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Martyn Andrews
Ken Clark
William Whittaker

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Martyn Andrews
University of Manchester

Ken Clark
University of Manchester and IZA

William Whittaker
University of Manchester

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IZA

P.O. Box 7240
53072 Bonn
Germany

Phone: +49-228-3894-0
Fax: +49-228-3894-180
E-mail: iza@iza.org

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ABSTRACT

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Using data from the first fourteen waves of the British Household Panel Survey, we estimate a discrete duration model of interregional migration in Great Britain. By exploiting retrospective information on residency we control for late entry as well as unobserved heterogeneity. We find considerable duration dependence in region of residence in the raw data, most but not all of which disappears when controlling for observable and unobservable differences between individuals. Older workers are less likely to switch region while the better educated are more mobile. There are also some differences between males and females in their likelihood to migrate.

JEL Classification: C14, C23, C41, J24, J61, R23

Keywords: migration, duration, hazard, panel data, regional labour markets

Corresponding author:

Ken Clark
School of Social Sciences
University of Manchester
Manchester M13 9PL
United Kingdom
E-mail: ken.clark@manchester.ac.uk

I. Introduction

Inter-regional differentials in unemployment and earnings ought not to persist if there is a healthy flow of migrants between regional labour markets. In Great Britain, there is evidence that such differentials do persist and that flows of workers from poorer performing regions to stronger ones are relatively weak, particularly so during periods of recession when most needed. This apparent market failure contributes to the persistence of inter-regional inequality in labour-market outcomes, productivity growth and poverty.

Low migration rates are all the more surprising given that there is evidence to suggest that migration raises earnings, employment probabilities, and subjective well-being, at least for some groups of workers (see Andrews et al.(2007) and Whittaker (2008) and references within). From a human capital perspective, an individual or household might consider migrating if these gains are not offset by the costs of moving, which are typically not observed in datasets. These costs include the monetary costs of moving home and the possible psychological costs of uprooting family and other ties formed in the host region. Furthermore, if migration improves the quality of match between worker and firm, policies to encourage migration may be beneficial at the individual, regional, and national level. For such policies to be successful in encouraging migration, it is important to identify which personal and labour market factors lead to inter-regional migration.

Previous research on migration in Britain suggests that males, those without children, the better educated, and younger generations are consistently found to be most mobile whilst housing constraints faced by council tenants and mortgage holders hinder migration (Hughes and McCormick, 1981, 1985). There has been mixed evidence on the effect of individual unemployment. Pissarides and Wadsworth (1989) find that unemployment discourages migration while Boheim and Taylor (1999) find the opposite. There is also mixed evidence on the effect of regional labour-market differences on migration rates (McCormick, 1997; Jackman and Savouri, 1992; Hughes and McCormick, 1994; Pissarides and Wadsworth, 1989).

Another cause of low migration rates is that individuals may become less likely to migrate the longer they reside in their current region. It is important to establish the extent to which this persistence, or duration dependence, exists, and yet there is virtually almost no evidence for Great Britain, or anywhere else. The reason is that one needs to observe individuals over long-periods of time, and such longitudinal datasets do not exist. The alternative is to exploit retrospective questions about how long individuals have resided at their current address and region. In this paper, we analyse the British Household Panel Survey (BHPS) because it has such information. Moreover, because it is a panel, we are able to control for unobserved heterogeneity. This is important, because it is well-known that ignoring unobserved heterogeneity can lead to spurious estimates of the degree of duration dependence. We also need to deal with the fact that we have many left-censored spells (so-called late entry), because the duration is constructed from a retrospective question. To our knowledge, this is the first study to place regional migration in Great Britain within a duration model and one of few studies of anywhere that estimates the degree of duration dependence (whilst controlling for unobserved heterogeneity).

In Section II we describe how we use the BHPS to construct spells of residence in a given region for the individuals that we analyse. In Section III we present our methodology and in Section IV we discuss our results. Section V concludes the paper.

II. Data

The BHPS was first sampled in 1991 when 10,300 individuals (5,500 households) were interviewed across Great Britain. Households in this nationally representative sample have since been interviewed annually. The BHPS follows individuals who move residence and the extensive questionnaire on labour market and personal characteristics captures individuals' circumstances both pre- and post-migration. The panel nature of the survey thus enables the construction of detailed histories for individuals.

To investigate the determinants of migration, our analysis uses the first 14 waves of the BHPS (1991-2004). We exclude students, the retired, and those in the armed forces, because migration for these groups is unlikely to be for labour market reasons. Our sample consists, therefore, of those aged 16-64 who are either employed or unemployed/inactive. Throughout we analyse males and females separately.

Each individual is interviewed once a year (at a date that varies from year to year). The data form an unbalanced panel comprising 6,266 females and 5,986 males observed over 44,366 female-years and 39,569 male-years. In Great Britain, there are eleven standard statistical regions, and a migration occurs if an individual changes region between one year and another. Duration in each region (a 'spell') is measured in integer years.

Because we are interested in the labour market effects of migration, our definition of migration excludes those who change region but remain with their existing employer (for example, those moving to be closer to their place of work, or relocations for internal promotion reasons). Thus, where an individual is employed post-migration, we analyse those who change job following migration. There are 511 male migrants in our sample out of 5,986 males, and 544 female migrants from 6,266 women (see Table 1), converting to ever-migrated rates of 8.68% for females and 8.54% for males. On the other hand, the annual migration rate is 1.63% for females and 1.71% for males. These migration rates are lower than those found in previous studies of the UK/GB since we are using movements across the eleven standard statistical regions of Great Britain as the definition of migration rather than relatively smaller movements across local authority boundaries. Note that Census data indicate that two-thirds of migrants move less than 10km while only one if fifteen move more than 200km (Champion, 2005).[1]

The BHPS contains essential retrospective information without which our analysis is not possible. In their initial interview, respondents are asked how long they have resided at their current address. This provides us with elapsed duration at their current residence. From this we are able to construct information about each individual's spells of residence in a given region.

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[1] Our rates are similar to the regional rates of 1.6% and 1.8% found by Jackman and Savouri (1992) and Boheim and Taylor (1999) respectively.

We start the duration `clock' when an individual turns 16 years old, or, if in education, when the individual finishes her studies. Thus where someone has never moved home, her elapsed duration is measured from age 16 or time completed education. For someone who has moved since turning 16 or completing her education, we observe duration as the number of years at the current address. We define the elapsed duration of individual *i*'s first spell when first observed in the BHPS as $\underline{a}_{i1}$. Thus, for many individuals, their first spell is left-truncated, as it starts before 1991, and $\underline{a}_{i1} > 1$. Individuals whose first spell starts in 1991 or later are not left-truncated, defined by $\underline{a}_{i1} = 1$. The econometric methodology below needs to distinguish between these two sub-samples of individuals. Of 6,266 females and 5,986 males, 3,771 females and 3,381 males have left-truncated first spells. The sample of left-truncated first-spells is referred to as a stock sample and left-truncation is referred to as late-entry. The remaining spells form a flow sample. The unit of observation is our analysis is a spell: there are 14,425 spells in the data, giving the average number of spells per individual as 14,425/12,252=1.18.

Figure 1 gives six stylised examples of individuals in our data. The first four individuals have left-truncated first spells. The other two are new to the labour force, starting either in 1991 (the `mature student') or later than that (the `16-year-old entrant').

The duration of the individual's first spell is denoted a_{i1}. Thus, for an individual whose first spell starts in 1991, and finishes in 1992 (maybe because they migrate), then $\underline{a}_{i1} = 1$, $a_{i1} = 2$, and so the number of years the first spell is observed in the

BHPS is two $(a_{i1} - \underline{a}_{i1} + 1 = 2)$. For the second individual in Figure 1, his first spell ends in 2001 and so his duration is 11 years.

It is important to note that our duration variable measures time spent in a region. As individuals may move within a region, our derived duration variable differs from the 'years at address' variable given in the BHPS. For example, the second individual in Figure 1 could have changed address but remained in his current region numerous times over the 11 years in the region. Using years at current address will therefore understate the time spent in a region. Years at current address has been (incorrectly) used in numerous past studies analysing inter-regional moves, in particular; Hughes and McCormick (1985) using the GHS, and Boheim and Taylor (2002) and Buck (2000) using the BHPS.

Some individuals have more than one spell. The duration in spell s is denoted a_{is}. Consider the `migrant' in Figure 1. The last year observed in his first region is 1998 and so $a_{i1} - \underline{a}_{i1} + 1 = 8$. The duration of his second spell is $a_{i2} = 6$. In general, $\sum_s a_{is} - \underline{a}_{i1} + 1 = m$, where m is the number of Waves of BHPS that the individual is observed in.

There are three reasons why spells end: an individual can migrate, leave the sample ("attrit"), or the spell is right-censored in 2004. Attrition occurs because an individual leaves the labour force (retires or dies) or leave the BHPS. We define two binary indicator variables: $m_i = 1$ if an individual migrates and $c_i = 1$ if the spell is completed. A completed spell can either end in migration $(c_i = 1, m_i = 1)$ or attrition $(c_i = 1, m_i = 0)$; otherwise the spell is right-censored $(c_i = 0)$. In Figure 1, four spells are right-censored. Attrition is denoted by □ and migration by ■. In the data, there are 2,359 censored male spells and 2,642 censored female spells. From the completed spells, we can compute the raw hazard rate to completing a spell, which is 4,603/39,569=0.116 for men and 4,821/44,366=0.109 for women. Of the 4,603 completed male spells, 677 finish as a migration (14.7%); for females, these figures are 4,821, 722 and 15.0% respectively. As 14.7% out these 4,603 completed male spells end up in a migration, the raw hazard to migration for men is 677/39,569=1.71%. For women it is 722/44,366=1.63% because 15.0% of completed spells end up as a migration.

Attrition is a common problem with panel data, though there is evidence of high levels of response rates in the BHPS, with the initial four wave rates at 87%, 90% and 95% respectively (Buck, 2000). However, attrition is higher amongst migrants. This may be due to communication and/or information breakdowns between respondent and reporter. Buck (2000) gives a response rate of 72% for migrants between waves one and two, and Taylor (2006) claims at least one household member could be interviewed in 80% of all moving households over the first thirteen years of the BHPS.

Defining spells for mature students is potentially problematic. We stop the duration clock during the years they are being educated. When an individual has moved region during their studies and not returned, we reset our duration variable but do not record the change in region as a completed spell since migration here was for non-labour market reasons (the fourth individual in Figure 1). For other individuals we do not pause the clock because they might leave the labour force for labour-market reasons. These include women in domestic production, the long-term sick and disabled, and those on government training schemes.

To summarise, spell s for individual i is characterised by the following vector of information:[2]

$$(\underline{a}_{is}, a_{is}, m_{is}, c_{is}, \mathrm{x}_{\mathrm{is}}) \quad s = 1,\ldots,7.$$

For all spells apart from the first, $\underline{a}_{is} = 1$, and $\underline{a}_{i1} = 1$ if the individual enters the sample in 1991 or later. x_{is} represents all observed covariates, which can potentially vary over the elapsed duration of the spell and by calendar time. Each spell comprises $a_{is} - \underline{a}_{is} + 1$ rows (years) of data.

By cross-tabulating completed duration a_{is} with whether or not the individual migrates m_{is}, and computing the proportion of spells that end with a migration for $a = 1,2,3,\ldots$, the raw hazard is generated. These are plotted in Figures 2 and 3, for males and females separately, and are labelled "Raw Non-Parametric". Thus for males and females respectively the raw hazard rate falls from 4.24% and 4.39% in the first year to 0.80% and 0.58% for durations between 16 and 20 years. Clearly, the raw data exhibit migration inertia, in that the longer a person resides in a region the less likely she is to migrate. Said differently, the raw hazards exhibit negative duration

[2] Just one male has 7 spells.

dependence. Assuming durations are drawn from a Weibull distribution, the estimated Weibull parameter α is estimated to be 0.382 and 0.321 for males and females respectively. (See Section 4 below for details.) The raw Weibull hazard is also plotted in Figures 2 and 3. Below, we use duration modelling techniques to see whether this observed duration dependence is genuine (individuals get locked into regions as they get older because of attachments to jobs, schools, houses etc) or because we are observing sample selection in that some individuals with particular configurations of observable and unobservable characteristics are able to migrate more easily or want to migrate to find better labour-market opportunities.

The covariates used in our analysis relate to an individual's age, housing tenure, labour market status, education, family structure, marital status and region. Two further variables based on BHPS questions on preferences are included: whether or not an individual would like to move and whether or not she likes her current area of residence. A set of time dummies is also included.

In addition, to capture the effects of regional labour market differences, we include variables for regional labour market tightness and real wage. The tightness variable is the ratio of job-centre vacancies to claimant-count unemployment levels and is plotted in Figure 4. A clear dispersion in regional tightness rates has occurred since 1991, with northern regions in particular becoming more attractive with better vacancy to unemployment ratios. Regional real wage rates are computed as the ratio of average weekly earnings taken from the New Earning Survey to average house prices (level) obtained from the Halifax Building Society; these are plotted in Figures 5 and 6. Since 1991, regional real wages have diverged, peaking in dispersion during 2001, and have since begun to converge. Although regional wage differences have increased since 1991 (in favour of the southern regions), controlling for the level of house prices shows southern regions are relatively lower paid. For all regions the higher rates of growth in house prices to wages over the period have led to reductions in real wages. These differences in employment and earnings prospects across regions should act as an incentive to potential migrants.

III. Econometric methods

In this section, which draws heavily on Andrews et al. (2007), we describe the appropriate econometric methods for modelling the probability that an individual migrates as a function of elapsed duration, controlling for observed covariates and unobserved heterogeneity. Our data comprise an unbalanced panel of individuals $i = 1,...,N_t$ observed annually $t = 1,...,14$. (Recall that $t = 1$ is Wave 1 or 1991.) Each individual has a number of `spells' residing in a different regions, where there are a_{is} years in spell s. The appropriate econometric framework is that of discrete-time duration models, because an individual may migrate at any point between the date of interview in year t and the day before they are interviewed in year $t+1$, but we do not observe the precise date on which this happens.

The fundamental concept in modelling the determinants of migration decisions is the hazard function. The hazard for individual i in spell s, h_{ais}, is defined as the probability that an individual migrates at elapsed duration a, conditional on having survived to elapsed duration $a-1$:

$$h_a(\mathrm{x}_i, u_i) = \Pr(A_i = a \mid A_i \geq a) = f_a(\mathrm{x}_i, u_i) / S_{a-1}(\mathrm{x}_i, u_i) \qquad a = 1, 2, \ldots, a_i \text{ .}$$

Here, suppressing the spell subscript s for clarity, A_i is the latent duration in spell s of individual i, x_i is a vector of observed covariates, u_i is a ('frailty') term capturing all unobserved heterogeneity, $f_a(\mathrm{x}_i, u_i)$ is the probability of observing duration a, and $S_{a-1}(\mathrm{x}_i, u_i)$ is the probability of surviving to duration $a-1$. The explicit dependence of h_a, f_a and S_a on the vector of observable covariates and the unobservable emphasises the point that the hazards for all individuals would be the same if they had the same (un)observable characteristics. Recall that we denote the completed duration for individual i as a_i. Also recall that, for about half the individuals in the sample (3,381 men and 3,771 women), we have delayed entry for their first spell (i.e. $\underline{a}_i > 1$). Our econometric methods need to take account of this delayed entry. We also need to deal with the more common problem that the sample ends before an individual completes his first spell, that is right-censoring $(c_i = 0)$. Standard references on the econometrics of duration models include Wooldridge (2002) and Cameron & Trivedi (2005), however here we follow the exposition in Jenkins (2005).

To start, consider the standard case where spells are observed from when individuals enter the labour force, but for some there is right censoring (2,359 male spells and 2,642 female spells). The log-likelihood function for this sub-sample is given by (see Jenkins 2005, equation (6.9)):

$$\log L = \sum_i \log\left[\left(\frac{h_{ai}(\mathrm{x}_i, u_i)}{1-h_{ai}(\mathrm{x}_i, u_i)}\right)^{m_i} \prod_{a=1}^{a_i} \log[1-h_a(\mathrm{x}_i, u_i)]\right]. \qquad (1)$$

Recall that the indicator variable m_i equals unity if an individual migrates and zero otherwise. Effectively, we have an independent competing risks model, where completed spells $(m_i = 0, c_i = 1)$ are grouped together with the right-censored spells ($c_i = 0$). The likelihood for an individual who migrates at observed duration a_i is $(1-h_{i,1})(1-h_{i,2})...(1-h_{i,a_i-1})h_{i,a_i}$, whereas the likelihood for a individual who does not migrate at observed duration a_i is $(1-h_{i,1})(1-h_{i,2})...(1-h_{i,a_i})$. Here, $h_{i,a}$ is short-hand for $h_a(\mathrm{x}_i, u_i)$. (Suppose that, in Figure 1, we observe the first spell of the third individual from entry into the labour force, then her likelihood is $L_3 = (1-h_{3,1})...(1-h_{3,13})h_{3,14}$.)

A standard approach for estimating this model is to expand the data so that each individual contributes a_i rows per spell. Define a binary indicator variable y_{ia} which equals zero unless it is the last year individual i is observed ($a = a_i$) and the individual migrates ($m_i = 1$). (For the third individual in Figure 1, she would have 14 rows of data, with y_{3a} as $\{0,0,0,0,0,0,0,0,0,0,0,0,0,1\}$.) We can then write the log-likelihood for this sub-sample as

$$\log L = \sum_i \sum_{a=1}^{a_i} \{y_{ia} \log h_a(\mathrm{x}_i, u_i) + (1-y_{ia})\log[1-h_a(\mathrm{x}_i, u_i)]\}. \qquad (2)$$

This has the same form as the likelihood for a binary dependent variable model, and hence can be estimated using standard software. To model the effect of covariates on the hazard rate, it is usual to adopt the proportional hazards assumption

$$h(t; x) = h_0(t) \exp(\mathrm{x}\beta + u), \tag{3}$$

where t represents elapsed duration, continuously measured, and $h_0(t)$ is the baseline hazard. Under this assumption, the discrete hazard turns out to be the complementary log-log link function:

$$h_a(\mathrm{x}_i, u_i) = 1 - \exp[-\exp(\mathrm{x}_{ia}\beta + \gamma_a + u_i)] \qquad a = 1,2,..,a_i\,. \tag{4}$$

The γ_a terms are interpreted as the log of the non-parametric piecewise linear baseline hazard: $\gamma_a = \log h_{0a}$. γ_a are the parameters on a full set of dummies for elapsed duration $a = 1,2,...$ The notation x_{ia} explicitly acknowledges that the covariates may vary with elapsed duration or calendar time. An element of the vector β is interpreted as follows: a small change in x_k results in a small change in the log-hazard of β_k if x_k is a continuously measured covariate. If x_k is a binary covariate, $\beta_k = \log h_a(x_k = 1; \mathrm{x}, u) - \log h_a(x_k = 0; \mathrm{x}, u)$ (with an appropriate change in the definition of x).

If the baseline hazard is assumed to come from an underlying (continuous) Weibull distribution, then hazard at elapsed duration a is $\alpha\lambda a^{\alpha-1}$ with $\alpha > 0, \lambda > 0$. It follows that

$$\gamma_a = \log h_{0a} = \log(\alpha\lambda a^{\alpha-1}) = \log(\alpha\lambda) + (\alpha - 1)\log a \qquad a = 1,...,a_i\,.$$

Substituting into Equation (4) and absorbing $\log(\alpha\lambda)$ into the constant gives:

$$h_a(\mathrm{x}_i, u_i) = 1 - \exp[-\exp(\mathrm{x}_{ia}\beta + (\alpha - 1)\log a + u_i)] \qquad a = 1,...,a_i\,. \tag{5}$$

Instead of there being a complete set of duration dummies, there is a single variable $\log a$ recording elapsed duration for individual i. Testing the restrictions imposed by this parametric distribution on the unrestricted non-parametric hazard is straightforward.

We now deal with the problem of late entry. As noted, 7,152 individuals in our sample have left-truncated first spells ($\underline{a}_i > 1$), and so have already been at risk of migrating for some time, depending on their duration. The implication of this is that one is more likely to observe long rather than short durations. This is a classic sample selection problem. An individual with a left-truncated spell means that her contribution to the likelihood needs dividing by

$$S_{\underline{a}_i - 1}(\mathrm{x}_i, u_i) = \prod_{a=1}^{\underline{a}_i - 1} [1 - h_a(\mathrm{x}_i, u_i)],$$

the probability of surviving to the first period of the sample. But the denominator divides into the numerator very neatly, and this leads to the convenient cancelling result (Guo, 1993; Jenkins, 2005) so that the log-likelihood becomes

$$\log L = \sum_i \log\left[\left(\frac{h_{ai}(\mathrm{x}_i, u_i)}{1 - h_{ai}(\mathrm{x}_i, u_i)}\right)^{m_i} \prod_{a=\underline{a}_i}^{a_i} \log[1 - h_a(\mathrm{x}_i, u_i)]\right] \qquad (6)$$

and, amending Equation (2), the log-likelihood is also written

$$\log L = \sum_i \sum_{a=\underline{a}_i}^{a_i} \{y_{ia} \log h_a(\mathrm{x}_i, u_i) + (1 - y_{ia}) \log[1 - h_a(\mathrm{x}_i, u_i)]\}. \qquad (7)$$

This is very similar to the standard expression, except that the summation runs from the duration of the individual when she enters the data. (Because the first spell for the third individual in Figure 1 survived to Wave 1 of the BHPS, her likelihood contribution is $L_3 = (1-h_{3,8})...(1-h_{3,13})h_{3,14}$ and $y_{3,a} = \{0,0,0,0,0,0,1\}$.) As Equations (1) and (2) are special cases of (6) and (7), one can pool the stock and flow sub-samples.

One can now see how the baseline hazard can be estimated for *all* durations, from $a = 1$ to individuals whose recorded completed duration is a long time. This comes about by knowing how long time each individual resides in the current region, rather than just knowing how long since 1991, when the data in the BHPS were first sampled. Those in the flow sample tend to contribute to short durations and those in the stock sample to long durations: once we control for calendar time and age, the data are randomly drawn from both sub-samples, and so this doesn't matter.

The log-likelihood given in Equation (6) and the equivalent Equation (7) form the basis of our estimations below. The precise form of the hazard function is given in Equation (4) or Equation (5), the latter if the baseline hazard turns out to come from a Weibull distribution. In the first instance, one can ignore both the covariates and the unobserved heterogeneity to estimate the raw hazards (see Figures 2 and 3 above). The possibility that the baseline hazard comes from a Weibull seems a distinct possibility, and this considerably makes estimation easier, there being far fewer parameters.

It is well-known that estimating a model with covariates, but ignoring the unobservable, will bias the estimates of the baseline hazard, even if u_i and x_i are (statistically) independent. This means that the heterogeneity needs integrating out:

$$\log L=\sum_i \log\left\{\int_{-\infty}^{\infty}\left[\prod_{a=\underline{a}_{i i}}^{a_i} h_a(\mathrm{x}_i,u_i)^{y_{ia}}(1-h_a(\mathrm{x}_i,u_i))^{1-y_{ia}}\right]f_u(u_i)du_i\right\} \tag{8}$$

where $f_u(u_i)$ is the density of u_i. There are three choices, all standard in the literature. The first is to assume that log(u) is Gamma distributed, from which a closed-form solution is obtained (Meyer, 1990). Alternatively, if u is Normally distributed, Gaussian quadrature can be employed to approximate the Normal distribution, and the unobservable is integrated out numerically. In practice, these make little difference. The third possibility is to use discrete mixing, as advocated by Heckman and Singer (1984). See also Cameron & Trivedi (2005) for more details. Notice that equation (8) remains valid even with left-truncated data (Wooldridge, 2002, pp.704).

IV. Results

For males and females we can estimate either a non-parametric, piece-wise linear baseline hazard or a Weibull baseline hazard. Given these choices, we can also choose whether or not to control for unobserved heterogeneity. This gives four possible models for each gender. However, the raw non-parametric hazards (Figures 2 and 3) suggest that the Weibull specification is reasonable, and, as it reduces the number of estimated parameters considerably, we chose this as the specification of the baseline hazard. Of the three choices for modelling unobserved heterogeneity, we use Gaussian mixing. Using Gamma mixing makes little difference. For discrete mixing, finding a global maximum of the likelihood is difficult with models estimated on large samples and/or models with a high number of parameters (even with a Weibull baseline hazard). The variance of the unobserved heterogeneity term was significantly different from zero for both males and females.[3] Thus our preferred specification corresponds to equations (5) and (8). The estimated parameters from this model are reported in Table 2.

It is well-established that, when estimating unemployment duration models, not controlling for heterogeneity across individuals over-estimates the degree of negative duration dependence. Essentially, the sample selection effect of 'better' individuals leaving unemployment more quickly than the 'worse' individuals leads to spurious duration dependence in the observed data – the sample becomes increasingly dominated by worse individuals, whose exit rates are lower, as elapsed duration evolves. This argument applies to both observable and unobserved differences between individuals. When we consider migration, that is leaving a region rather than exiting unemployment, the distinction between better or worse individuals is less relevant because, while leaving unemployment is generally seen as a good thing, there is no presumption that leaving a region is necessarily to an individual's advantage. Nevertheless, there will exist some individuals who might be expected to migrate more quickly – "footloose" or "dynamic" individuals perhaps – hence, whether there is genuine duration dependence once we control for observable and unobservable differences between individuals remains an issue.

Figures 2 (males) and 3 (females) illustrate what happens. In the raw data, there is considerable duration dependence, with the Weibull parameter α being estimated as 0.382 and 0.321 for males and females. When we control for observed covariates (held at their mean values in the figures), the estimate of α increases to 0.693 and

[3] The parameter σ_u was estimated to be 1.087 for males and 1.026 for females. P-values were 0.00 for each.

0.610, respectively. In addition, when we control for observed covariates *and* unobserved heterogeneity, the hazard becomes very flat, with α estimated as 0.888 and 0.790 respectively. However, both these parameters are estimated to be significantly different from unity (the standard errors are 0.057 and 0.055 respectively), suggesting that there remains genuine negative duration dependence in the observed data.

Thus, the longer individuals stay in a region the less likely they are to migrate to another region of the UK. Finding negative duration dependence is not surprising, even though we have included age and year effects in our model. Gerber (2005) found a similar negative effect on Russian internal migration (0.547 for males and females combined) while Detang-Dessendre and Molho (1999, 2000) in a study of young French men and women also found a negative effect, with duration dependence being stronger amongst males. Negative duration dependence was also found for graduating students in Finland (Haapanen and Tervo, 2007). Of course, the important issue is to establish how much getting older contributes to duration dependence, and why. This is discussed shortly.

We now consider whether this duration dependence is of economic significance. We calculate that the baseline hazards fall from 0.00707 after one year to 0.00547 after 10 years for males (0.256 log-points); the numbers are 0.00861 and 0.00531 for females (0.483 log-points). (See Figures 2 and 3.) By comparison, below we find that a male with some qualifications is more to migrate than a male without any qualifications by some 0.452 log-points; for females, the estimate is 0.282 log-points. The effects of some other covariates are much bigger. In other words, the degree of duration dependence is not substantial when compared with other covariates.

The results in Table 2 also identify which individuals are more likely to migrate. In other words, we can establish which covariates shift the baseline hazard and in what direction. While there is some existing literature on this for the UK, it is largely based on cross-sections of households or individuals, some of whom have migrated. Thus, previous studies do not control for duration dependence or unobserved heterogeneity. In what follows we discuss the effect of the explanatory variables in shifting the baseline hazard.

Age is parameterised in seven age bands; Figure 7 plots predicted hazards by age, where all the other covariates are evaluated at their mean values. For both males and females, the migration hazard falls with age. This is a common finding in the literature, and is one obvious explanation as to why raw hazards decline much more quickly than their conditional counterparts (Figures 2 and 3). The inclusion of age alone reduces the rate of duration dependence from $\alpha = 0.382$ to 0.534 for males and from $\alpha = 0.321$ to 0.470 for females. There are many reasons why older individuals are less likely to migrate as they get older. The first is the rising non-pecuniary migration costs associated with the investment in social and family networks that individuals make when they live in the same area for an extended period of time. Second, a better knowledge of the local labour market may contribute to inertia. Third, it is possible that as individuals get older, they become more risk averse.

We model the effect of education by specifying dummies for the highest qualification obtained; these are: no qualifications, having some GCSEs, having some A-levels, having a degree and having a higher degree.[4] We find that the migration hazard is higher the better educated an individual is; Hughes and McCormick (1981, 1985) and Coleman and Salt (1992) find the same. A man with a degree is 89.3% [=(exp(1.090-0.452)-1)*100] more likely to migrate than a man with just GCSEs. The equivalent figure for females is 92.3%. Faggian et al. (2007) suggest that women graduates are more mobile than their male counterparts as a way of compensating for gender discrimination in the labour market.

We also find weak evidence that individuals with fewer children are more likely to migrate. Relative to those with no children, parents have a reduced likelihood of migration, although the precise magnitude of this effect and its statistical significance varies by gender and by number of children. It is likely that the dislocation associated with moving children from one region to another would also depend on the ages of the children, the quality of their social networks and their educational progress. In addition, the reduction in the probability of moving for those with larger families which is significant at the 10% level for males and females, may reflect additional housing demands: not only would private housing be more expensive, but it is also likely to be more difficult for council tenants with larger families to relocate.

[4] GCSEs are national exams taken by (almost) all young people in the final year of compulsory education, ie those aged 15 and 16. A-levels are national examinations taken in the final year at school, typically aged 17 and 18.

Some studies have found that some female migrants have lower earnings following a move, and are less likely to be employed (Andrews, Clark and Whittaker, 2008; Rabe, 2006; Taylor, 2006). This is when moves happen because of a spouse's or partner's job – such women are so-called 'tied' migrants (Mincer, 1978). We include variables relating both to the presence of a spouse and whether or not that spouse is in full-time or part-time employment. For males, a non-employed spouse has a positive but insignificant effect on the migration hazard. Males with spouses/partners are more likely to migrate (compared with their single counterparts) if their spouse/partner is unemployed and they are less likely to migrate if their spouse/partner is part-time. In both cases, the effects are poorly determined. Women with an unemployed or full-time spouse/partner are less likely to migrate. We would expect an employed spouse to reduce the migration probability as migration for such couples is likely to be more costly, requiring the termination of two jobs rather than one, however the magnitude of the estimates for males is somewhat counterintuitive as termination of a full-time job is presumably more costly to the household than leaving a part-time job. For females, a non-employed spouse is associated with a large, significant and negative effect on migration (a 29.4% reduction) - it might be appropriate to think of these women as "tied stayers".

In common with all of the existing literature, we find that those renting accommodation from a private sector landlord are much more likely to migrate that either those owning their own home outright (base category), or with a mortgage. The effect is stronger if the accommodation is furnished. For example, the migration rate is 79.8% (0.587 log-points) higher for males who have private rented accommodation compared with males who own their own home. These results are as expected, and reflect the relative costs of migrating. However, our estimate for council tenants is different to other studies. Unlike Hughes and McCormick (1981) who find that households with council tenancy are considerably less likely to move than households with any other kind of tenure, we find that being a council tenant has no effect for males (compared with owner occupiers), but significantly (at the 10% level) reduces the hazard for females by 26% (0.300 log-points). One might expect mortgage holders to exhibit higher migration rates since they have the potential funds available to facilitate a move, however the early 1990s recession plunged many mortgage holders into negative equity (Gentle et al. (1994) estimates as many as 21%). Furthermore, the amount of home repossessions during this time escalated (Malpass and Murie, 1994), which would have restricted migration. Moreover, since the recession, house prices have increased at an unprecedented pace, which makes movements to areas with better prospects more difficult for home owners. These factors combined explain why, in contrast to older studies, the migration propensities of male council tenants are no lower than those of home owners since the early 1990s.

For female council tenants the strongly negative effect of council tenancy may reflect the relatively high proportions of single women with children in this form of housing tenure. Limited employment prospects, coupled with the need to care for children, reduce the likelihood of migration for this group. This is partly explained by the difficulties of obtaining council accommodation in a new region.

We include two variables that record attitudes to migrating, being a preference for moving and a dislike of the current area. Both have large effects on the migration hazard. Males and females who indicate that they would like to move are respectively

111.7% and 136.3% more likely to move. While the inclusion of this variable may seem strange - of course individuals wanting to move are more likely to - our rationale for controlling for preferences was to help differentiate those unobservably more likely to move. The dummy variable for whether the individual likes their area was included with the intention of capturing local community or area effects. Such effects do appear to exist: we find males and females who like their current area have 33.6% and 36.7% reduced likelihoods to migrate respectively.

Employed men in non-manual occupations have a predicted hazard rate which is 47% (0.383 log-points) higher than men employed in manual occupations. This is statistically significant at conventional levels, however there is no significant effect for women. Manual workers have previously been found to have lower migration rates (Hughes and McCormick, 1994) and this may be the effect of local labour market specialisation – manual workers are likely to have skills much more industry-specific (and thus, potentially regional-specific) than non-manual workers. More transferable skills − which make it easier to find employment in another region − is the reasoning behind the higher non-manual migration rates and the relatively greater response of non-manual workers to employment differentials (Evans and McCormick, 1994). Compared with a man employed in a manual occupation, an unemployed man is much more likely to migrate (a hazard rate which is 84% or 0.610 log-points higher). The effect for women is small and insignificant. Hughes and McCormick (1989) and Boheim and Taylor (1999) (for males and females) find a similar result. The finding that individual unemployment positively affects male migration has been common in the literature (see, in particular, Pissarides and Wadsworth (1989)). For men, this fits well with a human capital interpretation of migration: unemployed men will have lower costs of moving since they will not be forfeiting a wage and are expected to move to a more prosperous region where employment is more likely.

If individuals migrate to improve their economic well-being (pay and job prospects), one would expect that, on average, individuals migrate towards the better performing/rewarding markets. In the literature, these effects are typically captured using regional unemployment and/or vacancy rates, regional wages and regional house prices (see McCormick, 1997, for example). The effect of wages is generally found to be in the direction one would expect (from low wage to high wage regions, see Pissarides & Wadsworth, 1989; Hughes & McCormick, 1994; Cameron & Muellbauer, 1998) An exception is Jackman and Savouri (1992), who use aggregate migration data. Regional unemployment differentials have been found to have the 'wrong' effect on migration with individual level data (Pissarides and Wadsworth, 1989; Hughes and McCormick, 1994), but conventional effects with aggregate data (Jackman and Savouri, 1992; Cameron and Muellbauer, 1998). The effect of vacancy rates is also found to have a different sign depending on study. House price differentials have typically been found to work in the direction expected, with Hughes and McCormick (1994) finding a small effect and Jackman and Savouri (1992) a stronger effect.

We include two variables: the real wage and labour market tightness. These refer to the individual's origin region. The real wage is normalised by a house price index to reflect regional differences in price levels, as well as differences in housing costs between regions. The results suggest that real wages have no significant effect on migration, though the estimated coefficients are negative (-0.432 for males and -0.278

for females) as predicted. The effect of labour market tightness is significant and correctly signed for males (-0.627) but insignificant and negative for females (0.046). A potential problem with these two aggregate variables, however, is that they exhibit insufficient variation as there are only 11 regions and 14 waves per gender. The estimated standard errors are large and are probably underestimated because of the well-known Moulton (1986) effect.

The bottom line is that we cannot detect convincing effects of these two variables on the migration hazard. If these variables are replaced by a set of year dummies, then the estimates tell us whether or not migration is pro-cyclical, controlling for everything else in the model. Figures 7 and 8 plot the predicted hazards over the sample period 1991 to 2004, holding all other variables at their sample means. There is a marked difference between males and females. For men, migration is strongly pro-cyclical: during the early 1990s recession, migration for males dipped to about 0.3% before recovering to peak at approximately 1.1% in 2000. Female migration did not vary over the business cycle: the p-value on a test of the joint significance of the year dummies is 0.326.

V. Conclusion

In this paper we model the hazard to regional migration using the BHPS from 1991 to 2004. Because there are no longitudinal datasets that follow individuals and/or households over long periods (literally, decades), there are very few duration models of migration. To do this, we exploit retrospective information on residency. This means that our duration model has to address so-called late entry. It also addresses the more familiar issue of unobserved heterogeneity, because otherwise our estimates of the degree of persistence, or duration dependence, are likely to be spurious. Our results are as follows.

Our first key finding is that there is considerable negative duration dependence in the raw data for both males and females. Much of this disappears once we control for individuals' observable and unobservable characteristics, but some duration dependence still persists. Compared with the effects of other covariates, it is not particularly strong. The age of the individual is very important in explaining why there is considerable duration dependence in the raw data, and is related to the fact that ties to schools, housing, social networks and the locality all become stronger as time goes on. Individuals may also become more risk averse as they get older.

Our second key finding is that we confirm many effects found in the literature, even though most studies use cross-sectional data. Confirming results from previous studies is important, now that we can control for duration dependence and unobserved heterogeneity.

In the introduction, we noted that migration flows are not sufficiently large to reduce regional differences in labour market outcomes. Our results do not explain why this is so, in spite of there being large returns to earnings and job-prospects from moving. On the other hand, our results do allow us to identify which individuals are more likely to migrate, and there are big differences across various observed characteristics. For example, our results show that the housing market has a strong effect on migration, whilst private renters are flexible and most likely to move, home owners are roughly as likely as council tenants to migrate. We suggest this is down to higher house price differentials over the 1990s creating barriers to home owners wishing to relocate to more prosperous regions. Policies aimed at reducing regional house price differentials, and/or making long distance moves less costly would facilitate regional migration.

Similarly, the higher the educational attainment, the more likely individuals are to migrate. It is possible that, with an increasingly educated workforce, we might see more migration in the near future. On the other hand, if the workforce gets older simply because the population is aging, then migration rates might be lower.

Throughout, we have modelled males and females separately. There are some clear differences in males' and females' decisions to migrate, relating to the effects of housing tenure, job status, spouse characteristics, and duration dependence. Future work on modelling migration should analyse household decisions, although these differences suggest that modelling such a decision may well be complex. Couples will, on the basis of these results, face conflicts over the migration decision. Borrowing ideas from the economics of household consumption and labour supply, where the relative bargaining power of the man and woman in the household is important, may prove fruitful.

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Table 1 Individual Migration Rates

	Males	Females
Number Migrations (a) (*m=1,c=1*)	677	722
Number Migrants (b)	511	544
Sample Size Person-Year (c)	39,569	44,366
Sample Size Persons (d)	5,986	6,266
Migration Rate (Person-Year) (a/c)	1.71	1.63
Migration Rate (b/d)	8.54	8.68
Number Completed Spells (e) (*c=1*)	4,603	4,821
Number Censored Spells (f) (*c=0*)	2,359	2,642
Number of Spells (e+f)	6,962	7,463
Left-truncated First Spell (inds)	3,381	3,771
Flow Sample (inds)	3,581	3,692

Table 2 Hazard tomigration, Weibull baseline hazard, Gaussian mixing

	Estimates				Sample %	
	Males		Females		Males	Females
Migration Rate					1.7	1.6
Log(Duration)	-0.112	(0.057)**	-0.210	(0.055)**	10.8^	11.4^
Age 18-19	0.361	(0.298)	-0.008	(0.287)	2.9	2.6
Age 20-23	0.286	(0.282)	-0.136	(0.266)	7.9	7.8
Age 24-29	-0.268	(0.293)	-0.444	(0.270)	15.5	15.9
Age 30-37	-0.436	(0.300)	-0.532	(0.277)*	22.3	22.9
Age 38-49	-0.785	(0.309)**	-0.954	(0.290)**	29.1	29.5
Age 50+	-0.980	(0.341)**	-1.170	(0.321)**	20.5	20.0
Mortgag(e Holder	-0.021	(0.148)	0.109	(0.147)	63.7	60.9
Council Tenant	0.030	(0.183)	-0.300	(0.177)*	14.2	17.2
Private Rent Unfurnished	0.433	(0.207)**	0.340	(0.201)*	3.9	4.0
Private Rent Furnished	0.587	(0.178)**	0.499	(0.183)**	4.2	3.3
Employed (Non Manual)	0.383	(0.110)**	-0.071	(0.122)	48.2	54.4
Unemployed	0.610	(0.149)**	0.130	(0.192)	8.8	24.5
Maternity/Family Care	1.790	(0.230)**	0.523	(0.139)**	1.1	20.8
Higher Degree	1.354	(0.266)**	1.204	(0.260)**	3.0	2.1
Degree	1.090	(0.188)**	0.936	(0.166)**	19.6	16.6
A-Level	0.877	(0.181)**	0.657	(0.166)**	22.8	17.1
GCSE	0.452	(0.176)**	0.282	(0.149)*	33.4	39.5
1 Child	-0.171	(0.124)	-0.315	(0.115)**	19.5	22.4
2 Children	-0.027	(0.147)	-0.206	(0.134)	15.7	17.5
3+ Children	-0.396	(0.235)*	-0.369	(0.200)*	6.0	7.1
Like To Move	0.750	(0.090)**	0.860	(0.088)**	40.8	39.3
Like Area	-0.409	(0.122)**	-0.458	(0.110)**	92.0	90.9
Spouse (Unemployed)	0.200	(0.142)	-0.348	(0.143)**	19.8	15.4
Spouse Employed (Full-Time)	-0.037	(0.119)	-0.379	(0.099)**	31.1	54.6
Spouse Employed (Part-Time)	-0.309	(0.171)*	-0.095	(0.254)	20.9	2.4
Log(Labour Market Tightness)	-0.627	(0.286)**	0.046	(0.279)	0.165^	
Log(Real Wage)	-0.432	(0.481)	-0.278	(0.435)	0.005^	0.004^
Constant	-8.873	(2.867)**	-4.609	(2.694)*		
N (Person-Year)	39,569		44,366			
Log-Likelihood	-2976.702		-3214.327			
ρ	0.418	(0.037)**	0.390	(0.036)**		
$\hat{\sigma}_u$	1.087	(0.082)**	1.026	(0.079)**		

+ See Equations (5) and (8) of main text.
** Sig. at 5%, * Sig. at 10%
^Exponential sample averages
Year dummies, Spouse' age and job status not reported
Base: Manual worker living in London in 1991, has no qualifications, children or spouse, owns their house outright and is aged 16-17 years old
12 quadrature points are used in both regressions.

Figure 1 Types of Spell

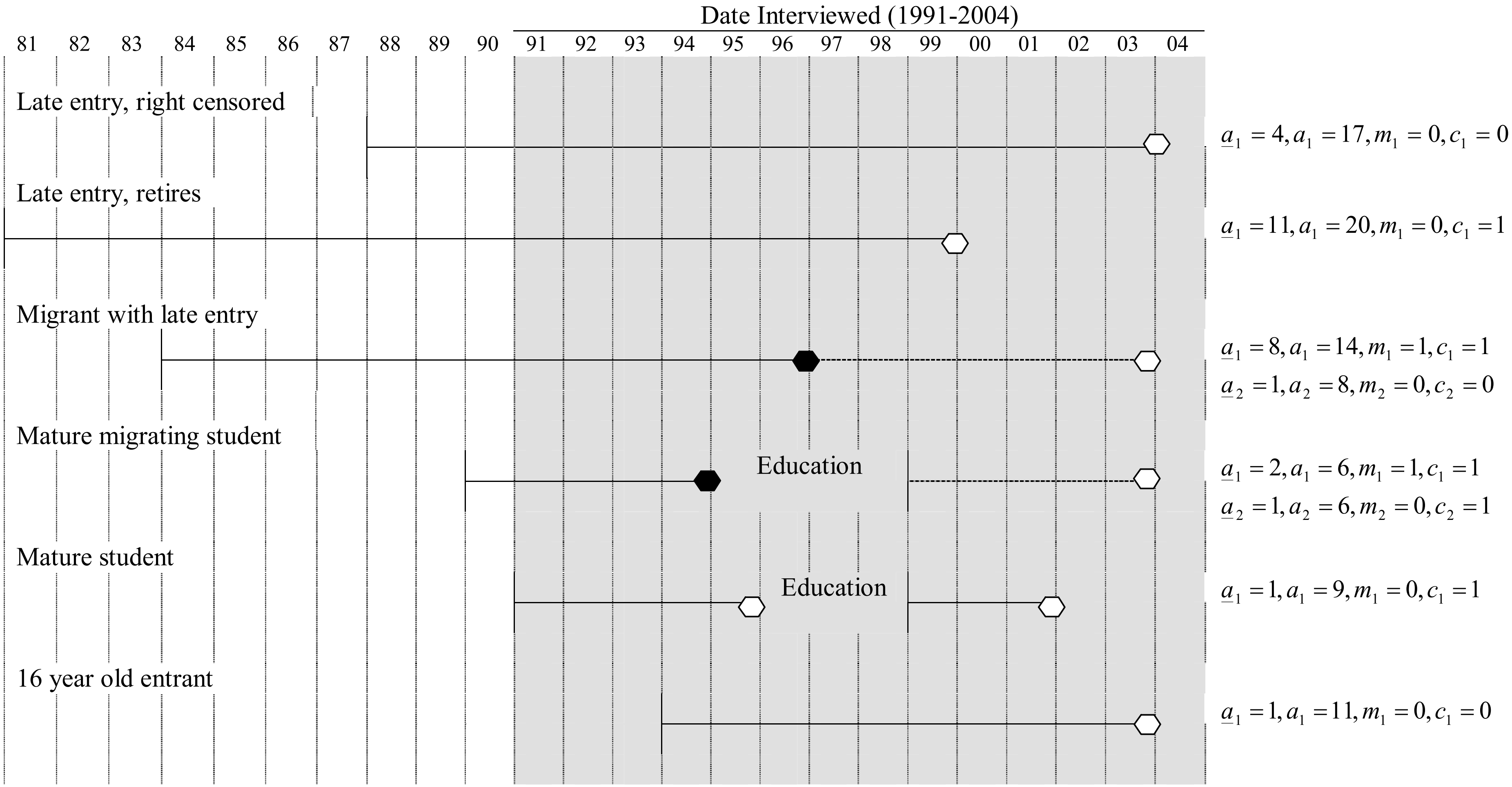


Figure 2 Male Hazards

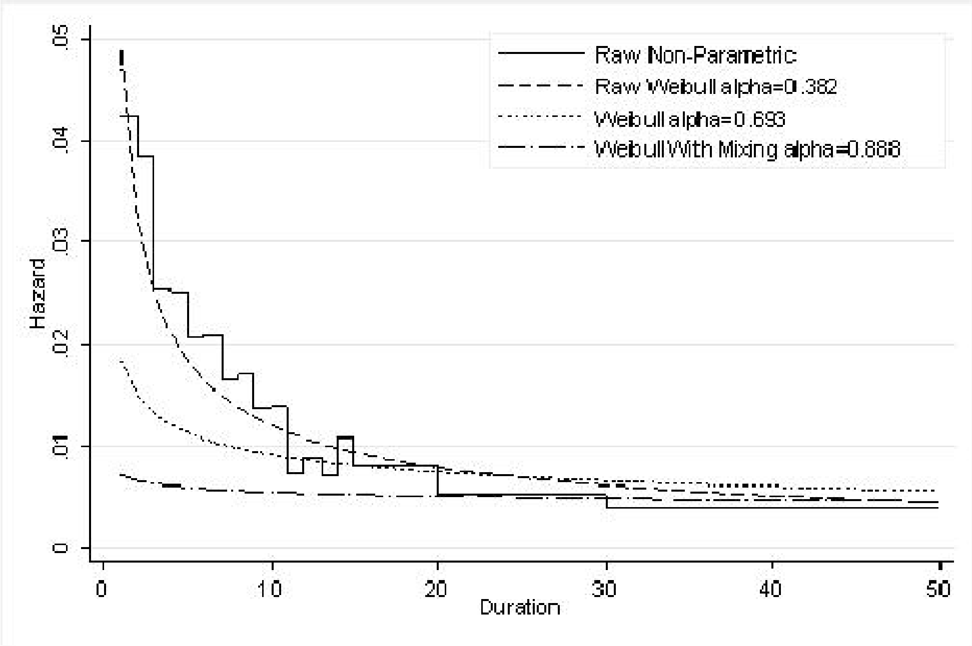


Figure 3 Female Hazards

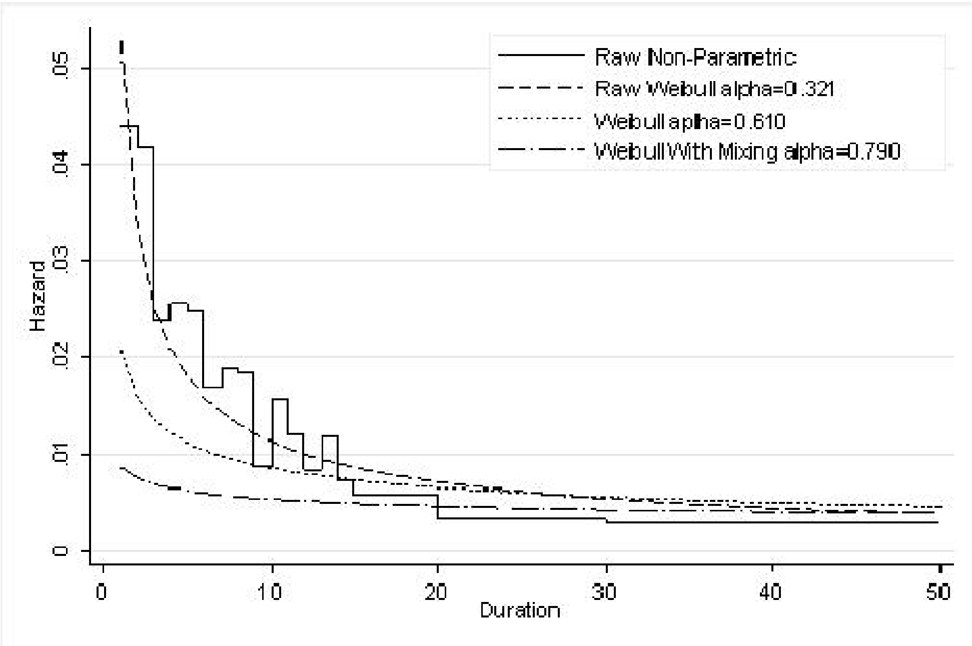
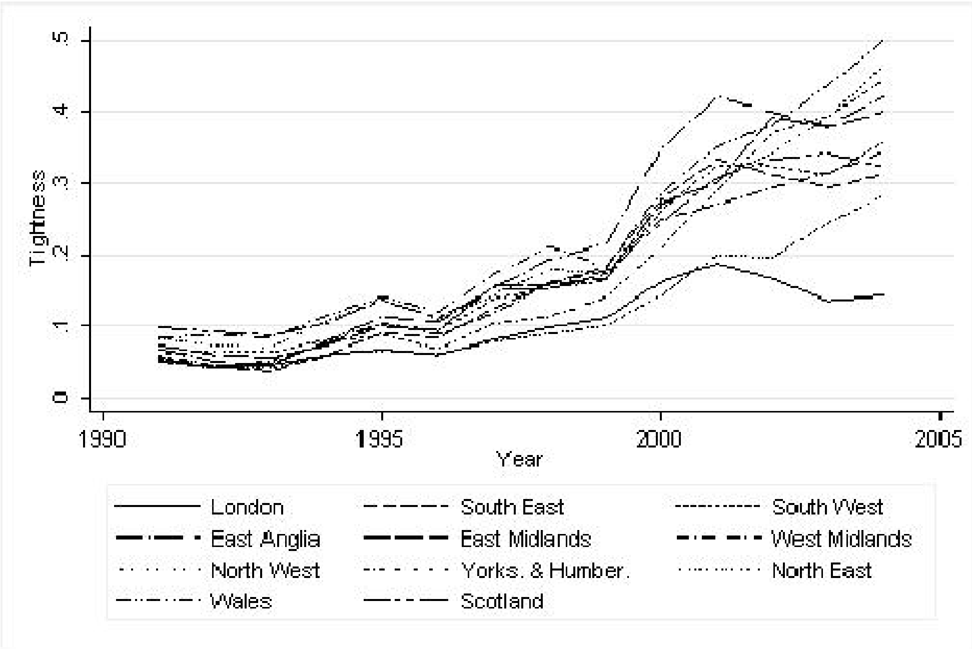
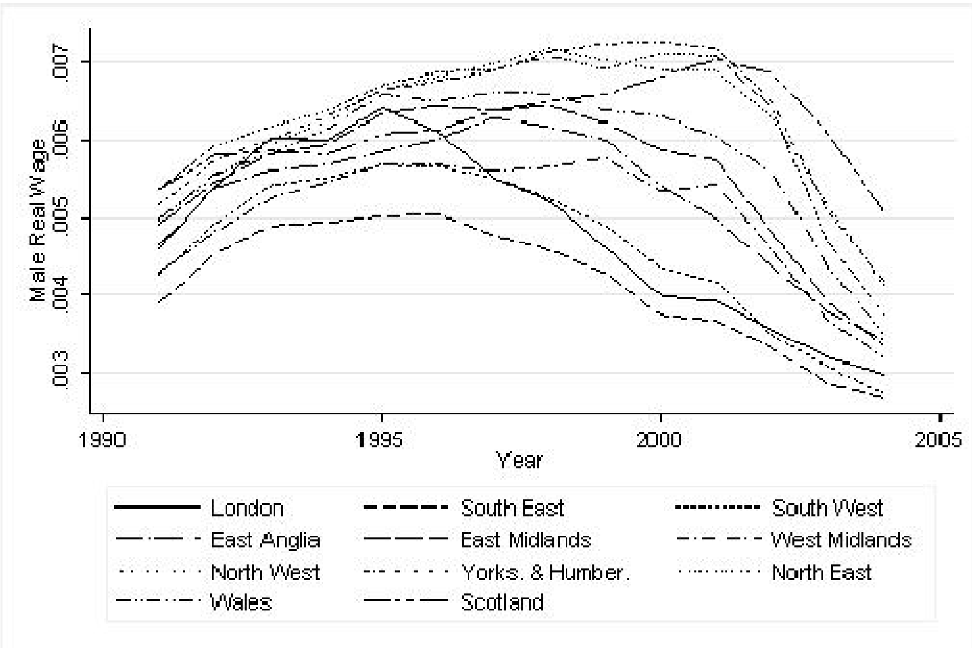


Figure 4 Regional Labour Market Tightness



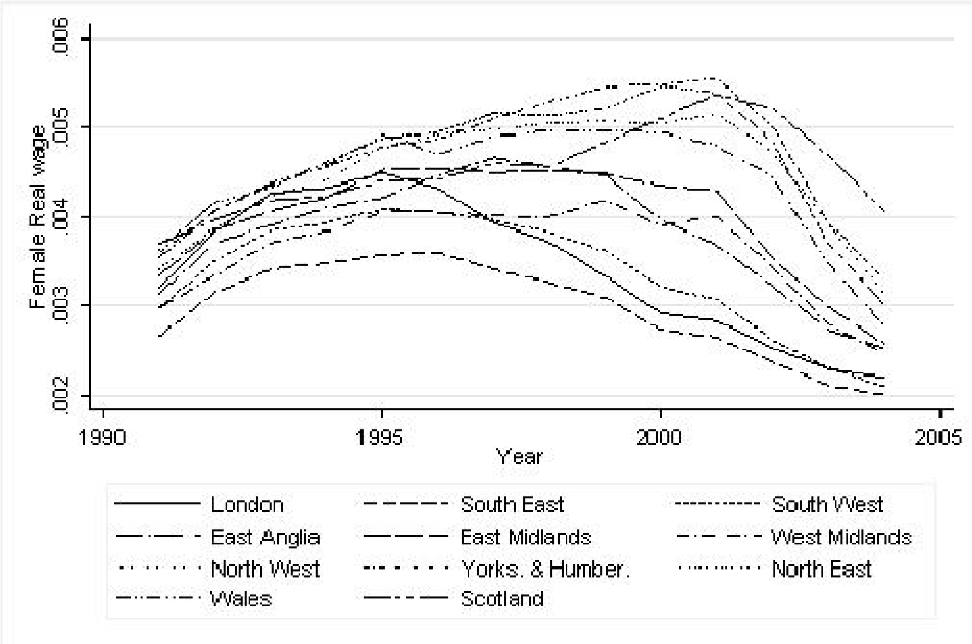
Tightness defined as job-centre plus vacancies divided by claimant-count unemployment rates
Data Source: Nomisweb

Figure 5 Regional Real Wage (Male)



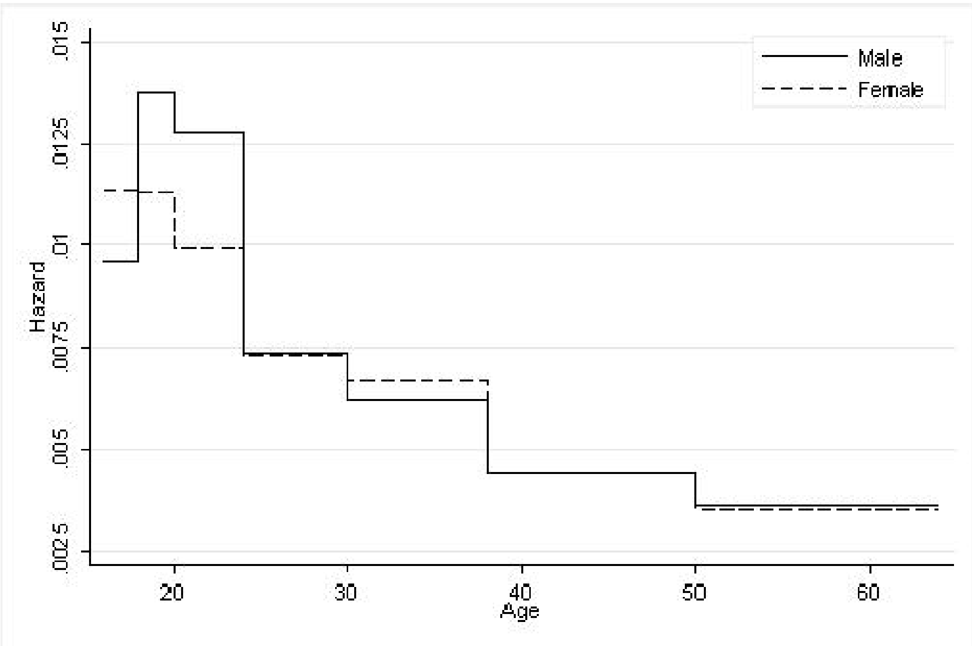
Real Wage defined as average regional wage rates (by manual status) divided by average regional house price
Data Source: New Earnings Survey, Annual Survey of Hours and Earnings, and Halifax Building Society

Figure 6 Regional Real Wage (Female)



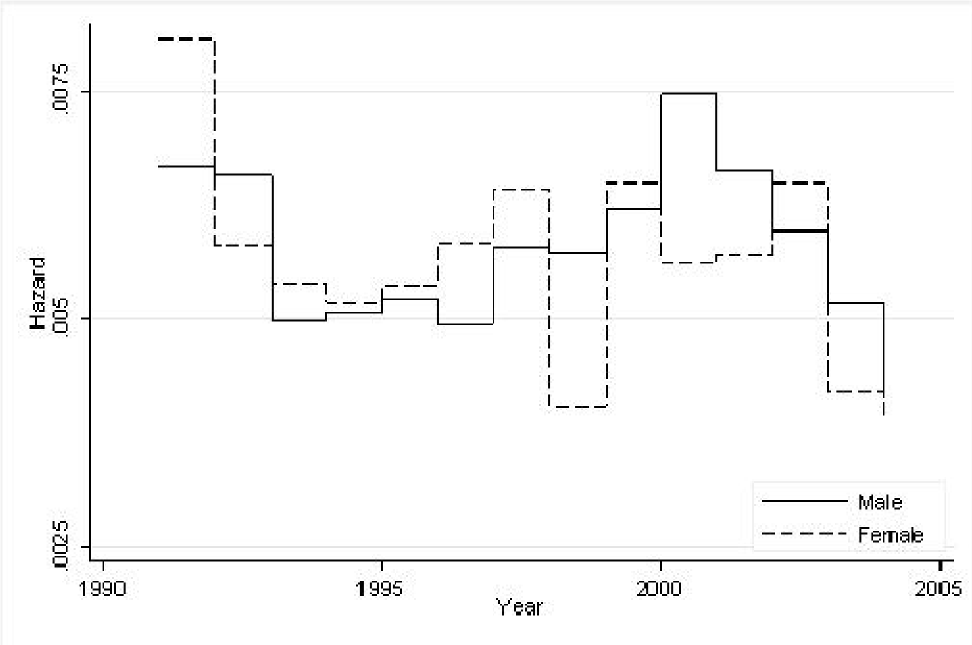
Real Wage defined as average regional wage rates (by manual status) divided by average regional house price
Data Source: New Earnings Survey, Annual Survey of Hours and Earnings, and Halifax Building Society

Figure 7 Weibull Age Hazards



Predicted hazard rates obtained holding all covariates (except age) at their mean values

Figure 8 Weibull Year Hazards (no aggregate variables)



Predicted hazard rates obtained holding all covariates (except year) at their mean values