NOTES

THE TURNOVER OF TEACHERS: A COMPETING RISKS EXPLANATION

Peter Dolton and Wilbert van der Klaauw*

Abstract—In this paper, we analyze the decision by teachers to leave the profession in a dependent competing risks framework. The econometric model allows for a flexible, semiparametric specification of the duration-dependence structure and of the unobserved heterogeneity distribution in each exit-specific hazard function. Our results obtained for a large sample of UK teachers affirm the importance of teacher salaries and opportunity wages in the turnover decision of teachers and illustrate the insight gained from differentiating between multiple destinations or exit types.

I. Introduction

Understanding teacher turnover and retention is important for the efficiency of educational administration. The extent to which relative earnings may influence this turnover is of considerable importance and constitutes the primary issue in this research. More specifically, we examine exactly what influences a teacher's propensity to leave teaching for a different career or for a nonlabor market alternative. A better understanding of teacher turnover could lead to more-effective policies aimed at reducing teacher attrition, especially of teachers in shortage subjects or geographic areas. It would also help educational authorities improve their predictions of future teacher attrition, which is important in determining the number of new trainees to recruit.

Research on teacher turnover by Murnane and Olsen (1989, 1990) and Murnane et al. (1989) has explicitly modeled the effects of salaries and opportunity costs on the length of stay in teaching for teachers in North Carolina and Michigan. As a measure of the opportunity wage, these studies have used either degree subject, an ability test score, or the average salary of a graduate in the same subject who did not become a teacher. The individual's opportunity wage of staying in teaching, is however, likely to depend on many other individual characteristics, and average salaries in the nonteaching sector may be a poor proxy for average potential salaries of ex-teachers in that sector. We use individual wage data on teachers to estimate teachers' earnings-tenure profiles and data on starting wages in the nonteaching sector to explicitly estimate individual-specific opportunity wages. We also compare our estimates to those obtained when using Murnane and Olsen's (1989) opportunity-wage measure and find the latter to be considerably less accurate and less conclusive.

A second shortcoming of existing studies is that they do not distinguish between the different destinations and reasons for leaving the job or occupation. This is important because salaries and opportunity wages are likely to have a different impact on the rate of leaving for a nonteaching job than on the rate of exit to a nongovernmental state, and similarly when we distinguish between voluntary exits for career reasons and exits caused by a contract ending or because of family reasons. Exits to nonemployment are particularly common for female teachers, who represent a majority of teachers, and distinguishing by type of exit will allow a more informative analysis of the importance of earnings and other characteristics on teacher attrition and the decision to leave the labor force. A new perspective on these aspects of teacher attrition is provided in the present study which uses a large cross-section data set on 1980 UK graduates to estimate competing risks models of teacher exit to these distinct destination states and by different reasons for leaving.

To characterize the attrition process, a proportional hazard model is specified that relates the rate of leaving teaching to a number of individual- and job-specific characteristics, such as the individual's (potential) earnings in the teaching and nonteaching sectors, regional labor market conditions, and the teacher's education and family background. Unlike previous studies in this area, in our estimations, we allow nonparametrically for the presence of unobserved heterogeneity as in Heckman and Singer (1984), adopt a flexible underlying baseline hazard as in Meyer (1990), and take into account the time-varying nature of various regressors. In addition—and perhaps most importantly of all—we explore empirically the different reasons for leaving the teaching profession in a dependent competing risks framework. The model is similar to that proposed by Han and Hausman (1990), in that it allows for the unobserved heterogeneity components in the exit-specific hazard rates to be correlated.

Our results affirm the importance of teacher salaries and foregone earnings in the tenure and turnover decisions of UK teachers, confirm the insight gained from differentiating between multiple destinations or exit types, and illustrate the importance of flexible baseline hazard modeling.

II. The Data Set and Modeling Wages

The data analyzed in this study represent a 1-in-6 sample of individuals who graduated from UK universities in 1980 and provide information about the 1980–1987 period in their early careers. The usable sample contains 6,098 graduates, of whom 3,484 were men and 2,614 were women. In this sample, 923 individuals were full-time school teachers in their first job. The variables used in this study are defined in the data appendix. A full description of the survey is contained in Dolton and Makepeace (1992).

An unusual feature of these data is that observations on earnings are available for the individuals in the sample at several points in their career. We use this information to estimate earnings-tenure profiles for teachers and starting-wage equations for those who entered the nonteaching sector. A drawback of the survey is that it covers only the early work history of graduates. Observing individuals at a maximum of 6.5 years in the labor force meant that our analysis of teacher attrition had to be restricted to the first exit out of the teaching profession (i.e., an observed spell in teaching may include more than one teaching job provided the spell in teaching is unbroken).

Out of the 923 spells in teaching, 340 (37%) are exits out of teaching with all other spells right censored at the time of the 1987 survey. The typical teacher in our sample is female, received a bachelor's degree from a polytechnic (UNIV = 0) rather than from a
university, had attended a public high school (SCHTYPE = 0) rather than a private one, had no postgraduate qualifications (ACA = 0, NACA = 0), and experienced around three months of unemployment before accepting the teaching job (UNBJ1). Of all teachers, 71.5% are female, 7.5% obtained a certificate of education (CERT = 1), 41% have a bachelor’s in education (BED = 1), and 38% a postgraduate certificate of education (DPGCOE = 1). Secondary-school teachers (SECONDARY = 1) outnumber primary-school teachers 83.5% to 16.5%. Further, 6% of teachers obtained a postgraduate academic qualification (ACA = 1), while 4% received a nonacademic professional qualification (NACA = 1). Almost 10% of the teachers in our sample reported that they had started their first job rather reluctantly (RELC = 1), and 13% taught in the greater London area (LONDON = 1).

Since it is one of the main aims of this paper to study the effect of teacher salaries and opportunity wages on teacher retention, it is important to describe the construction of these wage variables. First, we know the starting salary for each teacher in our sample. Second, for teachers who have not left the profession by 1987 (the “stayers”), we observe the salary earned in 1987. With wage information at two points in time and given that individuals generally started their first job in teaching at different dates, it is possible to estimate the earnings-tenure profile for teachers.  

\[
\frac{\ln W_i(t) - \ln W_0}{y} = Z_i' \gamma + \alpha_1 y^2 + \alpha_2 y + \omega_1
\]

where \( \ln W_i(t) \) and \( \ln W_0 \) are the (log) real wage earnings of teacher \( i \) at the time of the survey in 1987 and at the time of starting the first job, and \( \omega_1 \) is an i.i.d. normally distributed error term. The variable \( y \) represents the number of complete academic years a teacher has been in the profession in 1987, which corresponds to the number of pay increments achieved by the person in the teaching profession in the UK. This variable is distinct from job tenure as it measures completed academic years where a pay increment is awarded as opposed to simply computing “months on the job.” In the estimation of this equation, we also included a selection-bias correction term to account for the fact that teachers who stayed in teaching are a self-selected subsample of teachers, who may on average experience greater wage growth or have fewer opportunities in the nonteaching and nonemployment sectors.

The vector of individual characteristics \( Z_i \) includes several measures of human capital affecting teacher wage growth, such as the individual’s educational background, unemployment and pre-1980 work history, the (log) starting wage, and the regional unemployment rate in the year of starting the teaching job (UNEM(1)). Note that the linear and quadratic terms in tenure \( y \) allow for a variety of nonlinear earnings-experience profiles. To a large extent, the yearly teacher salaries in the UK are predetermined and follow fixed pay schedules negotiated by teacher unions, leaving local education authorities only little control over teacher salaries. The teacher earnings-tenure profiles estimated here can be interpreted as an estimate or approximation of these wage schedules and can therefore be treated as exogenous with respect to the individual teacher’s career choices.

Given estimates of \( \gamma_1, \alpha_0, \) and \( \alpha_1 \), we can predict an individual teacher’s salary at each point in time (each duration \( t \)) as \( W_i = \ln W_0 + (Z_i' \gamma' y + \alpha_0 y^2 + \alpha_1 y + \omega_1) \), where \( y \) represents the number of pay increments, or the number of different academic years the individual has been in teaching, corresponding to the duration \( t \).

To obtain individual-specific measures of (expected) starting salaries in the nonteaching sector, a (log) starting-wage equation was estimated using two different sources of wage data. First, we observed the starting wage of ex-teachers who had opted for a nonteaching job. Second, the survey included starting-wage information on all graduates whose first full-time job was outside the teaching sector. These two sources were combined to estimate the following equation:

\[
\ln W^{*}_i = Z_i' \gamma' + \alpha_1^* y + \omega_2
\]

where \( W^{*}_i \) is individual \( i \)’s starting wage in the nonteaching sector, and \( Z_i \) is a vector of individual characteristics valued in nonteaching jobs, such as educational background and work experience attained before graduating in 1980. The region’s unemployment rate was included as a measure of local labor market demand, and \( r \) is the total work experience (in months) obtained as a teacher (which is only positive for ex-teachers).

Restricting the sample to include only those individuals who had chosen for a nonteaching career (possibly after leaving a teaching job) may result in biased wage-equation parameter estimates. To correct for this sample-selection bias in the estimation of this equation, we included two different selection-bias correction terms (discussed in the supplementary appendix): one for the sample of ex-teachers, and one for the sample of graduates who had chosen an alternative career upon graduation.

The estimated starting-wage equation was used to predict each teacher’s opportunity wage at every level of teaching experience as follows: \( \hat{W}_i = W_i + Z_i^* \gamma + \alpha y + \phi \), where \( \phi \) is an estimate of the expectation \( E[\omega_2 | \text{NONTCH} = 0] \), the expected value of the disturbance term given that these individuals all (first) chose a teaching job. The two procedures described above provide us with a predicted teaching salary and opportunity wage at each potential tenure level for all teachers in the sample.

### III. Econometric Specification and Estimation

To study teacher retention and attrition, we estimate reduced-form hazard functions of a teacher’s first spell in the teaching profession. Individuals leave the teaching force for different reasons and end up in

\[ 4 \text{ It is therefore not surprising that we found the selection-bias correction term to be insignificant.} \]

\[ 5 \text{ In calculating } y, \text{ we assumed each academic year to start in September.} \]

\[ 6 \text{ In preliminary estimations of this equation, we also included } t^2. \text{ Its coefficient was found to be insignificant.} \]

\[ 7 \text{ In the estimation, the variable } t \text{ was further instrumented. The instruments used were linear, quadratic, and interaction terms of variables in } Z \text{ as well as the additional exogenous variables in the hazard function.} \]
different destination states. In this case, the observed exit time or duration \( t_i \) is characterized by a censoring indicator and an exit type indicator. In the case of \( K \) mutually exclusive and exhaustive destination states, let the random variable \( C, (C = 1, \ldots, K) \) represent the exit type. Then, at each point in time, we can describe the exit process in terms of \( K \) transition intensities defined as

\[
h^{(t)}(t) = \lim_{dt \to 0} \frac{P(t \leq T < t + dt, C = k | T \geq t)}{dt}.
\]

The total hazard rate \( h(t) \) is then the sum of all \( K \) transition intensities at time \( t \): \( h(t) = \sum_{k=1}^{K} h^{(t)}(t) \).

It is common to think of a model with multiple destinations as a model in which the transition intensities are the hazard functions of \( K \) independent destination-specific latent durations or survival times. The actual exit time and exit type can then be interpreted as realizations of random variables \( T \) and \( C \) defined as

\[
T = \min \left( T^1; k = 1, \ldots, K \right)
\]

\[
C = \arg \min_i \left( T^i; k = 1, \ldots, K \right)
\]

where each independent random variable \( T^i, k = 1, \ldots, K \), is a latent duration, representing the length of stay before an exit of type \( k \) occurs in the absence of all other types of exit risks. If only \( C \) and \( T \) are observed, this model is often referred to as an independent competing risks model. (See Lancaster (1990), section 7.5.) We will assume each of the transition intensities to be of the proportional hazard type with

\[
h^{(t)}(t) = h^{(t)}(t) \exp \left( X_i(t) \beta \right), k = 1, \ldots, K
\]

where \( h^{(t)}(t) \) is the risk-specific baseline hazard at time \( t \), \( X_i(t) \) is a vector of possibly time-dependent covariates for individual \( i \) at time \( t \) (normalized at the sample averages at time \( t = 0 \)), \( \beta \) is a vector of unknown parameters, and \( v_i^k \) is an individual and risk-specific unobserved heterogeneity component, assumed to be independently distributed from \( X_i(t) \). In our case, \( X_i(t) \) includes the predicted (logged) earnings in the teaching sector, \( \ln W_p \), and in the nonteaching sector, \( \ln W_n \), and other individual characteristics influencing exit decisions. In the manor suggested by Moffitt (1985), Meyer (1990), and Han and Hausman (1990), the baseline hazard will be estimated jointly with the parameterized observed heterogeneity component. This semiparametric estimation procedure has the advantage that it prevents inconsistent estimation of the covariate coefficients due to a misspecified baseline hazard and it simultaneously provides a nonparametric estimate of the baseline hazard function.\(^8\)

As shown by Dolton and van der Klaauw (1994), given that \( T^1 \) and \( T^2 \) are independent (conditional on the unobserved heterogeneity components), the probabilities entering the likelihood function, \( P(t_j \leq T^1 < t_i + 1, T^2 \geq t_i) \) for uncensored observations and \( P(T^1 \geq t_i, T^2 \geq t_i) \) for right-censored observations, can be calculated as products of the following univariate probabilities:

\[
P(t_j \leq T^1 < t_i + 1) = P \left[ \int_0^{t_j} h^{(1)}(u) \, du \leq \int_0^{t_i} h^{(1)}(u) \, du < \int_0^{t_i+1} h^{(1)}(u) \, du \right]
\]

\[
= P \left[ -\log \left( \int_0^{t_j} h^{(1)}(u) \exp \left( e^{X_i(t) \beta v_i^1} \right) \, du \right) < e_j \right]
\]

\[
\leq -\log \left( \int_0^{1} h^{(1)}(u) \exp \left( e^{X_i(t) \beta v_i^1} \right) \, du \right)
\]

\[
= \left[ 1 - \exp \left( -e^{X_i(t) \beta v_i^1 \gamma_j(t_j+1)} \right) \right] \exp \left( -\sum_{j=1}^{l} e^{X_i(t) \beta v_i^1 \gamma_j(s)} \right)
\]

\[
P(T^1 \geq t_i) = \exp \left( -\sum_{j=1}^{l} e^{X_i(t) \beta v_i^1 \gamma_j(s)} \right)
\]

for \( j = 1, 2 \), where \( \gamma_j(s) = \int_0^{s} h^{(1)}(u) \, du \), \( T_j \) is the uncensored latent duration, and \( e_j \) (minus the logarithm of the integrated hazard function) has conditional on \( X_i \), an extreme value distribution with distribution function \( F(e_j) = \exp \left( -\exp (-e_j) \right) \). Note that the value of \( X_i \) is assumed to be constant inside each \([s - 1, s)\) interval.

In the estimations, we will allow the risk-specific unobserved heterogeneity terms to be correlated. Therefore, even though the latent durations are independent conditional on the two heterogeneity terms \( v^1 \) and \( v^2 \), the unconditional durations could now be correlated. If we are willing to assume that each risk is of the proportional hazard type, then it was shown by Heckman and Honore (1989) and by Han and Hausman (1990) that all parameters of the model, including the joint heterogeneity distribution, are identified under regularity conditions that are satisfied in the model we estimate here.

Generalizing the Heckman-Singer approach to our competing risks model, we estimate the bivariate distribution of \( v^1 \) and \( v^2 \) as a discrete multinomial distribution with \( J \) mass points \( \mu = (\mu_1, \mu_2), j = 1, \ldots, J \), with probabilities \( P(v^1 = \mu_j, v^2 = \mu_k) = \lambda_{jk} \). Then the marginal likelihood function is

\[
L = \prod_{i=1}^{N} \sum_{j=1}^{J} \lambda_{jk} P(T^1 > t_i, T^2 > t_i)^{1-d_i}
\]

\[
\times \prod_{k=1}^{J} P(t_i \leq T^1 < t_i + 1, T^2 > T^1)^{(c_k - 2) d_i}
\]

with \( j \neq k \) and where \( d_i \) is the censoring indicator with \( d_i = 1 \) for a complete uncensored spell and \( d_i = 0 \) if the duration is right censored at \( t_i \) and the indicator function \( 1 (\cdot) = 1 \) if the argument is true, and \( 1 (\cdot) = 0 \) if not.

One of the weights \( \lambda_{jk} \) has to be normalized so that the probabilities sum up to one, and, for each risk, we impose the normalization \( \exp (\mu_{jk}) = 1, k = 1, 2 \). Concerning the estimation of \( J \), a practical approach is to estimate the model for increasing values of \( J \) until the likelihood fails to increase. Maximization of the likelihood \( L \) will be very slow.) In that case, it can be shown that \( P(t_i \leq T^1 < t_i + 1, T^2 > T^1) = 0.5 P(t_i \leq T^1 < t_i + 1, T^2 > t_i) + 0.5 P(t_i \leq T^1 < t_i + 1, T^2 \geq t_i + 1) \).
result in consistent parameter estimates, both when the regressor variables are constant over time and when they are time dependent.10

IV. Estimation Results

The estimates of the dependent competing risks models are reported in tables 1 and 2. Table 1 reports the results when we distinguish between exits to the nonteaching sector and to the nonemployment state. Table 2 reports the results when we distinguish between voluntary exits (where “exit for career reasons” was given as the reason for leaving) and exits due to involuntary and family reasons.11 Corresponding estimated baseline hazards are plotted in figures 1 and 2 for the destination-specific competing risks model and figures 3 and 4 for the reason-specific model. Taken in conjunction, these results provide a rich explanation of teacher turnover that hitherto has been disguised in single risk model estimates.

The explicit modeling of wage prospects in teaching and outside teaching yields the insight that higher opportunity wages increase the tendency among teachers to switch careers and leave the profession. Conversely, the intensity of leaving teaching for the nonemployment state and the propensity to quit teaching either voluntarily or for family reasons is solely influenced by teacher wages, not by wages in the outside option. This is not surprising, as it was not possible to estimate the model separately for male and female teachers.

To attempt to assess the robustness of the wage and “opportunity wage” results to our method of predicting wages inside and outside teaching, we also adopted a measure of the opportunity wage comparable to that used by Murnane and Olsen (1989), using average log starting wages by degree subject in the nonteaching sector based on a nationally representative sample of all graduates who graduated in 1980.13 These results are reported using average earnings by many different subjects in the second row of table 4 and by the same few subjects considered by Murnane and Olsen in the third row of table 4. For our data, it was found that, when using the Murnane and Olsen measure, the wage effects, while qualitatively similar, are much less precisely estimated. In particular, the estimated opportunity wage whether and when to quit in order to start a family.12 Such a decision is influenced by the wage she will forgo when quitting.

10 This follows from extending the analysis of Sueyoshi (1992) along the lines by Meyer (1986).
11 This grouping of exit reasons was motivated by a preliminary analysis in which we found strong similarities between involuntary exits (exists caused by the ending and nonrenewal of a contract) and exits due to family reasons. A cross-tabulation of the two different exit type distinctions is shown in table 3.
12 Because of the relatively small number of male teachers in the sample, it was not possible to estimate the model separately for male and female teachers.
13 Our measure is slightly different and actually preferable to that used by Murnane and Olsen (1989) because they in fact do not use average earnings by degree subject of graduation but by the subject the person teaches (which, of course, may not necessarily be the same).

### Table 1.—Dependent Competing Risks Model by Destination State

<table>
<thead>
<tr>
<th>Variable</th>
<th>Exit to Nonteaching Sector</th>
<th>Exit to Nonworking State</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>S.E.</td>
</tr>
<tr>
<td>TWAGE</td>
<td>-2.669</td>
<td>1.871</td>
</tr>
<tr>
<td>NTWAGE</td>
<td>5.879*</td>
<td>3.549</td>
</tr>
<tr>
<td>MALE</td>
<td>0.309</td>
<td>0.651</td>
</tr>
<tr>
<td>CERT</td>
<td>-0.544</td>
<td>1.012</td>
</tr>
<tr>
<td>BED</td>
<td>-1.326</td>
<td>0.835</td>
</tr>
<tr>
<td>DPNGCOE</td>
<td>0.318</td>
<td>0.616</td>
</tr>
<tr>
<td>ACA</td>
<td>0.506</td>
<td>1.085</td>
</tr>
<tr>
<td>NACA</td>
<td>2.702**</td>
<td>1.279</td>
</tr>
<tr>
<td>UNBJJ</td>
<td>0.068</td>
<td>0.043</td>
</tr>
<tr>
<td>SCHTYPE</td>
<td>1.124</td>
<td>0.873</td>
</tr>
<tr>
<td>RELC</td>
<td>0.767</td>
<td>0.614</td>
</tr>
<tr>
<td>SCLASS</td>
<td>0.319</td>
<td>0.231</td>
</tr>
<tr>
<td>SECONDARY</td>
<td>0.088</td>
<td>0.725</td>
</tr>
<tr>
<td>LONDON</td>
<td>-0.169</td>
<td>0.724</td>
</tr>
<tr>
<td>SCIENG</td>
<td>-0.642</td>
<td>0.781</td>
</tr>
<tr>
<td>UNEM</td>
<td>-0.081</td>
<td>0.075</td>
</tr>
<tr>
<td>exp (µ1)</td>
<td>0.000</td>
<td>-.</td>
</tr>
<tr>
<td>exp (µ2)</td>
<td>1.000</td>
<td>-.</td>
</tr>
<tr>
<td>note1</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.257**</td>
<td>0.083</td>
</tr>
<tr>
<td></td>
<td>0.375**</td>
<td>0.189</td>
</tr>
<tr>
<td></td>
<td>0.000</td>
<td>-.</td>
</tr>
<tr>
<td></td>
<td>0.368</td>
<td>-.</td>
</tr>
<tr>
<td>CORR (e¹1, e¹2)</td>
<td>0.449</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Log-Likh: -2000.01; number of spells: 923.
** Significant at the 5% level; * significant at the 10% level. No standard errors are reported for parameters of the unobserved heterogeneity distribution that were normalized or whose estimates were on the boundary of the parameter space.

### Table 2.—Dependent Competing Risks Model by Reason for Leaving

<table>
<thead>
<tr>
<th>Variable</th>
<th>Exit Voluntary</th>
<th>Exit Involuntary/ Fam. Reasons</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>S.E.</td>
</tr>
<tr>
<td>TWAGE</td>
<td>-1.456</td>
<td>1.094</td>
</tr>
<tr>
<td>NTWAGE</td>
<td>3.605**</td>
<td>1.728</td>
</tr>
<tr>
<td>MALE</td>
<td>0.481</td>
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<tr>
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<td>-0.777</td>
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</tr>
<tr>
<td>BED</td>
<td>-1.035**</td>
<td>0.474</td>
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<tr>
<td>DPNGCOE</td>
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<td>0.379</td>
</tr>
<tr>
<td>ACA</td>
<td>1.243**</td>
<td>0.377</td>
</tr>
<tr>
<td>NACA</td>
<td>2.044**</td>
<td>0.606</td>
</tr>
<tr>
<td>UNBJ1</td>
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</tr>
<tr>
<td>SCHTYPE</td>
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<td>0.439</td>
</tr>
<tr>
<td>RELC</td>
<td>0.393</td>
<td>0.362</td>
</tr>
<tr>
<td>SCLASS</td>
<td>0.241*</td>
<td>0.135</td>
</tr>
<tr>
<td>SECONDARY</td>
<td>0.076</td>
<td>0.411</td>
</tr>
<tr>
<td>LONDON</td>
<td>-0.232</td>
<td>0.376</td>
</tr>
<tr>
<td>SCIENG</td>
<td>-0.494</td>
<td>0.460</td>
</tr>
<tr>
<td>UNEM</td>
<td>-0.083*</td>
<td>0.045</td>
</tr>
<tr>
<td>exp (µ1)</td>
<td>0.000</td>
<td>-.</td>
</tr>
<tr>
<td>exp (µ2)</td>
<td>1.000</td>
<td>-.</td>
</tr>
<tr>
<td>exp (µ3)</td>
<td>0.000</td>
<td>-.</td>
</tr>
<tr>
<td>exp (µ4)</td>
<td>0.000</td>
<td>-.</td>
</tr>
<tr>
<td>λ1</td>
<td>0.239**</td>
<td>0.081</td>
</tr>
<tr>
<td>λ2</td>
<td>0.000</td>
<td>-.</td>
</tr>
<tr>
<td>λ3</td>
<td>0.000</td>
<td>-.</td>
</tr>
<tr>
<td>λ4</td>
<td>0.761</td>
<td>-.</td>
</tr>
<tr>
<td>CORR (e1², e2²)</td>
<td>1.0</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Log-Likh: -2010.55; number of spells: 923.
** Significant at the 5% level; * significant at the 10% level. No standard errors are reported for parameters of the unobserved heterogeneity distribution that were normalized or whose estimates were on the boundary of the parameter space.

### Table 3.—Cross-Tabulation Destination State versus Reason for Leaving

<table>
<thead>
<tr>
<th>Destination State</th>
<th>Reason for Leaving</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Voluntary</td>
<td>Invol./Fam.</td>
</tr>
<tr>
<td>Nonteaching sector</td>
<td>66</td>
<td>19</td>
</tr>
<tr>
<td>Nonemployment sector</td>
<td>66</td>
<td>189</td>
</tr>
<tr>
<td>Total</td>
<td>132</td>
<td>208</td>
</tr>
</tbody>
</table>
effects on the voluntary exit rate and the rate at which individuals switch careers are no longer statistically significant and vary strongly in magnitude depending on the number of different degree subjects considered.

A potential issue of concern with our predicted wage measures is that the selectivity corrections in both wage (growth) equations are inevitably conditional on error-distribution specifications and on particular exclusion restrictions. To investigate the sensitivity of our results to the inclusion of selectivity-bias corrections, we ran our baseline model with predicted wages obtained from wage equations that were not augmented with a selectivity-bias correction term. These results are reported in rows four to six of table 4. Most of the coefficient estimates remain similar to those in the baseline specification. Hence, we infer that our results are not very sensitive to the inclusion of a selection-bias correction term in the estimation of the wage (growth) equations.

A common finding of empirical work of this kind is that there are differential turnover propensities for teachers of different educational background, gender, social class, and ability. Some of this is due to differences in opportunity wages and some caused by differences in opportunity costs of working in the labor market. More precisely, those more likely to leave the labor force and to quit for family reasons are women from higher social classes and privileged schools whose real opportunity cost of having children is lower. Clearly, we see that those with an education degree (BED) (which is of lower value in careers outside teaching) are less likely to quit teaching and to leave for a nonteaching job. Those with professional postgraduate degrees, on the other hand, are more likely to leave teaching, irrespective of destination or reason. Another factor supported by the data is that those who initially entered the profession reluctantly (those who reported that they accepted their first teaching job because they could not find other employment) are more likely to exit involuntarily or for family reasons and to exit to the nonemployment state.

Looking at the coefficients relating to the joint distribution of the unobserved heterogeneity components, we have only weak evidence of its presence and of a significant correlation among risks. This is confirmed by estimating the same model with a flexible baseline hazard without unobserved heterogeneity. For both models, a likelihood ratio test suggests we can reject the joint presence of these effects. Further specification testing was performed by estimating the same model with a Weibull baseline hazard instead of a flexible baseline. For this parametric baseline specification, we cannot reject the presence of unobserved heterogeneity and in both models find the

14 Note that the estimates indicate that the unmeasured heterogeneity distribution can be best described by a two-point distribution of the mover-stayer type, with some teachers predicted to remain in teaching with probability one. In both cases, we could not reject the hypothesis that, conditional on the presence of unobserved heterogeneity in both hazards, the correlation between them was zero.
two heterogeneity terms to be positively significantly correlated. However, further analysis shows that this result is most likely due to the misspecification of the underlying baseline as Weibull. This can be seen from figures 1 to 4 which plot the flexible baseline hazard estimates for each risk.

The figures reveal that many exits occur at twelve-month intervals at tenure levels corresponding to the end of each academic year. Clearly, this is the result of the convention that teaching contracts most commonly end at the end of an academic year and that this is the time most appropriate for people to resign. Often, there are also two smaller peaks at the twelve-month tenure intervals, but they appear in this plot to be rising over time with evidence of clearer positive duration dependence. This is consistent with the main group being modeled here which are women choosing to leave teaching to have a family.

Looking more closely at figure 3, we see that voluntary exits, like exits to the nonemployment state, occur with the highest probability at 12, 24, and 36 months, but otherwise do not seem to have a clear time trend. Figure 4, graphing the underlying baseline hazard for the involuntary/family reasons exit, exhibits the same spikes at yearly intervals, but they appear in this plot to be rising over time with evidence of clearer positive duration dependence. This is consistent with the main group being modeled here which are women choosing to leave teaching to have a family.

V. Conclusion

The economic policy implications of our econometric estimation results should not be understated, although they cannot be described in detail here. Most obvious are the results that point to the importance of the wage and relative foregone earnings in turnover decisions. These results suggest at the most simplistic level that the higher the opportunity wage outside teaching the more likely teachers are to leave teaching for an alternative career. In addition, the higher the wage in teaching the less likely the teacher is to quit a teaching job for career or family reasons. Our results imply a clear link between relative wages and teacher turnover. Such a relationship has an important policy dimension for efficient educational staffing.

Notes:
1 Average log-starting wages in the nonteaching sector by degree-subject categories: biological sciences, mathematical sciences, physical sciences, and all other subjects pooled together.
2 Average log-starting wages in the nonteaching sector by degree-subject categories: biological sciences, mathematical sciences, physical sciences, and all other subjects pooled together.

15 Ridder (1987) and Dolton and van der Klaauw (1995) reported a similar finding for the single risk model of significant unobserved heterogeneity when a restrictive baseline hazard is used and insignificant heterogeneity (and negligible omitted heterogeneity biases in the estimated covariate coefficients) when a sufficiently flexible baseline hazard is adopted. Sueyoshi (1992), on the other hand, in a Monte Carlo simulation study, found serious biases in the estimated coefficients of explanatory variables when the bivariate heterogeneity distribution in a competing risks model with nonparametric baseline hazards was misspecified. Although biased, the estimated coefficients did accurately capture the qualitative effects of these variables.

16 Fitting a Weibull hazard \( h(t) = \alpha t^{\beta - 1} e^{-\alpha t} \), we get \( \alpha = 1.649 \) (standard error 0.407), implying positive duration dependence, but this is consistent with our view that such a model is misspecified.

17 An alternative explanation for the (initially) increasing baseline hazards in the figures would be that individuals learn during the first few years in teaching about the quality of their match, that is, their compatibility with teaching, as in Jovanovic (1979).
The problem of educational administrators is to devise a tenure-wage profile that retains the right numbers of staff of the appropriate experience and qualifications. Clearly, a school needs a balance of senior and junior teachers in order to effectively discharge all their duties. If earnings were, relatively speaking, too low at the bottom end of the career structure, then one would expect very few junior staff to be employed. This may have important adverse short-term consequences. However, in the long run, it will mean that the school would employ no senior qualified staff. Therefore, what is needed is a wage profile in the career that induces the right number of people to stay in the job. Our results are a small step towards a greater understanding of this process.

Another area in which our results could have important implications is in the appropriate treatment of women teachers. Many women teachers will leave their teaching job, not necessarily to change occupation, but to leave the labor force temporarily for family reasons. A careful study of these decisions is of vital importance in the recruitment, training, and retention decisions of educational administrators.

An important contribution of this paper has been to confirm the earlier finding by Murnane and Olsen (1989) of a positive effect of “opportunity wages” on teacher attrition in the UK. Using similar opportunity-wage measures as those in their paper, our estimates provided only weak support for their results. While qualitatively similar, the specific wage effects were found to be imprecisely estimated and quite sensitive to small changes in the definition of their wage measure. Using our more disaggregated, individual-specific measure of opportunity wages, we obtained more-precise and more-conclusive estimates that affirm the importance of opportunity wages and teacher salaries on teacher attrition in the UK.

The econometric methodology used in this paper could also have important implications for applied work in other fields. Our results illustrate the importance of distinguishing between different types of exit risks and suggest the overriding importance of using a flexible baseline hazard to model the tenure/contract structure in teaching. With a flexible specification of the baseline hazards, the dynamic selection bias caused by the presence of omitted unobserved heterogeneity was found to be negligible in our analysis. It is an interesting topic for future research to study whether this finding holds for other applications as well.

REFERENCES


DATA APPENDIX

The survey of 1980 UK graduates was carried out by the Department of Employment. The respondents were sampled once at the beginning of 1987 and asked detailed questions about the nature of their degree, periods of training and further education, qualifications undertaken at the postgraduate level, and jobs and spells of unemployment, as well as information about social and family background. There are 3,978 male and 3,163 female graduates in our original sample. This sample size is reduced by omitting individuals from the sample who did not respond to key questions relating to earnings, occupational choices, or other variables used in the econometric investigation. The usable sample was 6,098 of whom 3,484 were men and 2,614 were women. In this sample, 923 individuals were school teachers in their first job. This appendix gives a definition of the variables used in the analysis. A detailed description of the data along with summary statistics are in a supplementary appendix available from the authors on request.

Variable Definitions

TWAGE: predicted value of the teacher’s log-salary, ln \( \hat{W}_t \) (computed as detailed in the text). All salary information used in our analysis has been indexed with April, 1976, as base year.

NTWAGE: predicted value of the teacher’s log-starting salary in the nonteaching sector, ln \( \hat{W}_t \) (computed as detailed in the text).

SCHTYPE: 1 if the respondent attended an independent school, 0 otherwise.

SCLASS: an ordinal variable for the social class of parents by their occupation: 6 for professional occupation, 5 for an intermediate, 4 for a skilled (nonmanual), 3 for a skilled (manual), 2 for a partly skilled, and 1 for unskilled.

MALE: 1 if the respondent is male and 0 if female.

UNBRI: The number of months unemployed following graduation prior to first job.

NACA: 1 if respondent has professional qualification, 0 if not.

ACA: 1 if the respondent has a master’s or a Ph.D. degree, 0 if not.

LONDON: 1 if respondent’s region of employment was greater London, 0 elsewhere.

SECONDARY: 1 if the respondent was a secondary-school teacher, 0 otherwise.

CERT: A dummy variable taking the value 1 if the teacher had received a (nondegree) certificate of education, 0 if not.

BED: 1 if the teacher had a bachelor’s degree in education, 0 if not.
INSTRUMENT RELEVANCE IN MULTIVARIATE LINEAR MODELS

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Abstract—A measure of the relevancy of instruments used to estimate the coefficients of a linear multiple regression model is discussed. A method for computing the measure using only standard results from ordinary least squares and two-stage least squares estimation is described. The method is illustrated using an empirical example.

I. Introduction

In a recent paper, Shea (1997) discussed the measurement of instrument relevance in the context of the estimation of multiple regression models. He proposes that a partial $R^2$ measure, denoted by $R^2_p$, be calculated. Unfortunately, one of the formulae given by Shea is capable of misinterpretation and might lead to the incorrect calculation of sample values of $R^2_p$ in applied work. The purpose of this note is to provide clarification and a simple alternative to the four-step method for the computation of $R^2_p$ suggested by Shea (1997, p. 349).

Section II contains details of notation, and section III contains results on the calculation of sample measures of instrument relevance. An empirical example is given in section IV. Concluding remarks are made in section V.

II. Model and Measure of Instrument Relevance

The linear model to be estimated is written as

$$y = X\beta + \epsilon,$$

in which $y$ and $\epsilon$ are $T \times 1$ vectors, and $X$ is a $T \times k$ matrix. The $T$ elements of $\epsilon$ are independently and identically distributed with zero mean and variance $\sigma^2$. When one or more of the regressors of equation (1) is asymptotically correlated with the error term, ordinary least

* Significant at the 5% level.

† DURAT was instrumented.

Notes: Number of nonmissing starting wage observations: 5248 Adj. $R^2$: 0.174.
* Significant at the 5% level.

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