Successful employer search? An empirical analysis of vacancy duration using micro data

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Abstract

This paper provides the first estimates of the determinants of the duration of employer search in the UK. We model duration until either a vacancy is successfully filled or withdrawn from the market. The econometric techniques deal with multiple vacancies and unobserved heterogeneity (correlated risks), using flexible and parametric baseline hazards. The hazards to filling and withdrawing exhibit negative and positive duration dependence respectively, implying that the conditional probability of successful employer search decreases with duration. We also find that ‘good’ vacancies are less likely to fill, consistent with there being skill shortages in the sample period.

Keywords: vacancy duration, lapsed vacancies, competing risks

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1 Introduction

Search theory is becoming one of the dominant models used to explain both micro and macro labour-market phenomena, especially the dynamics of unemployment — see Mortensen & Pissarides’ recent (1998, 1999) surveys. However, empirical work has concentrated far more on workers’ than on employers’ search behaviour. This is in spite of evidence which suggests that, in many labour markets, workers rarely refuse job offers — see Barron, Black & Loewenstein (1987), Holzer (1988), van den Berg (1990), Barron, Berger & Black (1997a) and Manning (2000). If, in equilibrium, the worker’s acceptance probability is close to unity, it follows that employer search is important in understanding what factors determine transitions between unemployment, employment and non-employment. There is a large microeconometric literature that has estimated the hazard out of unemployment using unemployment duration data, but there is far less evidence for vacancies. Employer search remains an under-researched area.

One particular issue that has received little attention is the fact that employer search is not always successful, resulting in vacancies which are withdrawn from the market without being filled. Genuinely unfilled vacancies may be a result of skill shortages, with associated macroeconomic implications such as potentially lower productivity growth and higher wage growth (Haskel & Martin 1996). To understand the determinants of skill shortages, it is necessary to analyse both those vacancies that tend to have longer durations, and those vacancies that are eventually withdrawn from the labour market.

Although there is some evidence on vacancy characteristics which lead to longer search durations (see Section 2), there is almost no evidence on vacancies which are withdrawn from the market. This may be because economists do not believe that employers post vacancies and then subsequently withdraw them from the market, perhaps because it suggests that employers are ‘irrational’ in their search strategies. But in many ways the process of withdrawing a vacancy is analogous to the process by which job-seekers leave the labour market, a process which has been studied in the literature on labour market transitions (van den Berg 1990).

A second reason may be that there is very little information on the eventual fate of
vacancies. In fact, in the UK, ‘cancelled’ vacancies are common. The proportion of all vacancies notified to the public employment service which are subsequently cancelled is between 20% and 30% over the period of our study (NOMIS 1985–2001). Machin (2003) notes that a substantial proportion of these cancelled vacancies are regarded by employers as ‘no longer existing’.

Are these cancelled vacancies actually withdrawn from the market, or do they merely represent employers filling their vacancies using other search strategies? We provide some evidence that many cancelled vacancies are indeed withdrawn from the market. We do this using a large sample of vacancies notified to a particular labour market in the UK. We estimate both the determinants of vacancy duration and the probability that an employer is ultimately unsuccessful in filling the vacancy (hereafter we refer to such a vacancy as lapsed). We are able to check that vacancies are genuinely withdrawn because we observe all job-seekers in the same market; another check is to estimate the hazard to lapsing, which theory predicts should exhibit a different shape to the hazard to filling.

We use far more detailed vacancy data than has previously been available. The data measure vacancy duration recorded to the nearest day, and provide detailed information on vacancy characteristics. We allow for the simultaneous advertising of groups of identical vacancies. Our econometric methodology allows for unobserved heterogeneity, which might be correlated between the filling and lapsing risks. We also model the underlying hazards non-parametrically and parametrically.

We show that it is ‘good’ vacancies that employers find hard to fill, which we interpret as evidence of skill shortages. We also shed light on employers’ search strategies, given that a substantial number of vacancies fill within the first week. Finally, we provide new evidence that the hazard to filling is downward sloping and that the hazard to lapsing is upward sloping.

The paper is structured as follows. Section 2 briefly covers the relevant literature, and Section 3 provides the theoretical framework. Section 4 describes the data, and Section 5 discusses our econometric methods. Results are presented in Section 6, and Section 7 concludes.
2 Recent literature

There are few microeconometric investigations of the duration of employer search, or vacancy duration, using firm-level data. This is particularly true for the UK where there are only three studies, none of which use duration modelling techniques (Beaumont 1978, Roper 1988, Adams, Grieg & McQuaid 2002). Van Ours & Ridder (1991, 1992, 1993) analyse Dutch data using duration techniques. Their findings suggest that the vacancy hazard displays positive duration dependence, even after allowance is made for the effect of unobserved heterogeneity: employers become less choosy as vacancy duration increases. Van Ours & Ridder (1993) have suggested that vacancy durations are mainly periods of selection rather than search, thereby casting doubt on the conventional sequential search model. Weber (2000) offers further supporting evidence in favour of the non-sequential search model. Gorter & van Ommeren (1999) and Gorter, Nijkamp & Rietveld (1996) show that vacancies that are advertised exhibit positive duration dependence, whereas those that use informal contacts exhibit negative duration dependence. Finally, Burdett & Cunningham (1998) estimate a non-monotonic vacancy hazard which increases rapidly in the first week, and falls slowly thereafter. Burdett & Cunningham argue that the majority of firms in their sample could not have used non-sequential search because so many vacancies fill in a very short space of time.

Thus it would appear that the shape of the baseline hazard depends on the search technology adopted by the employer. Those studies which find positive duration dependence tend to be those that analyse advertised vacancies, where employers tend to adopt a search period followed by a selection period. On the other hand, studies whose data comprise informal search methods or data from public exchanges tend to exhibit negative duration dependence, where the applicant arrival tends to be initially high but falls thereafter.

Of the factors that affect vacancy duration, the most important are the relationships with the total stock of vacancies and the total stock of job-seekers in the market. Increasing the vacancy stock increases search duration (the so-called ‘congestion effect’), while increasing the stock of job-seekers reduces search duration. Both are predicted by standard models of search. More stringent entry requirements with respect to age, education and
work experience increase vacancy duration (Gorter & van Ommeren 1999, Behrenz 2002). Similar US evidence is provided by Barron, Bishop & Dunkelberg (1985). Barron et al. (1997a, 1997b) and Burdett & Cunningham (1998) also show that vacancy duration is increased where the training period is longer. Most studies find that the wage does not have a significant effect on vacancy duration, an exception being Adams et al. (2002) who find a positive and significant effect.

Vacancies with long durations are, almost by definition, ‘hard-to-fill’. However, a literature also exists which analyses the determinants of hard-to-fill vacancies as reported in employer surveys. This literature shows that reports of hard-to-fill vacancies are negatively related to hourly wages, union recognition, the share of part-time vacancies in the firm, the amount of training offered, unsocial hours, the use of word processors and the local unemployment rate, and positively related to firm size and employment growth (Mason & Stevens 2003, Haskel & Martin 2001, Green, Machin & Wilkinson 1998, Campbell & Baldwin 1995, Bosworth 1993). The existence of hard-to-fill vacancies has often been interpreted as an indication of skill shortages. However, this view has been questioned. Green et al. (1998) and Haskel & Martin (2001) show that there is only a partial overlap between firms reporting a skill shortage and simultaneously reporting a hard-to-fill vacancy.

Evidence on the existence of lapsed vacancies is as follows. Van Ours & Ridder (1992) find that 4% vacancies are cancelled according to employers (“because the need for the new employee disappears …[or] because of the changing economic performance or re-organisation of the firm …[or] these vacancies were hard to fill and lasted too long.”) However, the authors ignore them because they are a small percentage. Barron et al. (1985) also use employer survey data and find that 28% of employers did not recruit for the position. They could not analyse these ‘lapsed’ vacancies because of the design of the survey. This is the same data used by Burdett & Cunningham (1998), who also ignore lapsed vacancies. There is therefore some evidence that lapsing is a widespread phenomenon, albeit one which has not been formally analysed.
3 A theoretical framework

The canonical model is one of sequential search, and this has been applied to employers as well as job-seekers: see Lipmann & McCall (1976, pp.181–185) for an early description of the basic employer-search model. Burdett & Cunningham (1998) is a more recent example. However, some empirical work has suggested that employers use a non-sequential search strategy whereby a period of search is used to accumulate a number of applicants, at least one of whom is subsequently selected. Therefore, although the arrival rate of applicants is initially high because the vacancy has been advertised or posted with an employment agency, the hazard rate is initially low (possibly zero) during the search period.

A high applicant arrival rate is also consistent with so-called ‘stock-flow’ theories of matching as proposed by Coles & Smith (1998) and tested by Coles & Petrungolo (2003). Stock-flow matching suggests that, if there is some kind of ‘marketplace’ in which search frictions are low, a new vacancy to the market will have an initially high applicant arrival rate because potential matches come from the entire stock of job-seekers. Clearly, these two explanations are closely related since an advert or an employment agency serves as a marketplace. However, the non-sequential model suggests that although the applicant arrival rate will be initially high, the hazard should be low because firms wait for a pool of applicants to arrive. In contrast the stock-flow theory allows for firms to accept applicants immediately.

Is the sequential or non-sequential model consistent with the data? Figure 1 plots the raw hazard to filling for the vacancies in our sample (described more fully in Section 6). It is clear that many applicants arrive and are accepted almost immediately: the hazard is actually highest on day 1, although there are also subsequent peaks at weekly intervals.

[FIGURE 1 HERE]

This is consistent with the finding of Burdett & Cunningham (1998), who suggest that the majority of firms in their sample cannot have used non-sequential search. In what follows we therefore use a sequential search model. This does not rule out, however, the
possibility that applicants arrive initially very quickly but then at a greatly reduced rate because of stock-flow matching considerations.

Define $V_m$ to be the discounted revenue stream of a firm which successfully fills a vacancy, and $V_n$ to be the revenue stream of the firm which has a vacancy to fill and which is searching for a suitable applicant. A standard expression (e.g. Cahuc & Zylberberg 2004) for the discounted flow of revenue per period is

$$rV_m = z_m + q(V_n - V_m),$$

where $r$ is the discount rate, $z_m$ is the revenue over and above the wage paid and $q$ is the per-period probability of the match separating. Over any short time period $dt$ a match yields a flow of revenue $z_m$ plus the expected cost deriving from the break-up of a match $V_n - V_m$.

The standard result in these models is the adoption of a stopping rule. If an applicant arrives, the optimal strategy is to accept if $V_m > V_n$. If no applicant arrives, the firm continues to search. The reservation productivity level, $z^*$, is that productivity level which leaves a firm indifferent between accepting and rejecting the applicant i.e. where $V_m(z^*) = V_n$.

The discounted revenue stream for a firm with a vacancy is

$$rV_n = (z_n - c) + \frac{\lambda}{r + q} \int_{z_m}^{\infty} (z_m - z^*)dF(z_m),$$

where $z_n$ is the revenue from producing with a vacancy. In general $z_n > 0$ because the firm can produce with a vacancy, albeit at a lower level of profit. $z_n$ is analogous to income received by a job-seeker which is not dependent on search, such as a means-tested benefit. $c$ is the per-period cost to the employer of keeping the vacancy open. This includes advertising and screening costs. $\lambda$ is the arrival rate of applicants to the employer. The remaining term is the standard surplus function, decreasing in $z^*$.

Finally, consider the discounted revenue stream from producing with an unfilled vacancy but not searching. The simplest assumption would be that the revenue flow for a firm which chooses not to search, denoted $V_l$, is just

$$rV_l = z_n.$$
In other words, the firm’s revenue is $z_n$ whether or not it chooses to search. If $V_l > V_n$ then the firm chooses not to search. Equivalently, if $z_n > z^*$ then it is more profitable to carry on producing with an unfilled vacancy than it is to search.

In a stationary model we would not observe a firm choosing to search and then changing its behaviour (i.e. lapsing a vacancy). However, in general, we would expect some of those parameters which affect $z^*$ (such as $\lambda$ and those that characterise $f(z_m)$) to change with elapsed duration. If they cause $z^*$ to fall, at some point the firm may choose to stop searching because $z^* < z_n$. Comparing (2) with (3) we can see that $V_n$ will fall below $V_l$ if the value of the surplus function falls below the cost of search, $c$.

The most likely explanation for this is that the arrival rate of applicants falls with elapsed duration. Theories of stock-flow matching suggest that this is the case. Employers who advertise a new vacancy initially receive a high rate of applicants because the potential pool of applicants comprises all those job-seekers currently in the market. If none of these initial applicants are acceptable, the applicant arrival rate falls. At this point the costs of keeping the vacancy open may outweigh the discounted benefits of continuing to search.

A second reason why $V_n$ might fall below $V_l$ is that the productivity distribution of applicants falls with elapsed duration. If $f(z_m)$ shifts to the left the surplus function falls and the benefit of search reduces. This seems particularly plausible in a market with a ‘recruitment cycle’ where there is a substantial inflow of potential applicants at particular times of the year. As time passes the better applicants leave the pool, shifting the distribution of remaining applicants to the left. In this case the firm may decide to re-advertise the vacancy at a later date.

We are now able to define the hazard rates for both filling and lapsing a vacancy, and to make some predictions about their shape. The probability that an employer will find an applicant acceptable is

$$
\mu = 1 - F(z^*) = \mu(c, \lambda, z_m, \sigma_{z_m}, \mu_c > 0, \mu_\lambda < 0, \mu_z > 0, \mu_\sigma \leq 0).
$$

The comparative statics are standard (e.g. Mortensen 1986). Employers become less selective (in that $\mu$ increases) as search costs increase, as the arrival rate of applicants decreases, as the wage decreases, or as the revenue flow increases. An increase in the
variance of \( f(z_m) \), denoted \( \sigma_{zm} \), has an ambiguous effect on \( \mu \) in theory, although a commonsense prediction is that employers will wait longer for a ‘bargain’. An increase in \( \sigma_{zm} \) increases the number of bargains and so \( \mu_\sigma < 0 \).

The hazard for a vacancy which fills, denoted \( h_1 \), is the product of the applicant arrival rate and the probability of acceptance. Therefore

\[
h_1 = \lambda \cdot \mu(c, \lambda, z_m, \sigma_{zm}). \tag{5}
\]

The arrival rate of applicants therefore has two influences on the vacancy hazard. There is the direct positive effect, but also an indirect negative effect. A fall in \( \lambda \) causes employers to become less selective, lowering \( z^* \) so that \( \mu \) goes up.

The hazard for a vacancy which is lapsed is denoted \( h_2 \) and depends on the same variables:

\[
h_2 = h_2(c, \lambda, z_m, \sigma_{zm}).
\]

Here the effect of the arrival rate of applicants on \( h_2 \) is unambiguous. As the applicant arrival rate or the quality of those applicants falls, the benefit of search must fall from (2), and so it becomes more likely that employers will lapse vacancies. Therefore, if \( \lambda \) falls with duration, the hazard to lapping increases.

It is useful to define the conditional (on exit) probability of lapsing a vacancy at any given duration, which is given by

\[
P = \frac{h_2}{h_1 + h_2}. \tag{6}
\]

Given that \( h_2 \) exhibits positive duration dependence, whether \( P \) increases with duration depends on whether \( h_1 \) exhibits positive or negative duration dependence—recall that Equation (5) suggests either. Empirically, it does not make sense that a vacancy, conditional on exit, is more likely to fill than lapse the longer is its duration. If \( h_1 \) is actually decreasing, then \( P \) will definitely increase with vacancy duration. However, if \( h_1 \) is increasing with duration (the indirect effect of \( \lambda \) dominates), \( P \) will still increase with duration if the positive duration dependence of \( h_2 \) dominates.

It is therefore important to identify which types of vacancy are more likely to lapse. The argument that there are skill shortages suggests that ‘better’ jobs have very low applicant
arrival rates, shifting the hazard to filling downwards and unambiguously increasing the conditional probability of lapsing.

4 Data and institutional background

The data we use are the computerised records of the Lancashire Careers Service over the period 1985–1992. During this period, the Careers Service fulfilled a similar role for the youth labour market as Employment Offices and Job Centres currently provide for adults. Its main responsibilities are to provide vocational guidance for youths and to act as an employment service to employers and youths. The latter includes a free pre-selection service for employers. Use of the Careers Service is voluntary for employers with vacancies.

The Careers Service holds records on all youths aged between 15 and 18, including those who are seeking employment. We observe every vacancy notified by employers to the Careers Service between March 1985 and June 1992. Vacancies in the data require both high- and low-quality job-seekers, and are representative of all entry-level jobs in the youth labour market. Although our data only cover one method of search by employers, it is an important method. 19% of all jobs for those aged 16–18 are filled by the Careers Service. In addition, a further 18% of jobs follow directly on from the Youth Training Scheme. The Careers Service is therefore involved, directly or indirectly, in 37% of job placements for young people in Lancashire.

Employers notify the Careers Service of the type of vacancy, including detailed information about the occupation, the wage, a closing date for applications and selection criteria. Job-seekers are then selected for interview and a contact is made. Either a match occurs or the pair each continue their search. A vacancy has one of two possible outcomes. Either the employer successfully fills the vacancy with applicants submitted by the Careers Service, or the use of this search method is abandoned before the vacancy is filled. In this case the vacancy is described as lapsed.

We argue that vacancies which lapse are genuinely unfilled. For this to be true, we need to be sure that vacancies which lapse are not subsequently filled by some other method of search. We check this by searching the career histories of all school-leavers between 1988
and 1992. We find that only a tiny proportion (about 1%) of lapsed vacancies previously notified to the Careers Service are filled by school-leavers using other search methods. This still leaves the possibility that these lapsed vacancies were filled by older job-seekers. This is extremely unlikely for three reasons. First, it is implausible to imagine that lots of older job-seekers are matching with these vacancies via some other search method, while none (less than 1%) of the 15–18 year olds do so (recall that we observe the population of 15–18 year-olds). Second, these vacancies are almost all specifically aimed at those who have recently entered the labour market. They offer low wages and many have some element of basic training. Third, a high proportion (40%) of lapsed vacancies subsequently re-appear at a later date and search among the same group of job-seekers again. It is unlikely that employers would switch from the youth labour market to the adult labour market and back again. More likely, they search the youth labour market, lapse the vacancy when they are unsuccessful and then wait until the next group of young people leave school before re-entering the marketplace. Nonetheless, because we do not observe older job-seekers in our data, we cannot rule out the possibility that these lapsed vacancies are actually filled by an older worker.

One further feature of these data is that employers may advertise several vacancies simultaneously. For example, a firm may want to hire 10 identical apprentice welders at the same time. These vacancies are called multiple vacancy orders. In principle, it is vacancies within an order that are the unit of observation, not the order itself. Unfortunately, the duration of individual vacancies within an order is not recorded, and needs to be inferred from the total duration of the whole vacancy order.

5 Econometric methods

The appropriate econometric framework is a mixed proportional hazards model with multiple destinations for discrete data. These are often referred to as competing risks models. The key assumption is the proportional hazards one; see van den Berg (2000, Section 8.2.1) for a comprehensive discussion of the assumptions needed for identification in such models. In particular, there is identification if there are two continuous covariates which
affect both the filling and lapsing hazards, with different parameters.

Most vacancies exit to one of \( R = 2 \) states, filled (denoted \( r = 1 \)), or lapsed (\( r = 2 \)), and a small number are censored (\( r = 0 \)). The two resulting sub-samples of data are \( \mathcal{E}_1 \), the set of filled vacancies, and \( \mathcal{E}_2 \), the set of lapsed vacancies. \( C \) denotes the set of censored vacancies. Each vacancy, subscripted \( i \), belongs to one and only one set. The random variables \( T_1, T_2, \) and \( T_0 \) represent the time it takes a vacancy to be filled, lapsed, or censored respectively. There are two heterogeneity terms \( v_1 \) and \( v_2 \), with joint density \( g(v) \), where \( v \equiv (v_1, v_2) \). Conditional on these heterogeneity terms, the corresponding survivor functions for filling and lapsing are \( S_1(t|v_1) \) and \( S_2(t|v_2) \) respectively; these denote the probability of survival to \( t \), given departure to destination \( r \).

Data are observed in unit intervals (days): \([0, 1), [1, 2), \ldots\). For each vacancy \( i \) a duration \( t_i^* \) is recorded if it is observed either filling, lapsing or censoring in the interval \([t − 1, t)\), where \( t_i^* = t.1(t − 1 ≤ \min(T_1, T_2, T_0) < t) \), and 1(.) denotes the indicator function. The observed destinations of vacancy \( i \) are recorded by three dummy variables, indicating filling \((c_1)\), lapsing \((c_2)\), and censoring \((c_0)\).

We assume that, conditional on \( v \), the three underlying stochastic processes describing time to filling, lapsing and censoring are mutually independent. Following Lancaster (1990), the likelihood for vacancy \( i \) is:

\[
L_i = \int_{-\infty}^{\infty} \left[ S_1(t_i − 1|v_{1i}) − S_1(t_i|v_{1i}) \right]^{c_1} \left[ S_1(t_i|v_{1i}) \right]^{1−c_1} \\
\times \left[ S_2(t_i − 1|v_{2i}) − S_2(t_i|v_{2i}) \right]^{c_2} \left[ S_2(t_i|v_{2i}) \right]^{1−c_2} dG(v_{1i}, v_{2i}).
\] (7)

The likelihood can be partitioned into two terms if it is assumed that \( v_{1i}, v_{2i} \) are independent. This assumption is potentially restrictive, but is necessary when dealing with the complexity of multiple vacancy orders (discussed later in this section). In the first instance, we focus on single vacancies where the risks are assumed correlated through the heterogeneity terms \( v_{1i}, v_{2i} \).
5.1 Single orders, correlated risks

The standard way to estimate discrete-time duration models is to form a panel of vacancies with the $i$-th vacancy contributing $j = 1, 2, \ldots, t_i$ observations. This is the ‘sequential binary response’ form (Prentice & Gloeckler 1978, Han & Hausman 1990, Stewart 1996, Wooldridge 2002). To do this, one defines a discrete hazard. This is, conditional on $v$, the probability of exiting to destination $r$ in the interval $[t - 1, t)$, given that an exit to destination $r$ has not already occurred:

$$h_{rt}(v_r) = \Pr(t - 1 \leq T_r < t, T_s > t | T_r \geq t - 1, v), \quad s \neq r.$$  

The proportional hazards assumption is parameterised as

$$h_{rt}(x'_i, v_{ri}) = \bar{h}_{rt}v_{ri}\exp(x'_i\beta_r) \quad (8)$$

$$= \bar{h}_{rt}\exp(x'_i\beta_r + u_{ri}), \quad (9)$$

where $u \equiv \log v, (u_1, u_2)$ has joint density $F(u_1, u_2)$, $x'_i$ is a vector of observable covariates and $\bar{h}_{rt}$ are the two baseline hazards.

After a lot of algebra, (see Wooldridge (2002), for example), it turns out that the likelihood for vacancy $i$ in this mixed proportional hazards model is

$$L_i(\beta_1, \beta_2, \gamma_1, \gamma_2, \ldots) =$$

$$\int_{-\infty}^{\infty} \prod_{j=1}^{t_i} h_1ij(\cdot)^{y_{1ij}[1 - h_1ij(\cdot)]^{1-y_{1ij}}h_2ij(\cdot)^{y_{2ij}[1 - h_2ij(\cdot)]^{1-y_{2ij}}} dF(u_{1i}, u_{2i}). \quad (10)$$

where

$$h_{rij}(\cdot) = 1 - \exp[-\exp(x'_i\beta_r + \gamma_{rij} + u_{ri})]. \quad (10')$$

The dummy variable $y_{rij}$ indicates whether vacancy $i$ exits to destination $r$ in the interval $[t - 1, t)$, and is zero otherwise. In other words, for both exit states we have a sequence of observations $y_{rij}, j = 1, \ldots, t_i$, all of which are zero except the last. If the vacancy is filled the last observation $y_{1ij}$ is recorded as unity, if it is lapsed $y_{2ij} = 1$, and if the vacancy is censored, both $y_{1ij} = y_{2ij} = 0$. These indicator variables play the same role as $c_{0i}, c_{1i}$ and $c_{2i}$ above. The proportional hazards assumption means that the covariates affect the
hazard via the complementary log-log link. Were \( v_{1i}, v_{2i} \) uncorrelated, filling and lapsing could be modelled separately, and we would have a discrete choice random effects model, with a complementary log-log link rather than the more common logit or probit links.\(^3\)

The parameters to be estimated are \( \beta_1, \beta_2, \gamma_{1j} \) and \( \gamma_{2j} \), where the \( \gamma_{rj} \) are collected into the vectors \( \gamma_1 \) and \( \gamma_2 \). The \( \gamma_{rj} \)s are interpreted as the log of a non-parametric piecewise linear baseline hazard, as \( \gamma_{rj} \approx \log \bar{h}_{rj} \) when \( x_i' \beta_r = 0 \). Because there are a large number of vacancies in the data, a flexible non-parametric approach is feasible. A possible restriction on the shape of the baseline hazard is provided by the Weibull hazard, \( \bar{h}_{rt} = \gamma_r \alpha_r t^{\alpha_r - 1} \).

In this case, the \( \gamma_j \) in (10') are replaced by \( \log \alpha_r \gamma_r + (\alpha_r - 1) \log j \), greatly reducing the number of parameters to be estimated.

In this paper, we adopt three approaches for modelling the bivariate unobserved heterogeneity. These are: (i) \textit{Gamma mixing}, (ii) \textit{Gaussian mixing}, and (iii) \textit{Discrete mixing}.

The standard argument for not using either of the two parametric densities is the lack of justification for either choice, and, as advocated by Heckman & Singer (1984), the use of discrete mixing should affect the baseline hazard less severely than if the wrong choice of parametric mixing is made. Abbring & van den Berg (2005) have recently shown that in many models the distribution of heterogeneity among survivors converges to a Gamma distribution. This provides some justification for our use of the Gamma distribution when modelling multiple vacancy orders, although, in fact, our choices are mainly pragmatic.

For single vacancies, we use Gaussian and discrete mixing. For bivariate Gaussian mixing, \( u_{1i} \) and \( u_{2i} \), which have variances \( \sigma_1^2, \sigma_2^2 \) and correlation \( \rho \), are reparameterised to uncorrelated standard Normal variates \( \epsilon_{1i} \) and \( \epsilon_{2i} \), which are then approximated by bivariate Gauss-Hermite quadrature. That is, \( \epsilon_{1i} \) takes on \( Q \) known discrete values \( \epsilon_{1ik}, k = 1, \ldots, Q \) and similarly \( \epsilon_{2il} \) takes on \( Q \) discrete values \( \epsilon_{2il}, l = 1, \ldots, Q \), thereby generating a \( Q^2 \) grid of values for an uncorrelated standard Normal distribution. The joint density for each point on the grid is also known, and are represented by Quadrature weights \( \omega_k \) and \( \omega_l \), and so the integral in Equation (10) is approximated by summation. Thus the likelihood
for each observation is written:

\[
L_i(\beta_1, \beta_2, \gamma_1, \gamma_2, \sigma_1, \sigma_2, \rho) = \\
\sum_{k=1}^{Q} \sum_{l=1}^{Q} \left[ \prod_{j=1}^{t_i} h_{1ij}(.)^{y_{1ij}} [1 - h_{1ij}(.)]^{1 - y_{1ij}} h_{2ij}(.)^{y_{2ij}} [1 - h_{2ij}(.)]^{1 - y_{2ij}} \right] \omega_k \omega_l,
\]

where

\[
h_{1ij}(.) = 1 - \exp[-\exp(x_i' \beta_1 + \gamma_{1j} + \sigma_1 \epsilon_{1ik})]
\]

\[
h_{2ij}(.) = 1 - \exp[-\exp(x_i' \beta_2 + \gamma_{2j} + \rho \sigma_2 \epsilon_{1ik} + \sqrt{1 - \rho^2 \sigma_2^2 \epsilon_{2il}})]
\]

The value of \( Q \) is determined by the investigator.

For bivariate discrete mixing, \( u_{1i}, u_{2i} \) and associated joint density \( f(u_{1i}, u_{2i}) \) in (10) are replaced by a bivariate discrete mass point approximation \((\bar{u}_{1m}, \bar{u}_{2m}, \pi_m), m = 1, \ldots, M^4\) Three obvious constraints are imposed on these \( 3M \) parameters to be estimated:

\[
\sum_{m=1}^{M} \bar{u}_{1m} \pi_m = 0, \quad \sum_{m=1}^{M} \bar{u}_{2m} \pi_m = 0, \quad \sum_{m=1}^{M} \pi_m = 1.
\]

Unlike Gaussian quadrature, \( \sigma_1^2, \sigma_2^2 \) and \( \rho \) are computed afterwards, rather than being parameters to be estimated. Collecting \((\bar{u}_{1m}, \bar{u}_{2m}, \pi_m), m = 1, \ldots, \pi_M\), into vectors \( \bar{u}_1, \bar{u}_2, \pi \), the likelihood is written:

\[
L_i(\beta_1, \beta_2, \gamma_1, \gamma_2, \bar{u}_1, \bar{u}_2, \pi) = \\
\sum_{m=1}^{M} \pi_m \left[ \prod_{j=1}^{t_i} h_{1ij}(.)^{y_{1ij}} [1 - h_{1ij}(.)]^{1 - y_{1ij}} h_{2ij}(.)^{y_{2ij}} [1 - h_{2ij}(.)]^{1 - y_{2ij}} \right],
\]

where

\[
h_{rij}(.) = 1 - \exp[-\exp(x_i' \beta_r + \gamma_{rj} + \bar{u}_{ri(m)})].
\]

The number of mass points \( M \) is determined by experimentation; it is usually obvious when to stop adding mass points as the new mass point might have a very low \( \pi \), or an existing mass point is just split into two, with little improvement in the likelihood. Inference is conducted conditional on \( M \).
5.2 Multiple orders, uncorrelated risks

As noted in Section 4, in practice many vacancies are grouped together in orders. Each order contains $V_i$ vacancies, where the orders are numbered $i = 1, \ldots, N$. Within an order, any number of individual vacancies may be filled before all the remaining vacancies are lapsed. If the duration of every filled vacancy within an order were recorded, then the fact that vacancies are grouped into orders would be of no consequence. Unfortunately, this is not the case. If all vacancies are filled before the order is lapsed, we only observe the duration of the vacancy filled last. Further, if any vacancies within an order remain unfilled when the order is lapsed, we only observe the time of laping. For each order we know how many vacancies are filled, denoted $W_i$. We need to infer the parameters describing the distribution of a single vacancy.

Four types of order are possible: (i) all are filled before any are lapsed or censored ($W_i = V_i$); (ii) all are lapsed before any are filled or censored ($W_i = 0$); (iii) all are censored before any are filled or lapsed; and (iv) $W_i$ are filled and $V_i - W_i$ are lapsed before any are censored. The likelihood for the whole sample is (each product corresponding to (i)–(iv)):

$$L = \prod_{i \in \{W_i = V_i\}} V_i^{V_i - 1}[S_1(t_i|V_i) - S_1(t_i - 1|V_i)][S_2(t_i|V_i) - S_2(t_i - 1|V_i)]V_i \times \prod_{i \in \{W_i = 0\}} [S_2(t_i - 1|V_i) - S_2(t_i - 1|V_i)]^{V_i}S_1(t_i|V_i)^{V_i} \times \prod_{i \in \{C_i = 1\}} S_1(t_i|V_i)^{V_i}S_2(t_i|V_i)^{V_i} \times \prod_{i \in \{0 < W_i < V_i\}} [S_2(t_i|V_i) - S_2(t_i|V_i)]^{V_i}S_1(t_i|V_i)^{V_i - W_i}[1 - S_1(t_i|V_i)]^{W_i}. \quad (13)$$

(See the Appendix.) This generalises Equation (7) above, seen by setting $V_i = 1$. The important difference between this likelihood and the one for single vacancies is that the data cannot be organised into sequential binary response form. Thus the survivor functions $S_1$ and $S_2$ need deriving from the hazard function given in (8):

$$S_r(t_i|v_{ri}) = \exp[-v_{ri}\exp(x_i\beta_r + \delta_r)], \quad (14)$$
where $\delta_{rj}$ is the integrated baseline hazard over the interval $[t-1,t)$. To recover the $\gamma_{rj}$ from the $\delta_{rj}$, use

$$\gamma_{rj} = \log[\exp(\delta_{rj}) - \exp(\delta_{rj-1})].$$

(See Stewart 1996). To examine whether the discrete-time Weibull $\tilde{h}_{rt} = \gamma_r \alpha_r t^{\alpha_r - 1}$ is an appropriate special case, then

$$S_r(t_i|v_{ri}) = \exp[-v_{ri} \exp(x'_i \beta_r + \log \gamma_r + \alpha_r \log t_i)]$$

replaces (14) above.

Integrating out the bivariate unobserved heterogeneity is much more difficult than in the single-order case. Because the data cannot be organised into sequential binary response form, Gaussian or discrete mixing is not feasible. Gamma mixing is often used because closed-form solutions can be obtained, but this also proved intractable. Thus we are left with uncorrelated Gamma mixing. This is feasible, because the likelihood given in Equation (13) can be factored into filling terms (subscripted ‘1’) and lapsing terms (subscripted ‘2’) and so $v_1$ can be integrated out independently of lapsing terms, and vice versa.

In other words, integrating out $v_{ir}$ from

$$S(t_i|v_{ri}) = \int_0^\infty \exp[-v_{ri} \exp(x'_i \beta_r + \delta_{rj})]dF(v_{ri}).$$

gives

$$S(t_i) = [1 + \sigma^2_r \exp(x'_i \beta_r + \delta_{rj})]^{-1/\sigma^2_r}.$$

See Meyer (1990). This is substituted into a version of Equation (13), but where the conditioning on $v_1$ and $v_2$ has been removed; this gives the likelihood for a model for multiple vacancy orders, but with uncorrelated risks.

### 5.3 Interpreting the parameters

Although we estimate a separate vector of coefficients $\beta_r$, $r = 1,2$ for filled and lapsed, each vector conveys no information about the effect of a single covariate $x$ on either the likelihood of exit via risk $r$ ($\Pi_r$), or the expected waiting time until exit via risk $r$ ($E_r$)
This is because $\Pi_r$ (and therefore $E_r$) depend on both $h_{1j}$ and $h_{2j}$ via the overall survivor function

$$\Pi_r = \sum_{j=1}^{\infty} h_{rj} S_{j-1}, \quad E_r = \frac{1}{\Pi_r} \sum_{j=1}^{\infty} j h_{rj} S_{j-1}, \quad S_j = \prod_{s=1}^{j} (1 - h_{1s} - h_{2s}). \quad (16)$$

However, a result provided by Thomas (1996) is particularly useful when proportional hazards are assumed. Instead of examining the effects of $x$ on the unconditional probability of exit, it is computationally much easier to focus on the probability of filling or lapsing conditional on exiting during the interval $j$. The conditional probability of lapsing is defined as:

$$P_j = \frac{h_{2j}}{h_{1j} + h_{2j}}. \quad (17)$$

This is the empirical equivalent of Equation (6) in Section 3. Thus, in addition to estimates of $\beta_1$ and $\beta_2$, we report the marginal effect of a covariate $x$ on the conditional lapsing probability, given by

$$\frac{\partial P_j}{\partial x} = \frac{h_{1j} h_{2j} (\beta_2 - \beta_1)}{(h_{1j} + h_{2j})^2}. \quad (18)$$

This formula applies to discrete variables as well as continuous ones, and applies whether or not the heterogeneity terms are present, let alone correlated. Standard errors can be obtained using the Delta Method.

6 Results

6.1 The raw data

Table 1 describes the sample, which covers the period 1985–1992. There are 14,510 vacancy orders containing a total of $\sum_{i=1}^{N} V_i = 17,759$ vacancies. Most vacancy orders (12,840) therefore contain a single vacancy. As already noted, a substantial proportion (34%) of vacancies lapse. Table 1 also summarises the dependent variable, the total time that a vacancy is open on Careers Service records. To calculate the underlying average duration of filled and lapsed vacancies that allows for genuine censoring or for the vacancy exiting to the other state, we compute ML estimates of the parameters $\gamma$ from an Exponential distribution using Equation (13). Vacancies which fill have a mean duration of eight weeks,
whereas vacancies which lapse have a mean duration of ten weeks. It makes sense that it takes longer for a vacancy to lapse than fill, on average. For multiple orders, we observe slightly lower average durations for filling, and much higher average durations for lapsing, which is a result of a relatively small proportion of multiple orders which lapse.

TABLE 1 HERE

Because the sample period is long relative to the average length of vacancies, the number of censored vacancies (vacancies which were still open at the end of June 1992) is small. There are just 147 censored vacancy orders, comprising 220 individual vacancies. Left-censoring does not occur as we have a flow sample. Finally, the third panel of Table 1 gives the number of the four types of order which make up the likelihood function Equation (13).

6.2 Preferred specification and baseline hazard

In Section 5 we described several possible specifications for modelling the data. Different specifications are required for (a) the choice between parametric and non-parametric baseline hazards, (b) unobserved heterogeneity and (c) multiple vacancy orders. In this section we explain how we select our preferred specification. Table 2 summarises the following six specifications, labelled A to F; Figures 2 and 3 plot some of the corresponding baseline hazards.

TABLE 2 HERE

Specification A is single vacancies, Gaussian mixing, whereas Specification B is single vacancies, discrete mixing. See Equations (11) and (12) respectively. Both have a non-parametric baseline hazard. There is no formal method for choosing between these two specifications. The main two differences between the models are that the correlation between $u_1$ and $u_2$ is much smaller for the Gaussian mixing, as is the variance of $u_1$ (unobserved propensity to fill), and that the shape of the baseline hazard to filling is better (see our discussion of Figure 4 below). It is also true that discrete mixing is sensitive to the choice of $M$. Our view is that the Gaussian model has a more plausible negative
correlation ($\rho = -0.314$). In terms of parameter estimates, it does not matter which is preferred.

For both types of mixing, we strongly reject the hypothesis that the variance of the distribution of unobserved characteristics is zero. We also reject a zero correlation. In Specification C we re-estimate A, but with uncorrelated risks. Very little alters, which does suggest that it is not particularly important to estimate this correlation, except to show that it is indeed negative. Of course, it makes perfect sense that a vacancy that has a high unobserved propensity to fill (a ‘good’ vacancy) will also have a low unobserved propensity to lapse. Suppose one is unable to observe potential revenue flow (defined as $z_m$ in the theory above). A good vacancy with a high $z_m$ and high $\lambda$ is more likely to fill, but also less likely to lapse, thereby generating a negative in the unobservables.

We next investigate whether a Weibull baseline hazard adequately characterises the underlying non-parametric baseline hazard. Figures 2 and 3 compare the estimated baseline hazard between the non-parametric Specification A and a parametric (Weibull) model, Specification D (again for single vacancies). In the former, there is some non-monotonicity in the hazards to filling and lapsing which occurs after 3 days. These spikes in the hazard may be an institutional feature of the data; for example, the Careers Service might open and close vacancies on a particular day of the week.

However, in Specification D, the Weibull parameters are both upward sloping and $\rho$ is estimated as -0.784. In other words, the Weibull is a poor approximation to the non-parametric equivalent, our preferred Specification A. Given that most of the action in the data is at shortish durations, where the Weibull is a poor approximation, it is possible that the -0.784 estimate is over-compensating for this. In Specification $E$, where we constrain $\rho = 0$, the estimated Weibull parameter for filling is once again negative.

Finally, we consider our one model that includes multiple vacancy orders, namely Specification F. Recall that this model has Gamma mixing, imposes a zero correlation, and also is estimated with a Weibull hazard. (A non-parametric hazard was asking too much of
the data.) It can be best compared with Specification E, although E has Gaussian mixing. The main differences are that the variances of unobservables are greater for the multiple orders specification, and that $\hat{\alpha}_2$ is lower (less upward sloping). In terms of parameter estimates, again it does not matter which is preferred.

In Figure 4 we plot the conditional probability of lapsing a vacancy $P_j$, calculated from Equation (17), for Specifications A to D discussed above. For A,B and C, the declining hazard for filling and the increasing hazard for lapsing (see Figures 2 and 3) means that the probability that a vacancy lapses must increase with duration. For D, it is upward sloping because $\hat{\alpha}_1 < \hat{\alpha}_2$. If one draws a horizontal line from $P_j = 0.5$, one gets an estimate of the duration at which vacancies are equally likely to fill as lapse. For specifications A and C, this is roughly 40 days. For B, it is implausibly low (2 days) whereas for D it is implausibly high (more than 120 days).

For A (our preferred specification) and C (the same, but with zero correlation), the shapes of the filling and lapsing hazards (and therefore the conditional probability of lapsing a vacancy) are entirely consistent with Section 3, providing the applicant arrival rate falls over time. Employers adjust by increasing the probability of lapsing whilst lowering the probability of filling vacancy. Because we cannot be certain that lapsed vacancies have not been filled elsewhere, it is possible that the upward sloping hazard to lapsing $h_2$ is also consistent with non-sequential search via another search channel; for example, employers might fill vacancies via the LCS quickly, but fill vacancies via newspapers only after some delay.5

6.3 Determinants of vacancy duration

The estimated effects for all the observed covariates are robust across all six specifications. Table 3 reports parameter estimates and marginal effects from our preferred specification A. There are two distinct objectives in reporting our parameter estimates. First, in this subsection, we report the effects of covariates on the duration of employer search, using
(primarily) the coefficient estimates \( \partial h_1 / \partial x \approx \hat{\beta}_1 \), and in particular we examine whether they are consistent with the predictions of the employer search model outlined in Section 3. We report evidence from Andrews, Bradley & Upward (2001) [hereafter ABU], who use the same data to report estimates of \( \partial \log \mu / \partial x \), so that we infer the effect of a covariate on \( \lambda \) as well as \( h_1 \). Second, in Subsection 6.4, we examine the marginal effect of covariates on the conditional probability that an employer lapses a vacancy, \( \partial P / \partial x \), given in Equation (17). In particular, we assess whether there is any evidence of skill-shortages by examining which types of vacancy are more likely to be removed from the market before they are filled.

[TABLE 3 HERE]

**Labour market tightness and applicant arrival effects, \( \lambda \)**

In almost all models of search in the labour market, the arrival rate of applicants is a decreasing function of labour market tightness, \( \lambda(V/U) \). Our measures of labour market tightness are the number of unemployed aged 18 or less and the number of vacancies in each local district for each month of the data.

The coefficient on ‘Unemployed \( \leq 18 \)’ in Table 3 shows that vacancies in labour markets with higher youth unemployment have significantly higher hazards to filling \( (\hat{\beta}_1 = 0.30) \), lower hazards to lapsing \( (\hat{\beta}_2 = -0.09) \) and are therefore significantly less likely to lapse \( (\partial P_j / \partial \log U = -0.097) \). As noted, labour market tightness operates via two opposing channels. There is the direct effect on applicant arrival rates \( \lambda \) and the indirect effect via the matching probability \( \mu \) (see Equation (5)). Additional evidence on the effect of the labour market tightness is available from ABU, who established that \( \partial \log \mu / \partial \log U = -0.17 \). Given \( h_1 = \mu \lambda \), we can infer that \( \partial \log \lambda / \partial \log U = 0.47 \). This large effect is consistent with the theory (in fact, only guaranteed if the offer distribution is log-concave) and so our conclusion is that an increase in unemployment increases the hazard because the increase in the number of contacts per vacancy outweighs the employer’s ‘more selective’ response. This is, of course, the same reason why vacancy hazards are downward-sloping as the applicant arrival rate declines over time.

The estimates for the stock of vacancies show no corresponding negative effect on the
filling hazard, with a positive, albeit small elasticity of 0.05. Clearly, this is disappointing and so we are unable to impose the homogeneity restriction that allows the covariate to be labour market tightness \( V/U \). On the other hand, finding increasing returns to scale is the norm in this literature (Petrongolo & Pissarides 2001).

In addition to labour market tightness variables above, we also consider two other characteristics of the local labour market in which the firm is located. The first is log population density to capture whether the matching probability or the arrival rate of applicants is higher in cities compared with rural areas, but this is insignificant. A better variable with which to capture applicant arrival effects is our measure of firm location. Firms located in town centres, and which are therefore more accessible to job-seekers (who have lower search costs), have significantly higher hazards to filling, with a differential of some 0.29 log-points. This offsets possible effects from higher competition, with more potential employers in town centres.

The third local labour variable we consider is the number of staff in a given Careers Office, normalised on the population of each district. It has a small negative elasticity of –0.194 on the hazard to filling a vacancy, suggesting that more staff generate fewer applicants per vacancy, which is somewhat unexpected.

The final variable we consider is firm size, where it is clear that the bigger the firm, the easier it is to fill a vacancy (there is a clear gradient over size bands 1–10, 11-30, and 31+). As this variable has no effect on the matching probability in ABU, again this is an applicant arrival effect \( \lambda \). (The negative effect of \( \lambda \) on \( \mu \) cancels out with the positive effect of lower search costs \( c \) for larger firms.) Unlike larger Careers Offices, larger firms can process more applicants. If larger firms have higher applicant arrival rates the theory predicts that \( h_2 \) will fall, which is what we find.

**The revenue flow from a match, \( z_m \)**

The most important component of \( z_m \) is the wage. There are three different types of wage offer in the data. About 80% of vacancies have a set pre-announced wage, where the wage is non-negotiable. The majority of these vacancies specify age and tenure profiles,
which reflects the rigid institutional nature of wage setting in the youth labour market. A small proportion of vacancies have a set pre-announced wage offer, but are still open to negotiation. The remaining vacancies have a negotiable wage offer and no pre-announced wage. For this third category there is no wage recorded in the data.

The important point is that both job-seekers and employers take the wage as given when they decide whether or not to form a match; in other words, simultaneity bias is not an issue. We argue that this is an accurate characterisation of the youth labour market, given the vast majority of vacancies in the data have a non-negotiable wage.

We model these effects as follows. We define $N$ as a dummy variable indicating whether a vacancy has a negotiable wage offer, and $D$ as a dummy variable indicating whether the wage is pre-announced. Interacting the dummies with the log real hourly wage rate $w$, where it exists, allows us to include all observations, even where a wage is not observed.

The prediction of the simple model above is that a higher wage should make employers more selective. Moreover, the wage can also affect the hazard via the applicant arrival rate $\lambda$. A higher wage will increase $\lambda$, which has an ambiguous effect on the hazard. Added to the employer selection effect above, the overall prediction is ambiguous.

The coefficients on $wDN$ and $wD(1 - N)$ capture the relationship between the wage and the vacancy hazard for vacancies with a pre-announced wage with and without negotiation. As with most of the literature, neither has any significant effect on the hazard to filling. But ABU found clear negative effects on the matching probability, which implies that a higher wage must generate more applicants, with the two effects cancelling each other out.

Those vacancies that have a pre-announced wage but which are still open to negotiation ($DN$) have significantly lower hazards to filling than the base group, namely vacancies with a set pre-announced wage only. This is intuitive for two reasons: first, negotiation takes time and, second, these jobs offer potentially higher wages than those with inflexible wages. Finally, about 17% of vacancies can also be negotiable but have no pre-announced wage: here there is no significant effect on the hazard to filling on $w(1 - D)N$.

Apart from the wage, we do not observe the revenue flow from a match directly. We do, however, have a number of vacancy characteristics which are likely to be good proxies.
These include the skill level, whether the vacancy is in a non-manual occupation, and the amount of training offered. Existing empirical evidence (Section 2) suggests that the greater the potential investment by the employer in the worker (through more training and so on) the longer it takes to fill a vacancy (lower vacancy hazard). Vacancies which require more investment by the firm may take longer to fill because the revenue flow is initially low during the training period. Once training has finished, the revenue flow is higher than for low-skill jobs, but this is discounted because of the probability of a future separation: the newly trained employee may leave the firm. Employers therefore become more selective (μ falls) and the hazard is lower. In addition, if higher quality vacancies attract more variable applicants, the vacancy hazard will be lower if the employer waits longer for a ‘bargain’. It may also be the case that vacancies with better characteristics (more training, higher skill) have steeper wage profiles which are not picked up by the starting wage.

Table 3 shows that non-manual vacancies have significantly lower hazards to filling (β̂1 = −0.41) than their manual counterparts, but that skilled vacancies have a significantly higher hazard to filling compared with unskilled vacancies (β̂1 = 0.15). More evidence that employers search longer for ‘better’ vacancies is provided by the training information. Vacancies offering day release to College (β̂1 = −0.34) or apprenticeship training (β̂1 = −0.48) have lower hazards. Only one of these four variables had any effect on the matching probability in ABU—an elasticity of −0.20 for non-manual—and so we are estimating large negative applicant arrival effects in three of the four cases.

A number of measurable characteristics refer to the selection criteria associated with a vacancy. These include the required level of educational qualification, required subjects studied at school, age and whether or not a written application is required. (For vacancies where no written application was required, the Careers Service would undertake the application procedure.) Some of these characteristics, such as qualifications, are directly related to the employer’s reservation productivity z∗, and are an attempt to limit the pool of potential applicants. We would therefore expect that higher criteria imply higher z∗ and longer search durations. In addition, there may be fewer of the better qualified applicants available to such vacancies. A consistent finding across several studies is that higher edu-
cational requirements increase the duration of a vacancy (van Ours 1991). Table 3 shows that vacancies requiring higher educational qualifications have significantly lower hazards to filling and therefore have longer search durations, taking longer the more educated the applicant.

The largest estimated effect is the requirement that a written application be submitted by the job-seeker ($\hat{\beta}_1 = \hat{-1.12}$). Increases in duration might be because written applications increase the application period, or because written applications increase the selection period, as in Van Ours & Ridder (1993). In fact, most of this effect is because of a much lower matching probability, an elasticity of $-0.72$ (ABU). Finally, applications requiring older job-seekers also have lower hazards, with an elasticity of $-0.38$.

### 6.4 Skill shortages — which vacancies lapse?

An important feature of our data is that a substantial number of vacancies are removed from the market before they are filled. As noted in the theory section, in a stationary world one would not observe lapsing. We predict that lapsing occurs because the applicant arrival rate falls, pushing the discounted revenue stream $rV_n$ below its reservation level $rV_l$. When the applicants dry up completely, this is when the employer learns that there is a skill shortage and hence lapses the vacancy. In this subsection we examine the issue of skill shortages from an entirely new angle, by examining which types of jobs take longer to fill, and those which are eventually removed from the market.

Alternative descriptive evidence comes from the ONS data referred to in the Introduction, namely the proportion of all vacancies notified to the public employment service which are subsequently cancelled. For July 1993, not long after the end of our sample period, this proportion is highest for skilled manual workers (35%), 30% for semi-skilled non-manual workers, 23% for skilled manual workers and 20% for unskilled manual workers.

In the competing risks framework that we adopt, we are able to determine which characteristics of a vacancy increase the probability of lapsing. The hypothesis that skill shortages cause vacancies to lapse suggests that those vacancies requiring more skilled applicants will take longer to fill and be more at risk of lapsing. An alternative hypothesis is that
lapsing is a result of low-quality jobs, in that they offer low wages or little training, being refused by potential applicants, in which case it will be low-quality vacancies which are more at risk of lapsing.

Estimates of $\partial P_j / \partial x$ are reported in Table 3. Generally, the results are consistent with the hypothesis that ‘good’ vacancies requiring more skilled applicants are more difficult to fill. Vacancies requiring higher educational qualifications are more likely to lapse. The net effect on $\partial P_j / \partial x$ is positive because the hazard to filling falls proportionately more than the hazard to lapsing. Other measures of vacancy quality also tend to have $\partial P_j / \partial x > 0$, and some with quite large semi-elasticities: non-manual vacancies (0.16), vacancies offering apprenticeship training (0.03) and vacancies requiring a written application (0.14) and older applicants (0.13) all have larger probabilities of lapsing.

Our estimates provide strong evidence that employer search is unsuccessful because the supply of suitable applicants falls below the level at which search is profitable. This may occur because the Careers Service filters out unsuitable applicants (low $\lambda$), or because employers reject applicants (lower $\mu$). Notice that most of these variables have been discussed already in the context of their impact on the hazard to filling (which is only half the story here), but it is generally the case that these vacancies have lower applicant arrival rates rather than lower matching probabilities.

All in all, we conclude that it is skill shortages which cause increases in employer search duration rather than the unattractiveness of certain vacancies to job-seekers. However, we cannot be certain that lapsed vacancies are actually withdrawn from the market. As noted in Section 4, it is possible, although unlikely, that these vacancies are subsequently filled by older applicants via a different search channel. Even if this is the case, these results still demonstrate that employers cannot fill these vacancies from the youth labour market; the conclusion that there are skill shortages still holds up.

7 Conclusions

This paper provides the first analysis of vacancy duration and the outcome of employer search using duration modelling methods for the UK, using a large sample of vacancies
for a particular market. Our results are of interest for two reasons. First, understanding employers’ search behaviour is an important, and yet under-researched, area. Second, we provide plausible evidence that a sizeable proportion of vacancies are removed from the market before they are filled, or are ‘lapsed’. Evidence on ‘hard-to-fill’ vacancies (those with long durations) is thin; apart from Beaumont (1978), our paper provides the only other analysis of lapsed vacancies.

Our key results are as follows:

1. For all specifications with non-parametric hazards, the hazard to filling is downward-sloping and the hazard to lapsing is upward-sloping, implying that the conditional lapsing probability increases with duration. This is consistent with the claim that lapsed vacancies are being withdrawn from the market (if they were being filled elsewhere, they would probably have downward-sloping hazards), but we cannot be certain that this is so. It is also consistent with a fall in the arrival rate and quality of applicants; the employer’s response is to increase the probability of lapsing a vacancy and decrease the probability of a filling a vacancy.

2. For all models with correlated risks, we always estimate a negative correlation. It makes good sense that a vacancy that has a high unobserved propensity to fill (a ‘good’ vacancy) will also have a low unobserved propensity to lapse.

3. A key variable in all search models is labour market tightness. An increase in unemployment increases the hazard because the increase in the number of applicants per vacancy outweighs the employers’ more selective response. The effect of the aggregate stock of vacancies is not well determined, implying non-homogeneity and increasing returns.

4. The wage does not affect the duration of employer search. However, in earlier work, ABU found clear negative effects on the matching probability, which implies that a higher wage generates more applicants.

5. A number of other covariates have a negative influence on the employer’s hazard, including the type of vacancy (non-manual and involves training) and selection cri-
teria (qualification, written application, older applicant). Generally, but not always, these are because the arrival rate of applicants is lower.

6. Finally, we find that employers find it difficult to find suitable applicants, because search takes longer and because these vacancies are more likely to be withdrawn from the market before they are filled. This is because it is good rather than bad vacancies which are hard to fill. Generally, these are the same vacancies as listed immediately above.

In short, we find that lapsed vacancies are important aspect of labour markets that have hitherto been ignored. In our data, we have evidence that lapsing is caused by skill shortages. Clearly, we need to know whether lapsing is a more general phenomenon, although data limitations suggest that this would not be easy.

Appendix: likelihood for multiple vacancy orders

Four types of order are possible, suppressing the $i$ subscript for clarity:

1. All are filled before any are lapsed or censored ($W = V$):

$$t_1 < \bar{t}; \ t_2 < \bar{t}; \ t_3 < \bar{t}; \ldots; \ t_V < \bar{t} \quad \text{or} \quad t_1 < c; \ t_2 < c; \ t_3 < c; \ldots; \ t_V < c,$$

but we only observe $y = \max(t_1, \ldots, t_V)$. The likelihood of observing this type of order is

$$V[1 - S_1(y)]^{V-1}[S_1(y - 1) - S_1(y)]S_2(y)^V S_0(y)^V.$$

2. All are lapsed before any are filled or censored ($W = 0$):

$$\bar{t} < t_1; \ \bar{t} < t_2; \ \bar{t} < t_3; \ldots; \ \bar{t} < t_V \quad \text{or} \quad \bar{t} < c$$

Here we only observe $\bar{t}$. The likelihood of observing this type of order is

$$[S_2(\bar{t} - 1) - S_2(\bar{t})]^V S_1(\bar{t})^V S_0(\bar{t})^V.$$  

3. All are censored before any are filled or lapsed:

$$c < t_1; \ c < t_2; \ c < t_3; \ldots; \ c < t_V \quad \text{or} \quad c < \bar{t}.$$  

Here we only observe $c$. The likelihood of observing this type of order is

$$S_1(c)^V S_2(c)^V [S_0(c - 1) - S_0(c)]^V.$$
4. $W$ are filled and $V - W$ are lapsed before any are censored:

$$t_1 < \bar{t}; \ldots; t_W < \bar{t}; \bar{t} < t_{W+1}; \ldots; \bar{t} < t_V$$

we only observe $\bar{t}$ and $W$. The $V - W$ lapsed vacancies have a likelihood

$$[S_2(\bar{t} - 1) - S_2(\bar{t})]^{V-W} S_1(\bar{t})^{V-W} S_0(\bar{t})^{V-W},$$

and the $W$ filled vacancies have a likelihood

$$[1 - S_1(\bar{t})]^W [S_2(\bar{t} - 1) - S_2(\bar{t})]^{W} S_0(\bar{t})^{V-W}.$$

In each expression above, contributions to the likelihood from the censored distributions are suppressed. The likelihood for the whole sample is (now explicitly indexing each vacancy order $i$ and replacing $\bar{t}_i$, $y_i$ and $c_i$ by $t_i$) given by Equation (13) of the main text.

Notes

1See Upward (1998, ch. 4) for fuller details, especially Section 4.3 on the representativeness of our data.

2Censoring is effectively a third state, but as the parameters of the censoring process are not modelled, some terms such as $S_0(t|v_0)$ do not appear.

3Uncorrelated models are routinely estimated in Stata or GLLAMM.

4These $M$ parameters vary over $i$ in the sense that the data decide which value of $m$ is associated with vacancy $i$.

5We are grateful to two referees for pointing this out.

References


Figures

Figure 1: Raw vacancy hazard
Figure 2: Baseline hazards to filling, various specifications

Figure 3: Baseline hazards to lapsing, various specifications
Figure 4: Probability of lapsing, various specifications
## Tables

### Table 1: Vacancy duration

<table>
<thead>
<tr>
<th></th>
<th>Mean duration (days)</th>
<th>ML estimate of duration (days)</th>
<th>No.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Single vacancies, ( V_i = 1 )</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Filled (( W_i = 1 ))</td>
<td>21.07</td>
<td>53.97</td>
<td>7234</td>
</tr>
<tr>
<td>Lapsed (( W_i = 0 ))</td>
<td>42.05</td>
<td>71.19</td>
<td>5484</td>
</tr>
<tr>
<td>Censored</td>
<td>60.69</td>
<td></td>
<td>122</td>
</tr>
<tr>
<td>Number of single vacancies</td>
<td></td>
<td></td>
<td>12840</td>
</tr>
<tr>
<td><strong>All vacancies</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Filled</td>
<td></td>
<td>50.80</td>
<td>11485</td>
</tr>
<tr>
<td>Lapsed</td>
<td></td>
<td>111.82</td>
<td>6054</td>
</tr>
<tr>
<td>Censored</td>
<td></td>
<td></td>
<td>220</td>
</tr>
<tr>
<td>Total no. of vacancies (( \sum_{i=1}^{N} V_i ))</td>
<td></td>
<td></td>
<td>17759</td>
</tr>
<tr>
<td><strong>All vacancies, by order</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All filled (( W_i = V_i ))</td>
<td></td>
<td>8548</td>
<td></td>
</tr>
<tr>
<td>Some filled (( 0 &lt; W_i &lt; V_i ))</td>
<td></td>
<td>242</td>
<td></td>
</tr>
<tr>
<td>All lapsed (( W_i = 0 ))</td>
<td></td>
<td>5573</td>
<td></td>
</tr>
<tr>
<td>Censored (( C_i = 1 ))</td>
<td></td>
<td>147</td>
<td></td>
</tr>
<tr>
<td>Total number of orders (( N ))</td>
<td></td>
<td>14510</td>
<td></td>
</tr>
</tbody>
</table>

*a* Assuming Exponential distribution, i.e. \( \gamma_j = \gamma \), a constant.
Table 2: Summary of specifications

<table>
<thead>
<tr>
<th></th>
<th>Single orders</th>
<th></th>
<th></th>
<th>Multiple orders</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Filled</td>
<td>Lapsed</td>
<td>Filled</td>
<td>Lapsed</td>
<td>Filled</td>
<td>Lapsed</td>
</tr>
<tr>
<td>Unemployed ≤ 18 (log U)</td>
<td>0.3041 (0.0350)</td>
<td>-0.0855 (0.0467)</td>
<td>0.2630 (0.0303)</td>
<td>-0.0577 (0.0429)</td>
<td>0.2893 (0.0327)</td>
<td>-0.0541 (0.0399)</td>
</tr>
<tr>
<td>Job vacancies (log V)</td>
<td>0.0536 (0.0257)</td>
<td>-0.1530 (0.0340)</td>
<td>0.0240 (0.0233)</td>
<td>-0.1661 (0.0323)</td>
<td>0.0504 (0.0243)</td>
<td>-0.1462 (0.0306)</td>
</tr>
<tr>
<td>Log wage if D(1 − N) = 1</td>
<td>0.0407 (0.0783)</td>
<td>0.2414 (0.1071)</td>
<td>0.0379 (0.0695)</td>
<td>0.2284 (0.0963)</td>
<td>0.0366 (0.0736)</td>
<td>0.2388 (0.0932)</td>
</tr>
<tr>
<td>σ₁, σ₂</td>
<td>1.0917 (0.1360)</td>
<td>1.5910 (0.1951)</td>
<td>4.2356 (n/a)</td>
<td>1.2768 (n/a)</td>
<td>0.9602 (0.0988)</td>
<td>1.2985 (0.0959)</td>
</tr>
<tr>
<td>ρ</td>
<td>-0.3141 (0.0848)</td>
<td>-0.0831 (n/a)</td>
<td>0*</td>
<td>-62155.78</td>
<td>-62008.81</td>
<td>-62158.18</td>
</tr>
<tr>
<td>log L</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Single orders</th>
<th></th>
<th></th>
<th>Multiple orders</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Filled</td>
<td>Lapsed</td>
<td>Filled</td>
<td>Lapsed</td>
<td>Filled</td>
<td>Lapsed</td>
</tr>
<tr>
<td>Unemployed ≤ 18 (log U)</td>
<td>0.2952 (0.0680)</td>
<td>-0.0760 (0.0538)</td>
<td>0.2562 (0.0278)</td>
<td>-0.0484 (0.0356)</td>
<td>0.3273 (0.0256)</td>
<td>-0.0627 (0.0308)</td>
</tr>
<tr>
<td>Job vacancies (log V)</td>
<td>0.0447 (0.0344)</td>
<td>-0.1190 (0.0385)</td>
<td>0.0504 (0.0213)</td>
<td>-0.1292 (0.0272)</td>
<td>-0.0344 (0.0201)</td>
<td>-0.2849 (0.0255)</td>
</tr>
<tr>
<td>Log wage if D(1 − N) = 1</td>
<td>0.2139 (0.1138)</td>
<td>0.1402 (0.1235)</td>
<td>0.0191 (0.0631)</td>
<td>0.2187 (0.0809)</td>
<td>0.0516 (0.0567)</td>
<td>-0.0837 (0.0681)</td>
</tr>
<tr>
<td>α₁ − 1, α₂ − 1</td>
<td>0.3252 (0.0275)</td>
<td>0.8065 (0.1291)</td>
<td>-0.2832 (0.0223)</td>
<td>0.4846 (0.0430)</td>
<td>-0.2200 (0.0129)</td>
<td>0.2174 (0.0201)</td>
</tr>
<tr>
<td>σ₁, σ₂</td>
<td>2.7602 (0.1313)</td>
<td>2.2270 (0.3099)</td>
<td>0.6015 (0.0631)</td>
<td>0.9791 (0.0702)</td>
<td>1.6210 (0.0643)</td>
<td>1.6663 (0.0905)</td>
</tr>
<tr>
<td>ρ</td>
<td>-0.7840 (0.0404)</td>
<td>0*</td>
<td>-62514.75</td>
<td>-62518.70</td>
<td>-77730.04</td>
<td></td>
</tr>
<tr>
<td>log L</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*See Table 3 for the other covariates that are included.

Specification A. Preferred specification: Gaussian mixing (Q = 8²), correlated unobservables, non-parametric baseline hazard.
Specification B. Non-parametric (Heckman-Singer) mixing (M = 5), correlated unobservables, non-parametric baseline hazard.
Specification C. Gaussian mixing (Q = 8²), uncorrelated unobservables, non-parametric baseline hazard.
Specification D. Gaussian mixing (Q = 8²), correlated unobservables, parametric (Weibull) baseline hazard.
Specification E. Gaussian mixing (Q = 8²), uncorrelated unobservables, parametric (Weibull) baseline hazard.
Specification F. All vacancies including ‘multiple orders’, gamma mixing, uncorrelated unobservables, parametric (Weibull) baseline hazard.

* Imposed.
### Table 3: Preferred specification (Model A)*

<table>
<thead>
<tr>
<th></th>
<th>Filled</th>
<th>Lapsed</th>
<th>Pr(lapsing)</th>
<th>Sample means</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\hat{\beta}_1$</td>
<td>p-value</td>
<td>$\hat{\beta}_2$</td>
<td>p-value</td>
</tr>
<tr>
<td>Unemployed $\leq 18$ (log $U$)</td>
<td>0.3041 [0.000]</td>
<td>-0.0855 [0.067]</td>
<td>-0.0972 [0.0000]</td>
<td>336.067</td>
</tr>
<tr>
<td>Job vacancies (log $V$)</td>
<td>0.0536 [0.037]</td>
<td>-0.1530 [0.000]</td>
<td>-0.0515 [0.0000]</td>
<td>51.661</td>
</tr>
<tr>
<td>Wage announced and negotiable ($DN$)</td>
<td>-0.2975 [0.005]</td>
<td>-0.1689 [0.251]</td>
<td>0.0321 [0.5013]</td>
<td>0.049</td>
</tr>
<tr>
<td>Wage not announced and negotiable ($(1-D)N$)</td>
<td>0.0516 [0.297]</td>
<td>-0.0479 [0.494]</td>
<td>-0.0248 [0.2744]</td>
<td>0.197</td>
</tr>
<tr>
<td>Log wage if $D(1-N) = 1$</td>
<td>0.0407 [0.603]</td>
<td>0.2414 [0.024]</td>
<td>0.0501 [0.1520]</td>
<td>£1.38</td>
</tr>
<tr>
<td>Log wage if $DN = 1$</td>
<td>0.0518 [0.845]</td>
<td>0.3886 [0.255]</td>
<td>0.0840 [0.4611]</td>
<td>£1.37</td>
</tr>
<tr>
<td>Log population density</td>
<td>0.0061 [0.820]</td>
<td>0.2995 [0.000]</td>
<td>0.0732 [0.0000]</td>
<td>10.527</td>
</tr>
<tr>
<td>Firm located in town centre</td>
<td>0.2901 [0.000]</td>
<td>-0.1098 [0.055]</td>
<td>-0.0998 [0.0000]</td>
<td>0.421</td>
</tr>
<tr>
<td>Log careers Service staff per personb</td>
<td>-0.1939 [0.000]</td>
<td>-0.0720 [0.274]</td>
<td>0.0304 [0.1531]</td>
<td>0.107</td>
</tr>
<tr>
<td>11–30 employees</td>
<td>0.0812 [0.071]</td>
<td>-0.1664 [0.012]</td>
<td>-0.0618 [0.0035]</td>
<td>0.219</td>
</tr>
<tr>
<td>31–100 employees</td>
<td>0.1750 [0.001]</td>
<td>-0.1851 [0.018]</td>
<td>-0.0898 [0.0004]</td>
<td>0.154</td>
</tr>
<tr>
<td>&gt; 100 employees</td>
<td>0.2167 [0.001]</td>
<td>-0.1408 [0.107]</td>
<td>-0.0892 [0.0021]</td>
<td>0.152</td>
</tr>
<tr>
<td>Firm provides training vacancies</td>
<td>-0.1529 [0.000]</td>
<td>-0.0858 [0.110]</td>
<td>0.0167 [0.3376]</td>
<td>0.357</td>
</tr>
<tr>
<td>Skilled</td>
<td>0.1509 [0.017]</td>
<td>-0.0745 [0.375]</td>
<td>-0.0563 [0.0427]</td>
<td>0.550</td>
</tr>
<tr>
<td>Non-manual</td>
<td>-0.4144 [0.000]</td>
<td>0.2111 [0.014]</td>
<td>0.1561 [0.0000]</td>
<td>0.556</td>
</tr>
<tr>
<td>In house training</td>
<td>0.0135 [0.855]</td>
<td>0.0033 [0.975]</td>
<td>0.0026 [0.9388]</td>
<td>0.057</td>
</tr>
<tr>
<td>Day release training</td>
<td>-0.3435 [0.000]</td>
<td>-0.5633 [0.000]</td>
<td>-0.0549 [0.0550]</td>
<td>0.098</td>
</tr>
<tr>
<td>Apprenticeship training</td>
<td>-0.4830 [0.000]</td>
<td>-0.3770 [0.001]</td>
<td>0.0264 [0.4791]</td>
<td>0.149</td>
</tr>
<tr>
<td>Average GCSE or just below</td>
<td>-0.2208 [0.000]</td>
<td>-0.0846 [0.217]</td>
<td>0.0340 [0.1202]</td>
<td>0.458</td>
</tr>
<tr>
<td>High GCSE</td>
<td>-0.4080 [0.000]</td>
<td>-0.3375 [0.000]</td>
<td>0.0176 [0.5633]</td>
<td>0.196</td>
</tr>
<tr>
<td>4 or more GCSEs</td>
<td>-0.5561 [0.000]</td>
<td>-0.8087 [0.000]</td>
<td>-0.0630 [0.1345]</td>
<td>0.093</td>
</tr>
<tr>
<td>English required</td>
<td>0.0005 [0.996]</td>
<td>-0.1239 [0.278]</td>
<td>-0.0310 [0.4089]</td>
<td>0.619</td>
</tr>
<tr>
<td>Maths required</td>
<td>0.2399 [0.039]</td>
<td>-0.4470 [0.007]</td>
<td>-0.1714 [0.0013]</td>
<td>0.043</td>
</tr>
<tr>
<td>English and Maths required</td>
<td>0.0007 [0.995]</td>
<td>-0.3620 [0.030]</td>
<td>-0.0905 [0.0896]</td>
<td>0.039</td>
</tr>
<tr>
<td>Science required</td>
<td>-0.0195 [0.826]</td>
<td>-0.2966 [0.014]</td>
<td>-0.0692 [0.0806]</td>
<td>0.195</td>
</tr>
<tr>
<td>Other subject required</td>
<td>0.0476 [0.675]</td>
<td>-0.4295 [0.007]</td>
<td>-0.1191 [0.0219]</td>
<td>0.055</td>
</tr>
<tr>
<td>Older applicants required (over 16)</td>
<td>-0.3833 [0.000]</td>
<td>0.1245 [0.054]</td>
<td>0.1267 [0.0000]</td>
<td>0.193</td>
</tr>
<tr>
<td>Written application required</td>
<td>-1.1176 [0.000]</td>
<td>-0.5718 [0.000]</td>
<td>0.1362 [0.0000]</td>
<td>0.175</td>
</tr>
</tbody>
</table>

* Specification A. Gaussian mixing ($Q = 8^2$), correlated unobservables, non-parametric baseline hazard.
  Also includes dummies for SIC (9), year (7) and month (11), and constant.
  Mean duration to filling $E_1$ estimated as 27 days, mean duration to filling $E_1$ 52 days, and conditional on exit probability that a vacancy fills is 0.498. See Equation (16). Hence mean duration to exit is 36 days.
  a Marginal effect on the probability of lapsing, evaluated at mean duration of 36 days. See Equation (18). $p$-value assumes that $h_1$ and $h_2$ are non-random. It can be shown, because $h_1 \approx h_2$ at mean duration, that this assumption is innocuous.
  b Per thousand.

Log $L$ = -62155.78
$s^2_v$ = 1.0917 [0.000]
$\rho$ = -0.3141 [0.000]
Vacancies = 7234
Orders = 5606

Orders = 12840
Acknowledgments

The authors thank The Leverhulme Trust (under grant F/120/AS) for financial assistance. We used Sabre 4.0 for the estimation of the CCR models, which was developed by the Centre for e_Science, Lancaster University and funded under grant ESRC award RES-149-25-0010. The data were kindly supplied by Lancashire Careers Service. The comments of Len Gill, Jonathan Wadsworth, Alan Manning and especially Chris Orme are gratefully acknowledged, as are those from participants at various presentations. These include the Manchester Universities’ Labour Workshop, the 1997 EEEG Overnight Workshop (Royal Holloway), the Departments of Economics at Leeds and Loughborough, and the Institute of Careers Guidance Workshops in Glasgow and Newcastle. The data used in this analysis are available on request.