PRELIMINARY DRAFT: PLEASE DO NOT QUOTE

State dependence, duration dependence and unobserved heterogeneity in the employment transitions of the over-50s

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Abstract
This paper examines transitions into and out of employment among men and women in the UK aged between 50 and the state pension age. Using nationally representative longitudinal survey data on 26,000 individuals, we begin by using standard duration models in order to examine the issue of duration dependence in transitions, allowing for unobserved heterogeneity. We then use a fourth order Markov model to estimate quarterly transitions allowing for potential endogeneity of initial conditions. The results support the hypothesis of endogenous initial conditions and allow various estimates of state dependence to be retrieved. Both types of dependence are shown to be important, which implies there is the potential for any individual to become trapped in non-employment and, ideally, policy should intervene as soon as an individual begins a period of non-employment

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1. Introduction

In common with many developed countries, the population of the UK is ageing. By 2020, it is expected that a third of the population will be over the age of 50 (Dean, 2003). The increased pressure that an older population places on the workforce means that there is increasing policy interest in encouraging older individuals to remain in paid employment. This was most recently acknowledged in the UK government's consultation document (DWP, 2006) which announced the policy objective of increasing by one million the number of older workers – that is, those aged 50 or over – in employment. Similar concerns are shared by international organisations, see OECD 2006.

Such an ambitious target and highlights the need to understand the nature of the employment decision for older individuals. This is subject to a number of rather specific influences that distinguish it from the employment decision for prime-age workers. Most obviously, older workers may face the decision of whether to retire. They are also more likely to be influenced by health considerations. The extent to which it is possible to explore these influences is determined by the availability of suitable individual-level data. This is currently limited in the UK but recent data developments promise to help fill the information gap. Specifically, the English Longitudinal Study of Ageing (ELSA) is a sample of those aged 50 or over in 2002 and collects information on an ongoing basis on a range of issues relating to ageing, including those relevant to the employment decision.

The most comprehensive research on the economic determinants of the retirement decision in the UK is Meghir and Whitehouse (1997) and Blundell et al. (2002) who both use the British Retirement Survey (BRS) to examine the retirement decision and who both suggest the role of economic incentives may be important. The BRS sampled individuals born between 1919 and 1933 and interviewed them twice, most recently in 1994. At this time, the youngest sample members were over the age of 60 so it is appropriate to consider alternative datasets that better capture the current stock of older workers. A number of studies have used the British Household Panel Survey (BHPS – a nationally representative longitudinal survey) as an alternative data source. However, this lacks sufficient detailed financial information to allow the issue of incentives to be considered directly. Haardt (2006) addresses this by imputing lifecycle profiles of earnings and benefits estimated using an auxiliary data source. He finds that earnings capacity has little effect on the decision to retire but benefit level are strong predictors. Haardt (2006) also finds evidence that (self-reported) health is correlated with employment decisions. Disney et al. (2006) explore this in more depth (again using BHPS) by allowing for the possibility that self-reported health may be a biased measure of actual health. Their results again show that deteriorating health is strongly linked to exits from work after addressing issues of endogeneity.

The analysis in this paper focuses on a different aspect of the employment transitions of older workers. We explore the extent to which the probability of being employed at a point in time depends on employment status at an earlier point in time and also whether the length of time spent in that earlier employment status is important. That is, we focus explicitly on the related issues of state dependence and duration dependence. We do this by using data from the UK Longitudinal Labour Force Survey and pursuing two alternative and interrelated modelling approaches: survival analysis and (high order) markovian models of transitions across labour market states. The first approach makes use of the retrospective information on spell duration available in the data to model the probability of spell exhaustion as a function of spell duration, providing estimates of duration dependence. The second approach models transitions by following individuals across labour market states over the five quarters when they are observed in the data, enabling an assessment of state dependence and its accumulation over quarters.

The importance of these issues to understanding the underlying processes governing the observed persistence in labour market states is clear. Under state dependence, or 'scarring', previous labour market status has a causal effect on later labour market status. For example, it may be that the experience of non-employment may by itself reduce the probability of later working (or searching for work). It is equally possible that state dependence can operate in a virtuous manner; having been employed in the past may increase the chances of being employed later. Under duration dependence, it is the length of time in a particular state that influences the probability of changing state. For example, it may be the case that a short period of non-employment has no adverse consequences on being employed subsequently but a prolonged period of non-employment may have a negative impact. Again, it is straightforward to think of a more positive counter-example whereby duration dependence acts to increase attachment to the labour market. Arulampalam et al. (2000) provide a brief discussion of the possible causes of state dependence. It may be that the experience of a state alters preferences or constraints in such a way that later employment is affected. Another possibility is that employers use periods of non-employment as a signal of low productivity. Alternatively, human capital deterioration during non-employment may reduce the probability of finding work. To the extent that these factors reinforce their effectiveness with unemployment spell duration, then we may see them also as determinants of duration dependence.

The existence of state dependence or duration dependence fundamentally alters interpretation of the determinants of employment. Most obviously, it requires that labour market status be viewed, at least partly, as the outcome of a dynamic rather than static process. Appropriate policy interventions to encourage labour market participation have to be developed accordingly. In the presence of state dependence, interventions should aim to prevent the occurrence of an adverse state. In the presence of duration dependence, it would be important to focus help as soon as possible on those entering an adverse state.

The econometric challenge in examining these dynamic issues is to control for the effect of unobserved heterogeneity. If an individual has a fixed (or long-term) characteristic that influences the probability of employment, not controlling for that characteristic will result in biased estimates of state or duration dependence. A more challenging (and related) problem is the so-called 'initial conditions' problem which arises when starting point of the process governing outcomes is not observed. In this case, it is not possible to observe whether the employment status of the individual when first observed (the initial condition) is the result of state dependence or unobserved heterogeneity. The models developed in this paper control for unobserved heterogeneity and the initial condition issue.

The remainder of this paper is organised as follows. In the next section, the data are described. Section 3 describes the two modelling approaches, the results of which are presented in section 4. Section 5 offers some conclusions.

2. The data

The analysis in this paper is based on the UK Labour Force Survey (LFS). The LFS is a quarterly survey of 60,000 households in the UK with a focus on those characteristics related to the labour market. It is carried out as a rotating panel with one-fifth of the respondents being replaced each quarter. Hence, each (fully-participating) household is interviewed five times over a period spanning 12 months. All adult household members at a given address are interviewed. The Longitudinal LFS (LLFS) links the quarterly surveys in the LFS so that it becomes possible to observe changes over time for households, families and individuals. The data used in this analysis include only those households who respond to interviews in all five quarters – a balanced panel.[1]

To maximise the estimation sample size, the dataset has been built by combining as many LLFSs as possible such that there is no overlap in the periods of time covered by any of the LLFSs.[2] The final dataset used LLFSs from Summer 1993 – Summer 1994 up until Summer 2003-Summer 2004. To identify the required sample, only those individuals aged 50 or over but under state pension age were chosen. In the UK, the state pension age is currently 65 for men and 60 for women so this means that the sample is composed of men who were aged 50-64 when first observed and women who were aged 50-59 when first observed. The number of observations available for analysis in the resulting dataset was 26,031.

Figure 1 below uses these data to show the change in the employment rate over the period 1993-2003 for men and women aged 50 or over but less than the state pension age. It is clear that over the period there has been an increase in the employment rate for both men and women. Furthermore, the increase for women is especially noticeable.

<Figure 1>

Table 1 describes the economic status of individuals when first interviewed. To concentrate on the main groups, only those accounting for at least a half of one per cent of cases are included in the table. It can be seen that about half the men and slightly more of the women were employed when first interviewed. Self-employment is much more common among men than women with the result that overall about two-thirds of men and slightly fewer women can be viewed as working. Unemployment is low in this population. More significant is economic inactivity; this accounts for about 29 per cent of men and 35 per cent of women.[3]

[1] The sample is provided with weights that address the issue of non-response and attrition in the data; these weights are applied in all the analyses in this paper.
[2] Overlaps were avoided in order to prevent double-counting of individuals and complicating the survey weights.
[3] Note that the figures in the text do not exactly match those in the Table 1. The reason for this is that the table only presents those categories accounting for at least a half of one per cent of all cases. The sum of these excluded categories fully accounts for the differences between the figures quoted and those apparent from the table.

Inactive people who would like to work are less common than those who would not like to work. For the former, the reason for inactivity is health-related in about half of all cases although there are other reasons such as domestic responsibility and the belief that no jobs are available. There appear to be few sizeable differences between men and women. For inactive individuals who do not want to work, such differences are more noticeable. Again, health problems are a commonly cited reason for not wanting to work. However, women often state that they do not want to work since they are looking after the family or the home. Very few men give this reason. Another important group is made up those who are retired. This accounts for 8 per cent of men and 4 per cent of women (or 37 and 15 per cent respectively of type 2 inactive men and women). Clearly, these are people who have retired before the state pension age.

<Table 1>

Of those not working but who have worked in the 8 years prior to interview, the experience of employment is often distant. Table 2 shows that for nearly half the men and 60 per cent of the women their last experience of employment was more than 5 years before the time of interview.

<Table 2>

In view of this, it is not surprising that transitions between employment and non-employment are relatively infrequent. Table 3 compares the labour market state at the start of the observation year with that at the end of the observation year. Nine per cent of employed men and ten per cent of employed women were not employed one year later. In the other direction, seven per cent of men and six per cent of women moved from non-employment to employment over the period of a year.

<Table 3>

3. The econometric models

In this section, the econometric models used for the analysis are presented. We begin with a standard duration model. The purpose of this is to provide an initial insight into the nature of duration dependence in transitions out of (or into) employment, together with an appreciation of the extent to which these transitions are influenced by observed characteristics. Next, we move to a high-order Markov model for transition probabilities over the five quarters spanned by the LLFS, which will allow us to look at the issue of state dependence and its accumulation over quarters.

3.1 A model of time to exit employment or non-employment

Given the characteristics of the data, and specifically the fact that we do not have information on multiple spells, we assess duration dependence by modelling the time it takes older workers to exit employment or non-employment using a discrete time[4] mixed proportional hazards (MPH) model in a single-spell framework (see van den Berg, 2001). This implies that we identify unobserved heterogeneity within single spells, not across spells. We do not consider endogenous selection into the initial labour market state at this stage, but will tackle the issue using an alternative modeling approach.[5] Given this set-up, the hazard for individual *i* of exiting in period *j* can be written

$$h_{ij}(t_j, \mathbf{x}_i \mid v_i) = 1 - \exp(-\exp(D(j) + \mathbf{x}_i\boldsymbol{\beta} + u_i))$$

where *D(j)* characterises the baseline hazard, v_i is the unobserved heterogeneity term such that $u_i \equiv \log(v_i)$ and $\mathbf{x}_i$ is a vector of covariates for individual *i*. Essentially, this is a model of transitions in which the identity of the departure and arrival labour market states plays no role, while the time it takes to exit from the departure state matters (Lancaster 1990). This complementary log-log specification results in the discrete time version of the proportional hazards model. We follow the example of numerous empirical analyses and assume that v_i is Gamma-distributed with unit mean and finite variance. This has the advantage of providing a

[4] Discrete rather than continuous time is a natural choice since the duration variables are measured to the nearest quarter.

[5] See Meghir and Whitehouse (1997) for a model with multiple spells and endogenous starting state.

closed form solution for the likelihood function (Lancaster 1990). We mitigate against possible bias arising from the assumption of a Gamma mixing distribution by specifying the baseline hazard flexibly rather than imposing on it a functional form. Han and Hausman (1990) and Seuyoshi (1992) show that this approach can reduce the bias resulting from unobserved heterogeneity.[6]

In writing the likelihood function, it is important to take account of the structure of the data. As described in section 2, individuals in the dataset were observed five times over the course of a year, with each of the observations separated by about 3 months. This means that most individuals will not be observed at the start of their spell but will instead have already been in their initial state (employment or nonemployment) for some time when first observed. In other words, the spell data are left-truncated ('delayed entry') and the likelihood function has to condition on survival in the initial state up to the time of first entering the dataset. Using standard results (see, for example, Jenkins 2005), the log-likelihood function for individual i can be written

$$\log L_i = \sum_{k=d_i+1}^{j} [y_{ik} \log h_{ik} + (1 - y_{ik}) \log(1 - h_{ik})]$$

where y_{ik} is a binary indicator variable such that y_{ik}=1 if the spell for individual i ends in period k and y_{ik}=0 otherwise and d_i is the duration of the spell at the time of entering the dataset. Since d_i varies across individuals, each individual's contribution to the overall log-likelihood function corresponds to a particular span of the overall duration of that individual's spell. Taking all individuals in the dataset together allows us to characterise the hazard function for the full range of observed durations.

3.2 A fourth-order Markov model of quarterly transition probabilities

As discussed in the Introduction, an alternative way to study employment dynamics is to look at state dependence by means of Markovian models of labour market transitions. In these models, transitions are identified by following individuals movements over time across a given set of labour market states, assuming that the probability of occupying a certain state at a given

[6] An alternative to specifying a distribution for the unobserved heterogeneity term is to approximate the distribution using a number of mass-points (Heckman and Singer, 1984). Attempts to estimate models of this kind encountered convergence problems.

point in time depends upon past states realizations up to a certain lag. An example of popular models in this class is provided by dynamic random effects, see e.g. Arulampalam et al (2000). Differently from MPHs, models in this class do not consider the impact of durations on transition probabilities, but explicitly model the identities of the states crossed during the transition (Lancaster, 1990).

Many models for labour market transitions used by previous research have focussed on first order dynamics, i.e. have assumed that the process of interest can be adequately described by looking only at the dependency between labour market states at two adjacent points in time, what is known as first order dynamics. In this paper we depart from these models and explicitly consider fourth order dynamics. There are three reasons for doing so. First of all, higher order models nest lower order ones, so that estimating fourth order dynamics will enable us to test the first order assumption made by previous studies. Second, given that we use quarterly data, estimating fourth order dynamics we are able to relate individual labour market states in a given quarter to states observed to up until the same quarter of the previous year, so that we are able to fully model within year dynamics. Finally, the fourth order approach enables us to derive measures of cumulated state dependence, generating an intermediate measure of dependence between random effect probits (that look at state dependence) and survival analysis (that study duration dependence).

Models of labour market dynamics face an initial conditions issue, which emerges when the process of interest is serially correlated and its starting values are not available in the data. In such circumstances, the unobserved initial condition will be embedded in current and lagged levels of the process investigated. Given that modelling transitions requires conditioning current labour market states upon the past, the unobserved initial condition generates the endogeneity issue discussed in Heckman (1981). Heckman proposed solving the issue by estimating the model of interest jointly with the distribution of the initial sample observation, and to model the latter as a function of pre-sample information and of the individual specific error component. Recently, Wooldridge (2005) has proposed an alternative solution, in the context of first order models, in which it is the individual specific error component to be modelled conditional on the first observation. While computationally attractive, the Wooldridge approach assumes that dynamics are first order. Therefore, we control for initial conditions by applying the Heckman approach to the case of fourth order dynamics.

Let e^*_{it} be the attachment to employment for individual i in quarter t, which depends upon the interaction between labour demand and supply, plus a series of control factors. While e^*_{it} is unobservable, in the data we have information on e_{it}=I(e^*_{it}>0), a dichotomous employment indicator. As customary in this set-up, we assume that the event occurs when the latent propensity is large enough, and we fix the thresholds for employability at 0 without losing generality. Since we are interested in within-year labour market transitions, we specify a model for employment transitions conditional on exogenous regressors x_{it} (that proxy for the potential and reservation wage, plus all the other relevant shifters) and on indicators of labour market states occupied in the four preceding quarters:

$$e^*_{it} = \beta' x_{it} + \lambda_1 e_{it-1} + \lambda_2 e_{it-2} + \lambda_3 e_{it-3} + \lambda_4 e_{it-4} + \varepsilon_{it}$$

The error term ε_{it} represents the convolution of all unobservable heterogeneity (either individual specific or purely volatile) that may influence employment, and is assumed to be independent from x_{it} . The problem of initial conditions emerges if ε_{it} is not independent of the indicators of past labour market states. Since such indicators may themselves be a function of individual specific attributes, independence of ε_{it} will in general be violated, inducing an endogeneity issue. The solution proposed by Heckman (in the case of first order models) consists of estimating the transition equation and the process determining lagged states jointly. Here we extend it to fourth order dynamics. We assume that past states are determined according to the following rule:

$$e_{it-s} = \mathrm{I}(\gamma_s' z_{it-s} + u_{it-s} > 0) \quad s=1,2,3,4$$

and control for the initial conditions issue by letting the unobserved component of these equations freely correlate with unobserved heterogeneity in the transition equation with correlation coefficient ρ_s. In addition, we also allow for free cross-process correlations in the equations for lagged states, with correlations coefficients σ_{hk}, $k<h$=2,3,4.

By making distributional assumptions about the unobserved components of the model, the sample likelihood can be derived and the parameter of interest estimated. Specifically, we assume that the vector of errors (ε_{it} u_{it-1} u_{it-2} u_{it-3} u_{it-4}) follows a five-variate normal distribution with zero mean and covariance matrix Ω . The matrix Ω has extra-diagonal elements given by the correlation coefficients defined above, and, given the dichotomous nature of the observed dependent variable, diagonal elements equal to unity. The cross-error correlation control for unobserved heterogeneity in the process governing employment transitions.

As discussed in, e.g., Arulampalam et al. (2000), lagged labour market states should be modelled as functions of pre-sample information and information on variables predating labour market entry, such as parental backgrounds. Unfortunately, the LFS does not contain information of the latter type. Therefore we use x_{it-s} to form each of the z_{it-s} vectors. This implies that we are assuming strict exogeneity of the regressors in the transition equation. We also exploit knowledge of the year in which the individual started occupying the state in which she is observed in at the first interview date, and complete the z_{it-s} vectors with the national GDP growth rate measured in that year, with the idea that initial labour market states, but not transitions, depend upon the macroeconomic conditions prevailing at the time. [7]

Estimation of transition probabilities enables assessment of the issue of state dependence, i.e. of the variation in the probability of employment induced by differences in employment histories, holding individual heterogeneity constant. To the extent that unobserved heterogeneity has been appropriately controlled for, state dependence provides estimates of the causal impact of past history on current outcomes. The measures of state dependence typically derived from dynamic limited dependent variable models is the 'marginal effect' associated with the lagged dependent variable of interest. Given the fourth order set up of this model, we present four such measures, each given by the marginal effect associated with each indicator of lagged states. In general, these measures will take the following form:

$$SD_j = \Phi(b'x+g_j)-\Phi(\beta'x), j = 1,2,3,4$$

[7] Meghir and Whitehouse (1997) use unemployment rates at the time a spell is first observed to instrument initial conditions. While they use contemporaneous unemployment rates in the transition equation, we flexibly control for aggregate economic conditions in the transition equation by means of time dummies.

where x contains continuous explanatory variables evaluated at their sample mean, and dummy variables set at zero, b and g are the estimates of β and γ, while Φ represents the standard normal cumulative density function (c.d.f.).

Observing dependency with different points in the past also enables us to quantify the accumulation of state dependence as the time spent in a spell of employment increases from zero to four quarters, providing an intermediate dependence concept between state and duration dependence. If the true model was first order, additional quarters spent participating should not increase current participation probabilities. We define cumulated state dependence as

$$CSD_2 = \Phi(\beta' x + \gamma_1 + \gamma_2) - \Phi(b' x)$$
$$CSD_3 = \Phi(\beta' x + \gamma_1 + \gamma_2 + \gamma_3) - \Phi(b' x)$$
$$CSD_4 = \Phi(\beta' x + \gamma_1 + \gamma_2 + \gamma_3 + \gamma_4) - \Phi(b' x)$$

i.e. as the marginal effects on current participation associated with having been participating for two, three or four consecutive quarters, relative to non participation in the past (note: $CSD_1 = SD_1$).

4. Results

In this section, we begin by presenting the results obtained from the MPH model outlined above. This is with a view to providing an insight into the degree of duration dependence characterising the data. Following this, the results obtained controlling for the endogeneity of initial conditions are presented.

4.1 MPH results

Table 4 presents the coefficient estimates resulting from the MPH models of time to employment entry (for those who were not employed when first observed) and time to employment exit (for those who were employed when first observed). The results are presented separately for men and women.

<Table 4>

The first set of estimated coefficients represent the baseline hazard. In all cases, there is evidence of negative duration dependence. That is, the longer an individual remains in their initial state, the smaller the probability of exiting from this state becomes. This is true for both employment entry and employment exit. It is also true for both men and women. The estimated baseline hazards over the first 10 years (40 quarters) of a spell for men and women are shown graphically in Figure 2. This highlights a number of features. First, as already noted, all spells are characterised by negative duration dependence; the hazards are highest towards the beginning of a spell and mostly decline monotonically thereafter. Second, the degree of duration dependence is much more marked when considering employment entry than when considering employment exit. The results suggest that the hazard of finding work soon after starting a non-employment spell is higher than the hazard of leaving employment soon after starting an employment spell. Over time, the hazards of employment entry and exit roughly converge so that, the hazard of employment entry is, if anything, lower than that of employment at long durations. Third, duration dependence appears slightly more marked for men than for women. This is particularly true when considering exits from employment. The hazards for men are higher in the early stages of a spell than those for women but they become more similar as the spell lengthens.

<Figure 1>

The results in Table 4 show personal characteristics to also be important. Older individuals have a smaller hazard of employment entry and a larger hazard of employment exit than younger workers. This is particularly the case shortly before state pension age, reflecting the retirement decision. The role of qualifications is less straightforward to interpret. Level of qualification appears unimportant for women's hazards and also for men's employment exit hazard. This is possibly reflecting the fact that qualifications are less important than experience among older workers. However, the employment entry hazard is higher for men with mid to low level qualifications than it is for those with no qualifications. Individuals still paying off the mortgage for their accommodation have a higher hazard of employment entry and a lower hazard of employment exit than individuals who own their property outright. This is true for both men and women and is likely to be capturing the higher cost of living associated with debt repayment. With regard to household composition, the presence of dependent children in the household has no effect on the hazards for men but increases the hazard of employment entry for women (but not the hazard of employment exit for women). This may be explained by the possibility that the children of women in this age group are likely to have reached – or be reaching – an age at which their mothers are able to consider re-entering the workforce following a period of time devoted primarily to childcare. Having a partner does not affect the employment entry hazard for men or women but does reduce the hazard of employment exit for men (but not for women). This may be capturing the increased need to work for those men partnered with non-earning women. It is difficult to discern much pattern in the effects of occupation or industry on employment entry and exit hazards but when considering regional variation, there is some evidence of employment exit hazards being higher in the northern regions of the country. Finally, there is little evidence of consistent (i.e. across men and women) seasonality in the hazards of employment entry or exit for men or women. There is no trend over time evident in the hazards of employment entry or exit. However, for both men and women there appears to be a significant increase in the hazard of employment exit in 1996.

At the bottom of Table 4, the estimated unobserved heterogeneity term is presented. This is significant at the 5 per cent level in all the hazards. The employment exit hazards are characterised by greater (and more significant) unobserved heterogeneity than employment entry hazards. For both types of transitions, unobserved heterogeneity appears more important for women than for men. This perhaps reflects the possibility that the participation decision is relatively straightforward for men while that of women may more often have to take into account other commitments such as child-raising and caring responsibilities. In any event, the test statistics presented in Table 4 point to the importance of accounting for unobserved heterogeneity.

4.2 Markov model results

The fourth order Markov model laid out in Section 3 has been estimated on the longitudinal component of the LFS for the years 1993-2004, separately for women and men, using the same set of control variables as in the MPH model

<Table 5>

Table 5 reports the estimated covariance structure of unobservables for men and women. Estimated coefficients in the first four lines refer to correlations between unobservables in the transition and initial condition equations. For both men and women, these coefficients are statistically significant at usual confidence levels, implying that initial conditions exogeneity can be rejected. The formal test of exogeneity reported at the bottom of the table indicates that the hypothesis can be overwhelmingly rejected in either case. The positive sign of the coefficients means that the unobserved factors that are associated to being in employment at a point in time also play a role in keeping individuals employed over time. One example of such factors could be unobserved labour market attachment. For women, unobserved heterogeneity appears to be more relevant than it is for men, since all the relevant correlations are larger. This evidence is consistent with the one emerged from the MPH modelling and could be given analogous interpretations.

The other estimated coefficients in the table refer to 'reduced form' correlations across initial condition equations. These are larger than estimates in the top part of the table, since those equations are unconditional on lagged indicators of labour market states. Overall, the estimated correlation structure indicates that there is some heterogeneity that is not captured by the regressors included in the model, justifying the adoption of the multi-equation set-up of the model.

<Table 6>

Table 6 reports the estimates of the measures of state dependence defined in the previous section, together with tests for the order of the Markov model. For men, it appears that dynamics are first order, since coefficients on lags larger than the first are not statistically different from zero, either individually and jointly. This finding is reflected in the estimated measures of state dependence and cumulated state dependence. While the marginal effects associated with the employment indicator lagged one quarter is sizeable (+47 percent) and significant, other marginal effects on lagged employment dummies are of negligible size and not statistically significant. As a consequence the accumulation of state dependence over quarters within a year is negligible, and what matters more for current employment is the employment status of the previous quarter, the hypotheses of higher order models being overwhelmingly rejected.

For women, instead, the fourth-order Markov hypothesis can not be rejected. By looking at individual coefficients on lagged dummies, the outcome of such tests appears to be driven by the fourth and first lags, coefficients on intermediate lags being not statistically significant. Thence, what matters more for current employment is employment in the previous quarter (with a marginal effect of 23 percent) and employment one year before (12 percent). These estimates impact on the accumulation of state dependence over the quarters observed, which is not entirely absorbed by the first lag, but also receives contributions by the fourth one. The latter can be interpreted as sort of seasonality effect in the employment transitions of older women and may reflect the fact that at this stage of the life cycle women are more likely than men to find employment in seasonal jobs.

Comparing the overall level of dependence from the past for men and women, results indicate that it is much larger in the former case, see the CSD_4 measure that summarises the accumulation of dependence over all the quarters observed in the data. As was the case with unobserved heterogeneity, such result is consistent with findings from the MPH analysis, i.e. that duration dependence was larger for men than for women. From the standpoint of economic interpretation, such evidence suggests that the factors that can trigger a virtuous circle of employability, such as human capital accumulation on the job or signalling effect, are less relevant for women, possibly due to the fact that in their case there are more alternatives to labour market participation, which may weaken the positive effects of continuous employment. In turn, this implies that policies that prevent episodes of non-employment, irrespective to some extent of individual attributes, may have a longer lasting impact on male labour market trajectories relative to female ones. On the other hand, the prevalence of heterogeneity for women as explanatory factor for overall persistence, suggests that in their case policies should aim at endowing individuals with the attributes relevant in affecting employability.

<Table 7>

Table 7 reports estimated coefficients for the transition equations of the model. For both men and women there are few factors that significantly influence employment transitions. For men, there are evident age effects, older individuals experiencing a lower likelihood of remaining employed over quarters relative to younger ones. Also, characteristics like the presence of dependent children, the presence of a partner or the type of living arrangements attract significant estimates in the employment transition equation. On the other hand, qualifications do not seem to matter much in affecting employment transitions. Similar remarks apply in the case of women, but here qualifications display more significant effects compared to men.

The Appendix Table reports estimates of the initial condition equations. We can note that here personal attributes retain more explanatory power than they do in the transition equation, reflecting the fact that these equations are unconditional on lagged labour market states. Also, these equations contain indicators of the GDP growth rate at the start of the spell, i.e. our instrument for initial conditions, which is generally highly significant in explaining the probability of the initial conditions.

5. Conclusion

In this paper we have modelled employment status for men and women aged between 50 and the state pension age. The modelling approach has not only allowed the existence of state dependence to be explored but has also allowed the degree of state dependence to be formally tested. These estimates have also allowed the existence of duration dependence – unconditional on spell length – to be explored.

Marked differences between men and women were apparent. For men, it appears that state dependence is the driver of transitions and that this is adequately captured by a first-order model. Unobserved heterogeneity is less important. For women, the dominant factor is unobserved heterogeneity rather than state dependence. However, state dependence is still important and is best characterised by a fourth-order specification. These findings on the relative importance of unobserved heterogeneity for men and women are what the preliminary MPH results suggest. However, unlike the MPH analysis, the preferred results presented in this paper allow for endogenous initial conditions. The importance of this has been demonstrated for both men and women. Furthermore, using economic growth contemporaneous to the start of the spell as the identifying instrument appears to work well.

The existence of both state dependence and duration dependence means there is the potential for any individual experiencing inactivity to become trapped in inactivity. This may be for a number of reasons such as skill deterioration, reduced morale or the establishment of a pattern of daily life that does not accommodate paid work. The appropriate policy response should help individuals avoid periods of inactivity while offering early help to those who experience a period of inactivity.

A more optimistic implication of the findings is that the combination of state dependence and duration dependence can also work to beneficial effect. In particular, if it is possible to intervene such that an individual moves into employment, the chances of being in employment at a later point in time are greatly increased the longer the period of employment. The longer the period of employment, the less likely it is for older workers to return to inactivity. Hence, there is a positive role for policy both in encouraging movements into work and supporting individuals who have entered work.

In both types of transitions, our findings indicate that the longer older men and women stay in a particular labour market state, the more likely that they remain in those states. From the view point of labour market policy-making, therefore, encouraging active workers to remain active during their initial period of activity while encouraging inactive workers to leave the state of inactivity earlier on seems the sort of intervention required.

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Tables

Table 1: Economic status when first observed by gender (col %)

	Male	Female
Employee	51	56
Self-employed	16	6
Unpaid family worker	0	1
ILO unemployed	5	3
Inactive but would like work		
- looking after family/ home	0	1
- long term sick or disabled	4	3
- believes no job available	1	1
- not looked	1	1
Inactive and would not like work		
- looking after family, home	1	10
- long-term sick or disabled	11	9
- not need or want job	1	3
- retired	8	4
- other reason	0	1
Base	14,857	11,174

Table 2: Length of time out of work for those not working but who have previously worked (col %)

	Male	Female
less than 3 months	4	3
3 months but less than 6 months	4	3
6 months but less than 12 months	6	6
1 year but less than 2 years	13	9
2 years but less than 3 years	10	7
3 years but less than 4 years	9	7
4 years but less than 5 years	7	6
5 years or more	47	60
Base	4,665	3,908

Table 3: Transitions between employment and non-employment (row %)

	When last interviewed (one year later):		
When first interviewed:	Employed	Non-employed	Base
Men			
- Employed	90.9	9.1	10,095
- Non-employed	6.6	93.4	4,694
Women			
- Employed	90.0	10.0	7,082
- Non-employed	6.2	93.8	4,056

Table 4: MPH estimates of time to enter or exit employment, by sex.

	Men		Women	
	Employment entry	Employment exit	Employment entry	Employment exit
Duration of spell in quarters (base: more than 20)				
- 1-2	3.565	1.532	3.239	1.071
	(14.34)**	(8.73)**	(9.80)**	(4.09)**
- 3-4	2.694	1.321	2.661	1.152
	(10.78)**	(8.36)**	(8.70)**	(5.01)**
- 5-8	2.096	0.578	1.654	0.821
	(8.83)**	(3.92)**	(5.58)**	(4.16)**
- 9-12	1.161	0.386	1.435	0.458
	(4.56)**	(2.44)*	(4.73)**	(2.25)*
- 13-20	0.555	-0.098	0.536	0.287
	(2.22)*	(0.69)	(1.86)	(1.64)
Age category (base: [50-53])				
- (53-56]	-0.242	0.096	-0.310	0.256
	(1.37)	(0.85)	(1.44)	(1.99)*
- (56-60]	-0.617	0.505	-0.849	1.003
	(3.50)**	(4.56)**	(3.71)**	(7.16)**
- (60-63]	-1.304	1.056		
	(6.29)**	(7.96)**		
- (63-65]	-2.207	2.604		
	(6.45)**	(15.79)**		
Highest qualification (see footnote) (base: no qualifications)				
- nvq5/6	0.309	-0.209	0.158	0.120
	(1.19)	(1.24)	(0.45)	(0.45)
- nvq4	0.486	0.022	-0.386	0.221
	(1.76)	(0.13)	(1.04)	(1.00)
- nvq3	0.478	-0.060	0.132	0.086
	(2.48)*	(0.53)	(0.39)	(0.43)
- nvq1/2	0.479	-0.187	0.442	-0.078
	(1.99)*	(1.20)	(1.73)	(0.48)
- other	0.101	-0.113	-0.242	-0.184
	(0.44)	(0.82)	(0.75)	(1.04)
Accommodation tenure type (base: owned outright)				
- mortgaged	0.531	-0.418	0.562	-0.502
	(3.63)**	(4.66)**	(2.77)**	(4.13)**
- rented/ rent-free	-0.042	-0.124	-0.113	-0.276

	(0.23)	(1.03)	(0.43)	(1.57)
number of dependent children (base: no children)	0.129	-0.026	0.732	-0.080
	(0.62)	(0.21)	(2.25)*	(0.41)
Partner (base: no partner)	-0.136	-0.350	-0.238	0.040
	(0.83)	(3.05)**	(1.12)	(0.29)
Occupation classification (base: manager/ administrator)				
- professional	0.011	0.003	1.325	0.385
	(0.04)	(0.02)	(2.62)**	(1.27)
- associated, professional & technical	0.115	-0.104	0.702	-0.048
	(0.48)	(0.64)	(1.48)	(0.18)
- clerical,secretarial	-0.113	0.038	0.257	0.039
	(0.40)	(0.21)	(0.71)	(0.19)
- craft and related	-0.303	-0.042	0.171	1.260
	(1.39)	(0.30)	(0.28)	(3.24)**
- personal,protective	-0.153	-0.119	0.284	0.276
	(0.46)	(0.52)	(0.67)	(1.10)
- sales	0.178	-0.136	-0.298	0.448
	(0.47)	(0.55)	(0.69)	(1.64)
- plant and machine operatives	-0.255	-0.044	0.273	0.518
	(1.09)	(0.31)	(0.55)	(1.51)
- other	-0.260	0.173	0.109	0.333
	(0.91)	(1.07)	(0.27)	(1.34)
Industry classification (base: manufacturing)				
- primary	0.479	-1.107	-0.504	-1.260
	(1.39)	(4.14)**	(0.53)	(1.91)
- energy	-1.769	0.654	0.297	3.374
	(2.20)*	(1.99)*	(0.31)	(2.27)*
- construction	0.300	-0.176	-0.448	0.014
	(1.35)	(1.23)	(0.54)	(0.03)
- wholesale, retail & motor trade	-0.330	-0.119	-0.012	-0.286
	(1.23)	(0.84)	(0.03)	(1.06)
- hotels & restaurants	0.367	0.318	-0.243	0.799
	(1.00)	(1.12)	(0.50)	(2.41)*
- transport, storage & communication	-0.194	-0.101	-0.475	0.079
	(0.79)	(0.66)	(0.75)	(0.21)
- financial intermediation	-0.041	0.388	-0.476	0.235
	(0.13)	(1.43)	(0.77)	(0.62)
- real estate, renting & business	0.449	-0.142	-0.269	0.194

activities				
	(1.71)	(0.93)	(0.64)	(0.70)
- public administration & defence	-0.057	0.139	-0.252	-0.140
	(0.22)	(0.75)	(0.52)	(0.45)
- education	0.032	0.060	-0.447	0.130
	(0.10)	(0.31)	(1.02)	(0.46)
- health & social work	0.300	-0.083	-0.272	-0.120
	(0.79)	(0.40)	(0.70)	(0.46)
- other	0.318	-0.467	0.149	0.423
	(1.09)	(2.33)*	(0.33)	(1.42)
Region of residence (base: south-east outside London)				
- North	-0.147	0.588	-0.265	0.523
	(0.52)	(3.04)**	(0.59)	(1.92)
- Yorkshire & Humberside	-0.137	0.305	-0.109	0.037
	(0.53)	(1.97)*	(0.30)	(0.16)
- East Midlands	0.175	0.117	-0.299	0.050
	(0.66)	(0.71)	(0.77)	(0.20)
- East Anglia	-0.303	0.099	-0.582	-0.126
	(0.78)	(0.45)	(1.22)	(0.42)
- London	0.143	-0.052	-0.112	0.512
	(0.62)	(0.34)	(0.33)	(2.50)*
- South West	-0.106	0.016	0.708	0.177
	(0.40)	(0.10)	(2.06)*	(0.80)
- West Midlands	-0.016	-0.228	-0.069	0.018
	(0.07)	(1.42)	(0.21)	(0.08)
- North West	-0.478	0.132	-0.521	0.308
	(1.95)	(0.86)	(1.51)	(1.45)
- Wales	-0.473	0.329	-1.108	0.076
	(1.37)	(1.62)	(2.20)*	(0.24)
- Scotland	-0.241	0.362	-0.358	0.397
	(0.93)	(2.29)*	(0.98)	(1.77)
- Northern Ireland	-0.899	0.190	-1.483	0.030
	(1.75)	(0.64)	(1.59)	(0.06)
Calendar quarter (base: Oct-Dec)				
- Q1: Jan-Mar	0.262	0.026	0.035	0.121
	(1.59)	(0.30)	(0.17)	(1.12)
- Q2: Apr-Jun	0.222	-0.167	-0.470	0.026
	(1.34)	(1.86)	(2.06)*	(0.23)
- Q3: Jul-Sep	0.289	-0.186	0.318	0.148
	(1.74)	(2.06)*	(1.63)	(1.38)
Calendar year (base: 1993)				

- 1994	-0.162	0.161	0.140	-0.290
	(0.46)	(0.85)	(0.30)	(1.14)
- 1995	-0.358	0.336	-0.237	0.060
	(0.95)	(1.76)	(0.45)	(0.23)
- 1996	0.238	0.601	0.000	0.749
	(0.69)	(3.19)**	(0.00)	(2.95)**
- 1997	-0.052	0.179	0.610	-0.110
	(0.15)	(0.94)	(1.30)	(0.43)
- 1998	0.063	0.140	-0.012	-0.141
	(0.18)	(0.75)	(0.03)	(0.56)
- 1999	-0.027	0.321	0.039	0.350
	(0.08)	(1.77)	(0.08)	(1.49)
- 2000	0.131	0.023	0.586	0.090
	(0.38)	(0.12)	(1.23)	(0.35)
- 2001	0.171	0.434	0.449	-0.012
	(0.49)	(2.38)*	(0.92)	(0.05)
- 2002	0.010	0.050	0.051	-0.330
	(0.03)	(0.27)	(0.10)	(1.36)
- 2003	0.308	0.006	0.003	-0.064
	(0.93)	(0.03)	(0.01)	(0.31)
Constant	-4.679	-3.700	-4.458	-3.949
	(9.47)**	(13.52)**	(6.35)**	(9.81)**
σ^2	0.977	3.694	2.938	8.248
	(1.91)*	(5.41)**	(2.96)**	(7.81)**
LR test statistic of σ^2=0 Critical value: $\chi^2(1,0.05)$=3.84	4.89	50.55	14.93	96.98
Log-likelihood	-1,352.02	-4,787.65	-906.14	-3,629.50
Observations	3,358	9,990	2,087	6,999

Absolute value of z statistics in parentheses. * significant at 5%; ** significant at 1%.

All qualifications are converted to approximate National Vocational Qualification (NVQ) equivalents. The rough academic equivalents are: NVQ1 - low-level qualification, age 16; NVQ2 – qualification, age 16; NVQ3 – qualification, age 18 ; NVQ4 – degree; NVQ5/6 – higher degree.

Table 5: Correlation structure of unobservables of the fourth order Markov model and tests for exogeneity of initial conditions

	Men		Women	
	coeff.	t-stat	coeff.	t-stat
ρ_1	0.714	(5.68)	0.882	(21.49)
ρ_2	0.720	(5.80)	0.855	(20.43)
ρ_3	0.713	(5.49)	0.812	(22.23)
ρ_4	0.691	(5.09)	0.762	(17.80)
σ_{32}	0.985	(610.48)	0.989	(700.19)
σ_{42}	0.962	(315.49)	0.968	(308.87)
σ_{52}	0.948	(260.88)	0.950	(210.74)
σ_{43}	0.983	(579.17)	0.987	(81.74)
σ_{53}	0.966	(352.23)	0.970	(100.54)
σ_{54}	0.983	(555.48)	0.986	(443.93)
	$\chi^2_{(4)}$	p-value	$\chi^2_{(4)}$	p-value
Wald test of exogenous initial conditions (H0: ρ_1=ρ_2=ρ_3=ρ_3)	52.25	0.0000	821.64	0.0000

Table 6: Estimated measures of state dependence, cumulated state dependence, and Wald tests for the order of the Markov model

	Men		Women	
	coeff.	t-stat	coeff.	t-stat
SD_1	0.469	(3.25)	0.232	(2.68)
SD_2	0.065	(1.37)	0.012	(0.21)
SD_3	0.024	(0.41)	0.060	(1.06)
SD_4	0.048	(0.66)	0.123	(2.27)
CSD_2	0.508	(3.21)	0.242	(2.25)
CSD_3	0.520	(3.02)	0.289	(3.29)
CSD_4	0.543	(2.84)	0.369	(4.03)
	χ^2(df)	p-value	χ^2(df)	p-value
Fourth order H_0: $\lambda_4 = 0$	0.41 (1)	(0.5235)	5.08 (1)	(0.0242)
Third order H_0: $\lambda_4 = \lambda_3 = 0$	0.43 (2)	(0.8068)	12.44 (2)	(0.0020)
Second order H_0: $\lambda_4 = \lambda_3 = \lambda_2 = 0$	2.03 (3)	(0.5660)	17.46 (3)	(0.0006)
First order H_0: $\lambda_4 = \lambda_3 = \lambda_2 = \lambda_1 = 0$	12.40 (1)	(0.0146)	30.56 (4)	(0.0000)

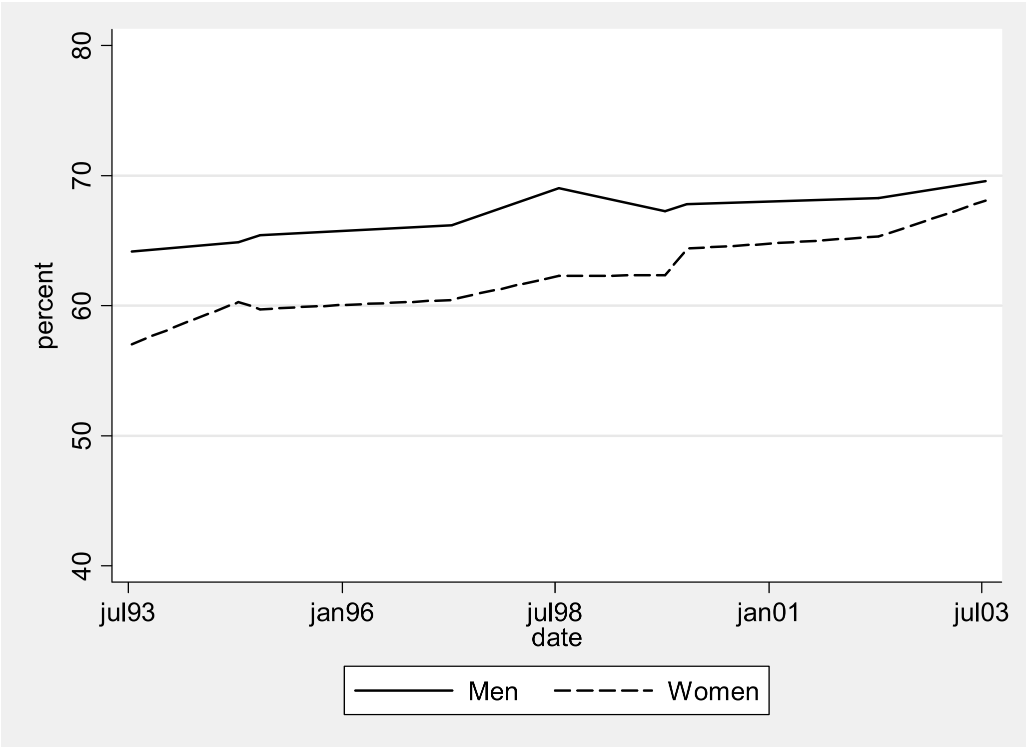
Table 7: Estimates of the employment transition equation from the fourth order Markov model

	Men		Women	
	coeff.	t-stat	coeff.	t-stat
Employed t-1	1.315	(3.45)	0.617	(2.65)
Employed t-2	0.169	(1.32)	0.031	(0.21)
Employed t-3	0.062	(0.40)	0.152	(1.05)
Employed t-4	0.126	(0.64)	0.313	(2.25)
Age category (base: [50-53])				
- (53-56]	-0.203	(3.21)	-0.129	(2.64)
- (56-60]	-0.408	(6.37)	-0.424	(8.32)
- (60-63]	-0.755	(9.93)		
- (63-65]	-1.146	(14.56)		
number of dependent children	0.148	(2.04)	0.217	(2.39)
Has partner	0.183	(2.87)	0.021	(0.41)
Accommodation tenure type (base: owned outright)				
- mortgaged	0.291	(5.37)	0.194	(4.19)
- rented/ rent-free	-0.201	(3.36)	-0.232	(3.46)
Highest qualification (see footnote) (base: no qualifications)				
- nvq5/6	0.050	(0.71)	0.201	(2.84)
- nvq4	0.090	(1.14)	0.136	(2.32)
- nvq3	0.100	(1.77)	0.093	(1.44)
- nvq1/2	0.012	(0.13)	0.003	(0.03)
- other	-0.240	(2.83)	-0.460	(5.83)
Region of residence (base: south-east outside London)				
- North	-0.432	(4.53)	-0.266	(2.67)
- Yorkshire & Humberside	-0.264	(3.24)	-0.086	(1.02)
- East Midlands	-0.061	(0.67)	-0.217	(2.43)
- East Anglia	0.012	(0.11)	-0.148	(1.37)
- London	-0.102	(1.15)	-0.170	(1.99)
- South West	-0.133	(1.70)	-0.035	(0.39)
- West Midlands	-0.070	(0.83)	-0.103	(1.27)
- North West	-0.282	(3.51)	-0.227	(2.80)
- Wales	-0.492	(5.25)	-0.417	(4.06)
- Scotland	-0.213	(2.63)	-0.200	(2.43)
- Northern Ireland	-0.444	(3.04)	-0.444	(3.51)
Industry classification (base: manufacturing)				
- primary	0.351	(2.93)	0.573	(4.13)
- energy	-0.406	(2.55)	-0.873	(2.61)
- construction	0.080	(1.21)	0.523	(2.52)
- wholesale, retail & motor trade	0.250	(3.46)	0.205	(1.91)
- hotels & restaurants	0.108	(0.71)	-0.005	(0.04)
- transport, storage & communication	0.089	(1.16)	0.104	(0.73)

- financial intermediation	-0.260	(1.89)	0.009	(0.06)
- real estate, renting & business activities	0.528	(5.71)	0.110	(1.07)
- public administration & defence	-0.060	(0.64)	0.195	(1.68)
- education	0.326	(3.08)	0.161	(1.47)
- health & social work	0.258	(2.31)	0.261	(2.59)
- other	0.376	(3.54)	0.159	(1.37)
Occupation classification (base: manager/ administrator)				
- professional	0.030	(0.35)	0.180	(1.64)
- associated, professional & technical	0.026	(0.31)	0.139	(1.39)
- clerical,secretarial	0.060	(0.58)	0.060	(0.77)
- craft and related	-0.025	(0.38)	-0.037	(0.27)
- personal,protective	0.397	(2.92)	0.030	(0.33)
- sales	0.240	(1.86)	-0.089	(0.84)
- plant and machine operatives	0.043	(0.55)	-0.061	(0.43)
- other	0.083	(0.94)	0.108	(1.20)
Calendar year (base: 1993; 2003 not identified)				
- 1994	-0.122	(1.11)	-0.103	(0.94)
- 1995	-0.043	(0.29)	-0.027	(0.19)
- 1996	-0.083	(0.62)	-0.134	(0.99)
- 1997	-0.068	(0.65)	-0.162	(1.52)
- 1998	0.021	(0.24)	-0.036	(0.41)
- 1999	0.076	(0.65)	-0.082	(0.77)
- 2000	-0.128	(0.90)	0.072	(0.49)
- 2001	0.073	(0.55)	-0.020	(0.14)
- 2002	0.007	(0.07)	-0.088	(0.83)
Calendar quarter (base: Oct-Dec)				
- Q1: Jan-Mar	0.005	(0.03)	0.032	(0.22)
- Q2: Apr-Jun	0.092	(0.75)	0.074	(0.59)
- Q3: Jul-Sep	0.020	(0.25)	-0.002	(0.03)
Constant	-0.345	(0.78)	-0.012	(0.05)
Log likelihood	-12166.104		-8548.5374	
Model chi2 (p-value)	823.50	(0.0000)	360.23	(0.0000)
Number of observations	11720		8020	

Figures

Figure 1: Employment rates among men and women aged between 50 and the state pension age, 1993-2003



Source: Longitudinal Labour Force Survey, 1993-2003

Figure 2: Estimated hazard rates of employment entry and exit over first 10 years (40 quarters) of spell, by sex