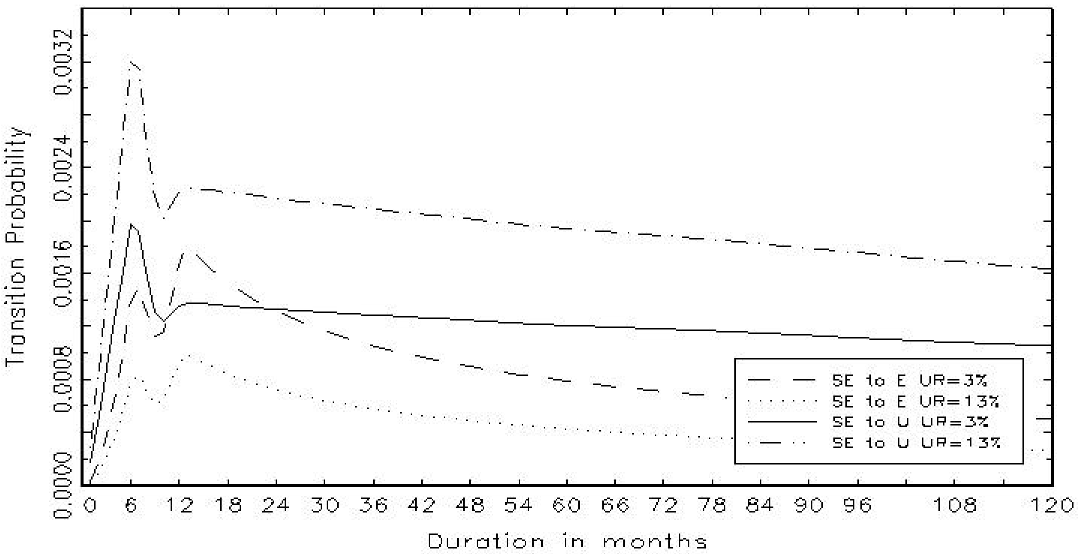
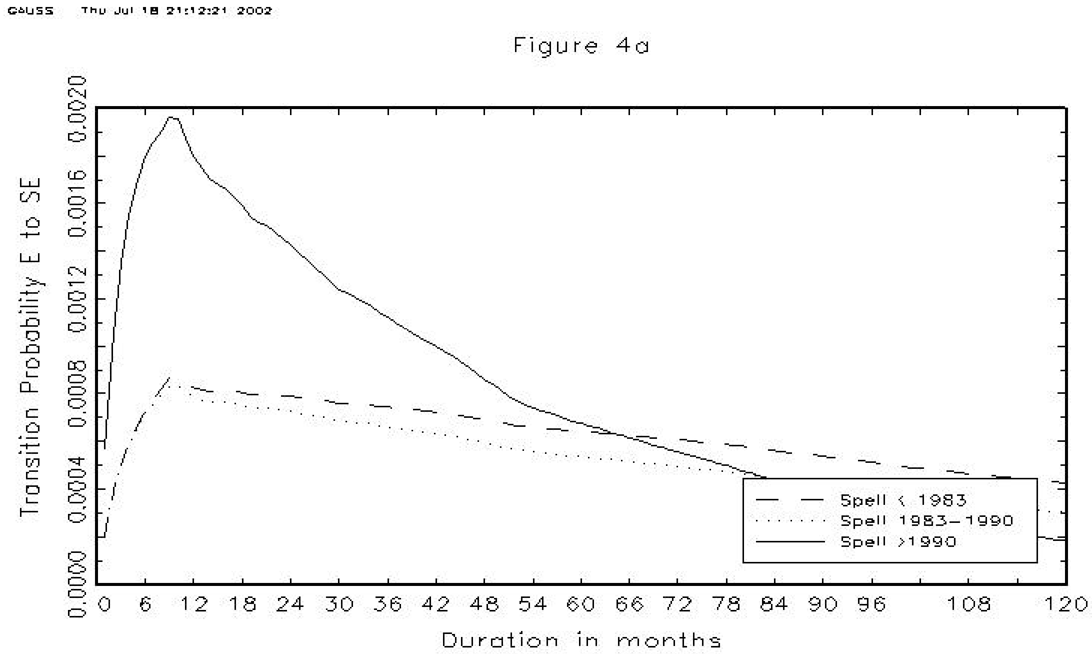
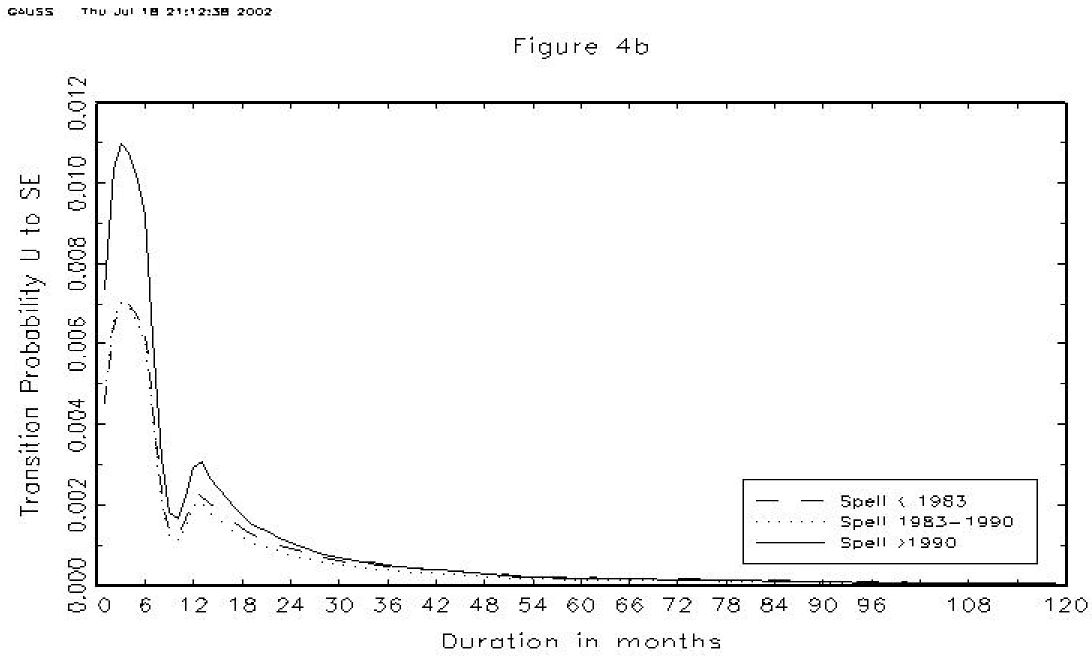
Figure 3b



Reference individual: white, 30 years old male, born between 1957 and 1967, with O-levels, no previous employment, self-employment or unemployment experience, and parents that were not self-employed. The spell started before 1983 and the national unemployment rate is set to 8%. The unobservable heterogeneity is integrated out. SE denotes self-employment, E employment and U unemployment.





Reference individual: white, 30 years old male, born between 1957 and 1967, with O-levels, no previous employment, self-employment or unemployment experience, and parents that were not self-employed. The spell started before 1983 and the national unemployment rate is set to 8%. The unobservable heterogeneity is integrated out. SE denotes self-employment, E employment and U unemployment.

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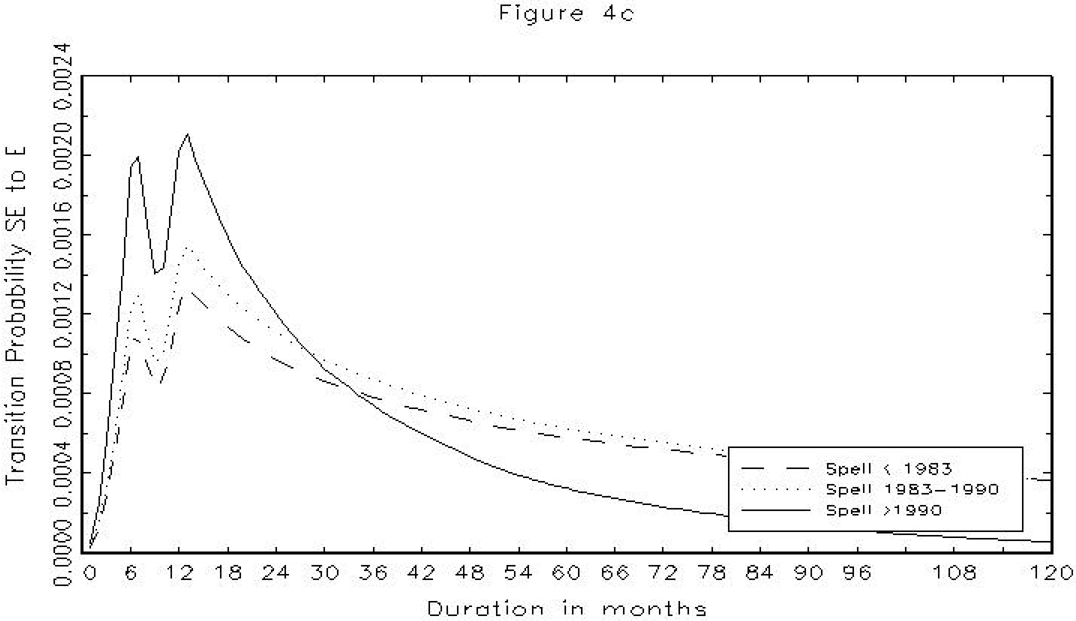
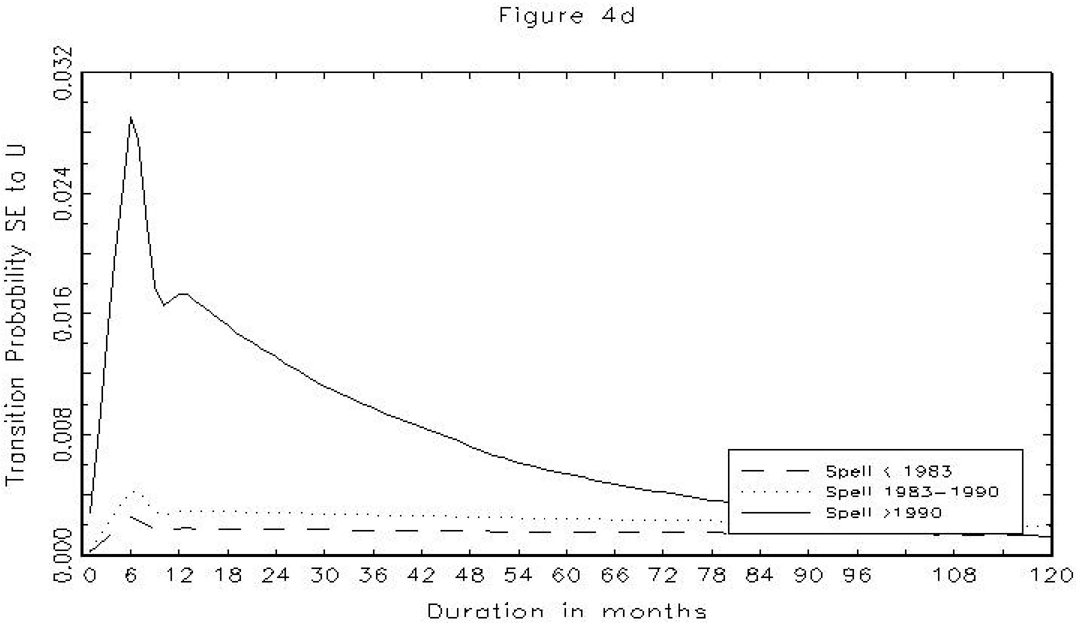


GAUSS Thu Jul 18 21:13:30 2002



Reference individual: white, 30 years old male, born between 1957 and 1967, with O-levels, no previous employment, self-employment or unemployment experience, and parents that were not self-employed. The spell started before 1983 and the national unemployment rate is set to 8%. The unobservable heterogeneity is integrated out. SE denotes self-employment, E employment and U unemployment.

Appendix A: EM algorithm

This appendix explains the implementation of the EM algorithm presented in Section 2.3. Section 2 introduces the likelihood function to estimate. Simplifying notation in equation (7), the final likelihood function for the whole sample is

$$L(W, v, p \mid \mathbf{t}_i, X_i) = \sum_i \left[ln \sum_{m=1}^{M} f_i(\mathbf{t}_i \mid X_i, v^m, W) p_m \right], \qquad (8)$$

where $f(.)$, is the contribution to the likelihood for each individual, conditional on v^m; $\mathrm{t}_i = \{t_i^1, t_i^2, ..., t_i^{C_i}\}$ is the vector with the elapsed duration in each spell; W is the vector of all parameters of interest; X_i is a vector of individual characteristics and p_m is the probability attached to every mass point v^m.

Taking derivatives in (8) with respect to W and rearranging terms we obtain,

$$\frac{\partial L(.)}{\partial W} = \sum_i \frac{\partial\, ln(f_i(. \mid v^m))}{\partial W} \hat{p}_m, \qquad (9)$$

where

$$\hat{p}_m = \frac{f_i(. \mid v^m) p_m}{\sum_m f_i(. \mid v^m) p_m}. \qquad (10)$$

The EM algorithm has two stages: expectation and maximisation. Giving initial values for all parameters of interest (including v^m and p_m), in a first stage we compute the probabilities $\hat{p}_m$ according to (10) and in a second stage we maximise the log likelihood function $L(.)$ with respect to W and v^m, obtaining $L_1(.)$; we then update $\hat{p}_m$ recalculating (10) and so forth. This procedure produces a local optimum for $L(.)$ and the estimated values for the mass point probabilities are constrained to be in the unit interval (Heckman and Singer 1982, 1984).

To guard against the failure to locate a global optimum a variety of starting values is used in the implementation of the EM algorithm.

Appendix B: Data

B.1. Selection criteria

	INDIVIDUALS	SPELLS
Males	4630	
Older than 55	-1185	
Proxy interviewed[1]	-220	
Without past information	-209 (204 in full time educ.)	
INTIAL SAMPLE	**3016**	**9387**
Individuals whose only spell started before age 16	-237	-237
Spells that started before age 16		-633
	2779	**8517**
Spells corresponding to or previous to the war		-99
Spells previous to leaving full time education	-58 (still in full time educ.)	-816
	2721	**7544**
Spells only in government training	-12	-12
Spells in government training		-304
Spells joined since they do not imply change of job status		-348
	2709	**6880**
Invalid values of variables	-183	-705
	2526	**6175**
Individual already retired	-16	-36
Individual long term sick	-109	-328
FINAL SAMPLE	**2401**	**5811**
% initial sample	**79.61**	**61.90**

(1) Proxy interviewed means that the individual did not answer the questioner but somebody else in the household provided the information about it.

B.2. Variable definition

Job status: self-defined classification:

- Employment (E): full or part-time dependent employment.
- Unemployment (U): unemployed individuals plus males doing something else or not working because they are taking care of their families. These two additional statuses are in general short spells that alternate with unemployment.
- Self-employment (SE).

Duration and previous experience (lagged duration):

- Duration: time spend in the present spell, in months.
- SE, E and U experience: time spend in each job status, previous to the present spell.

Demographic variables:

- Age: (age at the beginning of the spell) / 10.
- Non-white: dummy that equals 1 if the individual is not white.
- Higher degree, A-levels, O-levels: educational dummies.

- Mother and Father SE: dummy variables that equal 1 if the individual's mother or father were self-employed when he was 14 years old.
- Cohort67-76, Cohort57-66, Cohort47-56: dummy variables that equal 1 if the individual was born between 67 and 76, 57 and 66 and 47 and 56 respectively.

Variables relating economic conditions:

- NUR: national unemployment rate at the beginning of the spell, as a percentage. Source OECD.
- D83: time dummy that equals one for spells that started after 1983, when the EAS was introduced along all the UK.
- D91: time dummy that equals one for spells that started after 1991, when the EAS changed to the BSUS. The EAS changed name after 1991 and went under the control of the local Training and Enterprise Councils (TECs) instead of the Employment Department. The TECs could vary both the eligibility criteria and the terms of support given.

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