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THE TURNOVER OF UK TEACHERS: A COMPETING RISKS ANALYSIS

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The Turnover of UK Teachers : A Competing Risks Analysis[1]

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ABSTRACT

Persistent shortages of qualified school teachers in the UK continue to generate concern among policy makers and the media. The extent to which these market problems are due to the lack of retention associated with poor relative earnings rather than the lack of recruitment of qualified teachers is one of considerable importance. In this paper we study turnover decisions of teachers and show that increases in teacher salaries can be used to induce qualified teachers to remain longer in the profession.

The econometric modelling approach adopted in this paper is shown to yield important insights into the appropriateness of adopting a flexible, semi-parametric specification of the duration dependence structure and of the unobserved heterogeneity distribution in duration models. Moreover, the estimates exemplify the insight gained from distinguishing between multiple destinations or exit types.

(J.E.L. Fields: J45, J63, C41, I21)

1. Introduction

Concern about the supply of teachers continues to generate considerable interest in the UK. This interest is not confined to educationalists and policy makers, as it has been the subject of public debate and media attention. Government and politicans have berated teacher quality and professionalism whilst at the same time seemed surprised by recruitment and retention difficulties. Teachers themselves have expressed increasing dissatisfaction with their conditions of work and this has led to pay disputes, some of which have been accompanied by industrial action which in turn have culminated in many teachers leaving the profession and potential teachers not being recruited in the first place.

For most of the post-war period up to the early 1970s the demand for teachers in the UK exceeded the available supply. Since then a sharp fall in the number of pupils in schools has led to a small excess supply of teachers. However, shortages of skilled teachers continue to exist in certain subject areas, primarily in mathematics, physics and the sciences, and in certain geographic regions of the country, most markedly in the Greater London area. In addition, teaching appears to fail increasingly in attracting and retaining the academically most able college graduates, reinforcing the general view of the teaching profession as a low-status, low-saraly occupation only chosen by those with no better options. The corresponding concern about a perceived fall in the overall quality of the teaching force has increased interest in policies aimed not only at attracting promising college graduates to the profession, but also at retaining the most effective current teachers.

Low teacher salaries are often cited as the main cause of teacher shortages. Since the mid 1960s the teaching profession in the UK has sustained a considerable decline in relative earnings. Although the average real earnings of teachers has been rising over nearly the whole post-war period, when compared to all workers and non-manual workers over the 1965-1988 period, their relative salaries have fallen. With the exception of a couple of sharp pay raises in 1974/75 and 1980/81 (after the Houghton Report and Clegg Commission respectively) teachers' pay has been restricted, both in terms of starting salaries and increment scales. As a result, teachers' relative pay (compared to the non-manual earnings index) was some 10-13 percent lower in the 1980s than in the 1960s[1].

This decline in relative earnings, combined with a fall in the demand for teachers, has led to a steady decline in the proportion of university graduates who choose teaching as a

[1] Full details of teacher relative salaries and their movement over time are provided in Bee and Dolton (1994).

career[2] and a doubling since 1960 of the the proportion of teachers leaving the profession within the first six years of teaching to 37 percent in 1980. The resulting shortage in teachers has serious short and long term policy implications, not least of which is the threat of deleterious effects on the quality of recruitment and retention in teaching, and the consequences for the standards of education in the UK.

The existence and persistence of teacher shortages is closely related to the organizational structure of the teacher market and in particular to the structure of teacher salary schedules. The market for teachers in the UK is unlike most conventional labor markets in the sense that the public sector is a near monopolistic supplier of education and a near monopsonistic buyer of teacher services. The government dominates the demand for teachers and is directly responsible for the supply of trained teachers. Hence both the supply and demand for teachers is politically manipulable. Since the government sets guidelines for pupil/teacher ratios and maximum class sizes, and determines the size and funding of teacher training courses it has direct control over most of the major determinants of teacher supply and demand. More overtly, since the government decides on the overall level of public expenditures as well as the average level of teacher salaries, it has a pervasive influence over the market. One additional complication for the analysis of demand is that uses of these instruments under the control of the government are usually determined in isolation from each other and are subject to different pressures.

There are also factors, largely outside the control of the government that are important elements in a complex problem. The first, on the demand side, is the demographic changes in the birth rate and its regional geographical variation. To a large degree the government should be able to predict these changes but it has only limited influence over them. Large changes in this rate or its geographical disparities could cause wild swings in the demand for teachers. The second, on the supply side, is the changes in the other labor markets that attract potential teachers away from the profession. The government has only limited control over the relative pay and conditions in the other (private sector) occupations and therefore may exercise only indirect influence on the recruitment, retention and wastage of teachers.

While in the US teacher salary scales are set locally by each school district, in the UK

[2] In 1960, 50 percent of UK women graduates entered teaching on graduation. This figure declined to 32 percent in 1970 and 23 percent in 1980. The same pattern was observed for male graduates. In 1960, 21 percent of them entered teaching on graduation, by 1970 this had fallen to 12 percent and by 1980 to 6 percent.

uniform salary scales are set by the government (in negotiations with teacher unions) and apply throughout the country, leaving local authorities only limited control over individual teachers' salaries. The existence of a uniform salary structure could create imbalances within the teaching profession if differences among teachers were valued differently in external markets. While salary schedules are fixed for all teachers of a particular grade or post (eg. headteacher) with a particular level of qualification and experience, local authorities have some flexibility in appointing and promoting teachers to higher posts. There is some evidence that teachers in shortage subjects, skills and areas are in fact paid more than others with the same experience and qualifications, but the difference are very small (see Zabalza, 1979; and Dolton, 1990).

The relative insensitivity of teachers' compensation to differences in the alternative options available to them explains the difficulty in hiring and retaining teachers in the mathematics and science fields because college graduates trained in these subjects can command much higher salaries in business and industry. A similar argument can be made to explain shortages in the Greater London area as well as problems in attracting and retaining the academically most able.

The problems of teacher supply have been studied by many researchers over the years. In the UK Thomas and Deaton (1977), Zabalza (1979), Zabalza, Turnbull and Williams (1979), Blackstone and Crispin (1982), Dolton (1990) and Dolton and Makepeace (1993) were all concerned with the problems of teacher supply in the modern era of "shortage", while studies such as those by Zarkin (1985) and Manski (1987) considered the supply and market for teachers in the US. Little attention has been devoted to the issue of turnover in this work. The extent to which the market problems are due to the lack of retention rather than the lack of recruitment of qualified teachers is one of considerable importance. Over the last forty years teaching when compared to other occupations has had one of the highest retention rates of women, especially women with children, while the opposite has been true for men. For both groups, however, the exit rate out of teaching has increased and has been especially high among graduates with degree subjects and qualifications that are more highly rewarded in other professions as well as in certain geographic regions such as the Greater London area.

In this paper we focus on the issue of teacher retention and turnover. Exactly what influences a teacher's propensity to leave teaching for a different career or for a non-labor market alternative? The extent to which relative earnings may influence this turnover is of considerable importance and constitutes the primary issue in this research. A better understanding of teacher turnover can help in identifying and evaluating policies and conditions that are effective in retaining the most able teachers as well as teachers in shortage subjects and geographic areas. It would also help educational authorities improve their predictions of future teacher attrition, which in turn will lead to better forecasts of teacher demand. These forecasts are important in determining the number of new trainees to admit to teacher training programs. Given the rising costs of teacher training, it has become increasingly important to learn learn which (future) teachers are most likely to leave teaching.

Research on teacher turnover has mainly been confined to studies of teachers in the US. Most notably the work of Murnane and Olsen (1989, 1990) and Murnane et al. (1989), has explicitly modelled the effects of salaries and opportunity costs on the length of stay in teaching for teachers in North Carolina and Michigan. As measures of "opportunity costs" 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 costs of staying in teaching are however likely to depend on many other individual characteristics, and average salaries in the non-teaching sector may be a poor proxy of average potential salaries of ex-teachers in that sector. We will use individual wage data on teachers to estimate teachers' earnings-tenure profiles and data on starting wages in the non-teaching sector (including data on ex-teachers who entered this sector) to estimate individual specific opportunity wages, which we include as time-varying covariates in our empirical model.

A second shortcoming of existing studies is that they do not distinguish between the different destinations and reasons for leaving teaching. This distinction is important because salaries and opportunity wages are likely to have an effect on the propensity of leaving for a non-teaching job different from that on the propensity to stop working altogether. The latter is particularly common for female teachers, who represent a majority of teachers, and differentiating by type of exit permits a more informative analysis of the importance of earnings and other characteristics on teacher attrition and on the decision to leave the labor force. As re-entry rates into teaching from the different destination states differ substantially, in studying teacher attrition we should perhaps be most concerned with exits to destinations with the lowest re-entry rates. In addition, we will study exits by reason for leaving, distinguishing between voluntary exits and exits that are either involuntary or because of family or health reasons.

This study provides a new perspective on these aspects of teacher attrition in the UK by analyzing the early careers of a national sample of 1980 UK graduates who chose to become full time primary or secondary school teachers in their first job. Given that teacher exit rates are highest for teachers at the beginning of their careers, this sample is ideally suited for a study of teacher attrition.

To characterize teacher turnover behavior, this study employs proportional hazard models that relate the propensity to leave teaching to a number of individual and job specific characteristics, such as the individual's (potential) wage earnings in the teaching and non-teaching sector, 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 allow for the time-varying nature of various covariates. In addition, and perhaps most importantly of all, we explore empirically the different reasons for leaving the teaching profession in a competing risks framework, similar to that proposed by Han and Hausman (1990), which also allows for unobserved heterogeneity. Our results affirm the importance of teacher salaries and foregone earnings in the tenure and turnover decisions of teachers in the UK and exemplify the insight gained from distinguishing between different destinations or exit types. Our approach is shown to yield important insights into the appropriateness of adopting a flexible specification of the duration dependence structure and the sensitivity of covariate coefficient estimates to the inclusion and specification of unobserved heterogeneity distributions in duration models.

The next section of the paper briefly sets out the theoretical modelling context for the turnover decision. This is followed, in section three, by a description of the data to be used in the study. In that section we also discuss the estimation of the tenure-wage profile of teachers and their opportunity wages. Section four of this paper deals with the econometric specification and estimation of the model. The estimation results are presented in section five and section six outlines some qualifications of these results and their implications for policy programs aimed at reducing teacher attrition rates through salary increments.

2. A Simple Model of Teacher Turnover

To characterize teacher turnover we adopt a dynamic random utility model similar to that proposed by Flinn and Heckman (1982) and by Burdett et al. (1984) to study worker mobility patterns. At each moment an individual occupies one of three possible states: (1) employment in the teaching sector, (2) employment in the non-teaching sector or (3) the non-employment state, which includes the unemployment and out of labor force states. Let u_{ijt} denote the utility flow of individual i corresponding to state j, $j = 1, 2, 3$, at time t, with

$$\begin{aligned} u_{i1t} &= U(W_{it}, B_{it}) \\ u_{i2t} &= U(W^*_{it}, B^*_{it}) \\ u_{i3t} &= 0 \end{aligned} \quad [1]$$

Utility derived when employed in the teaching sector depends on the individual's earnings as teacher, W_{it}, and on nonpecuniary benefits B_{it}[3]. Similarly, when employed in the non-teaching sector, utility depends on W^*_{it} and B^*_{it}, the individual's earnings and non-monetary rewards in the non-teaching sector. Finally, when not employed utility is normalized to zero so that both utility levels u_{i1t} and u_{i2t} should be seen as relative to utility obtained in the non-employment state.

Because nonpecuniary benefits are not reported in our data set, we substitute into the utility functions the implicit nonpecuniary returns equations, which describe the nonpecuniary payoff in both sectors as functions of individual specific (possibly time-varying) characteristics Z_{it}. After decomposing the resulting utility functions into a stochastic and a predictable non-stochastic part, we specify

$$\begin{aligned} u_{i1t} &= \bar{U}_1(\hat{W}_{it}, Z_{it}) + e_{i1t} \\ u_{i2t} &= \bar{U}_2(\hat{W}^*_{it}, Z_{it}) + e_{i2t} \end{aligned} \quad [2]$$

where the e_{ijt} are i.i.d. random variables and $\hat{W}_{it}$ and $\hat{W}^*_{it}$ represent individual's i expected wage earnings in both sectors at time t.

Consider a utility maximizing individual i who upon graduation at time 0 has just started a teaching job. For this individual we know that $u_{i10} > max(u_{i20}, u_{i30})$. At random time intervals new information arrives or events occur which are represented by new realizations of the random utility components (e_{i1t}, e_{i2t}). These events are assumed to arrive with instantaneous arrival rate $\lambda_i(t)$. New realizations of these error terms could represent new values of both wage and nonpecuniary benefits associated with new job

[3] The nonpecuniary benefits include working conditions, prestige, job security, working hours, holidays and its complimentarity with family responsibilities.

offers in either the teaching or non-teaching sector, as well as new information about the environment or characteristics of the non-employment state, such as a change in the employment status of a spouse, the birth of a child or other changes in household composition. The end of an employment contract is another example of an event. It is important to note that the described information arrival process does not imply that a person needs to be searching for job offers all the time nor does it require that each choice alternative is always feasible or available. An absence of wage offers and the occurence of layoffs, for example, can be interpreted as very low draws of e_{i2t} and e_{i1t} respectively, or in the first case by an arrival rate close to zero.

Each time an event occurs or information arrives, the individual will reconsider his or her choice decision and will choose the alternative that maximizes utility, possibly resulting in a change of the choice or the state occupied. Conditional on an event occurring, the individual chooses among the three alternatives with probabilities $P_{ij}(t)$, $j = 1, 2, 3$. When the e_{ijt} are i.i.d. serially uncorrelated extreme value random variables, for example, these discrete choice probabilities at time t are of the multinomial logit type (McFadden, 1973).

In this framework exits could occur because of the following reasons. First, the non-stochastic utility components are time-dependent so that at the time of the next event it may be optimal for the individual to leave the teaching profession. The time or duration dependence might reflect a dependence of pecuniary or nonpecuniary returns in both sectors on the time spent in the teaching sector, i.e., the total tenure as teacher. Experience accumulated in teaching could ease transitions to jobs in which such experience will be highly rewarded. Mobility for these reasons occurs to other jobs in the education field, such as teaching in further or higher education, central or local government educational administration and jobs in the human service occupations such as social work, psychology and law. It is also possible that over time the utility obtained when staying at home (i.e., of leaving the labor force), may increase or alternatively the disutility of working may increase and eventually dominate the utility associated with working in either sector.

Second, there are several sources of uncertainty that could account for teacher turnover. Over time, attractive offers of jobs outside the teaching sector, represented by large realizations of e_{i2} may arrive which provide greater utility than the current teaching job. In addition, life cycle events such as marriage, the births of children, migration and retirement are all strong influences on teacher attrition. The employment status and career decisions of the spouse are also important. These events may reduce the utility of working relative to that of leaving the labor force. These events are represented by low draws of both e's. New realizations of teacher salaries and changes in the current working conditions and perceived nonpecuniary benefits could also make it optimal for the teacher to quit.

Another type of event may be a dismissal or layoff from the current teaching job or the end of a fixed term employment contract. All teachers in the UK face a period of at least one year's probation after which they may either be confirmed or not confirmed in their appointment. Some teachers are only appointed to fixed-term temporary contracts and are often compelled to leave when financial or school conditions dictate unavailability of a permanent job for them. Such temporary contracts are often occasioned by maternity leave of other teachers and usually last for only one or two terms. In rare circumstances teachers may be fired or transferred to other duties within a local education authority. If no other teaching job offer is available at the time, the resulting "choice" will imply an exit out of teaching.

Of course, some individuals are more sensitive to new information than others. If the teaching option strongly dominated the alternative options, it is less likely that new information will lead to a career change. If, on the other hand, the individual started the teaching job only because at the time no other jobs in the non-teaching sector were available, or if the individual was indifferent between working or staying at home, then the probability that new information could lead to an exit will be greater. Thus teachers who accept their first teaching job reluctantly will on average be more sensitive to new information that others. Some individuals may also be more or less likely to be fired/dismissed than others. This selection process, where individuals least committed to a teaching career are most likely to leave, primarily takes place within the first few years in teaching.

Comparing different types of teachers, teachers with better options and higher expected earnings outside teaching will, all else equal, be more likely to leave teaching than others. These teachers are more likely, on average, to have had atypically high and unrealistic expectations about the nonpecuniary benefits in teaching, and are more likely to have received atypically low offers outside teaching when the initial decision to enter teaching was made (see Murnane and Olsen, 1990). When new job offers outside teaching arrive, or when the teaching job was not what they had expected it to be, these teachers are more inclined to accept a job in the non-teaching sector.

With regard to a teacher's educational background, teachers whose training was directly oriented towards teaching are likely to have, relatively speaking, higher productivity in teaching than outside teaching, and the relative wages they will be able to obtain in teaching compared to other professions will be greater than for those with a more general training. We therefore expect those with a Bachelor's degree in education to be less likely to leave teaching than teachers with a mathematics or other science degree, whose background and skills are more easily transferred to other, possibly better-paying jobs, in other professions. Individuals who pursued a professional postgraduate qualification before starting their teaching job, on the other hand, are expected to be more mobile and susceptible to non-teaching job offers than others. The possession of such qualifications indicates that the individual has some preference for or interest in a professional non-teaching career, or better job opportunities in the non-teaching sector than individuals with a more teacher-specific educational background.

In studying a teacher's first exit out of teaching, we consider the two transition intensities corresponding to exits from teaching into non-teaching, denoted by $\lambda_{i2}(t)$, and from teaching to non-employment, $\lambda_{i3}(t)$. In the simple model described above, these transition intensities equal

$$\lambda_{ij}(t) = \hat{\lambda}_i(t) \cdot P_{ij}(t) \qquad j = 2, 3.$$

The corresponding hazard function for this exit process is then

$$h_i(t) = \lambda_{i2}(t) + \lambda_{i3}(t)$$

Duration dependence in the hazard rate and transition intensities reflects both the dependence of the arrival rate on tenure, i.e., on the length of time in teaching, as well as duration dependence in the choice probabilities.

In the empirical analysis in section 4 we will estimate reduced form versions of both the transition intensities $\lambda_{i2}(t)$ and $\lambda_{i3}(t)$ and of the hazard rate $h_i(t)$ as functions of $\hat{W}_{it}$, $\hat{W}^*_{it}$ and a number of individual characteristics measuring differences in preferences and in the nonpecuniary rewards received in each sector. It is important to note that these reduced form specifications are also consistent with an alternative version of this model in which agents are not assumed to be myopic. In a model with forward looking agents, current choices and transition rates will depend not only on current wages and tenure, but also on expected future wages in both sectors. The reduced form specification we will estimate will be consistent with such a model if current wages are sufficient statistics for uncertain future wages. This is, for example, the case if wages follow a first order Markov process[4].

[4] Attempts to include wage growth measures for both sectors failed because of the strong cor-

3. The Data Set

The data analysed in this study were obtained from a UK survey undertaken in 1987. The survey covered one out of every six individuals who graduated from universities and other institutions of higher education in 1980 and provides information about the 1980-1987 period in their early career. There are 3978 male and 3163 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 contains 6098 graduates of whom 3484 were men and 2614 were women. In this sample 923 individuals were full-time school teachers in their first job.

A full description of the survey is contained in Dolton and Makepeace (1992). The variables used in this study can be grouped into: i) social and personal variables; including the social class of the parents as measured by their occupations and gender; ii) educational variables; type of teacher training and education obtained, degree class (a measure related to GPA rank), postgraduate qualifications; iii) work and wage information; the complete work and unemployment history from 1980 to 1987, including, for each job held: sector and type of employment, occupation, starting salary and regional location of job.

One advantage of using this data set is that it contains a relatively large national sample of a cohort of teachers whose complete early teaching careers were observed even when it involved switching between teaching jobs and migration to other parts of the country. A second attractive 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 the information on teacher salaries to predict the experience-earnings profile for each teacher in the sample and use data on starting wages for those who entered the nonteaching sector to predict each teacher's opportunity wage at each level of teaching experience.

A drawback of the survey is that it only covers the early work history of graduates. Observing individuals for six and a half year in the labor force at a maximum, implied that our analysis of teacher attrition had to be restricted to the first exit out of teaching. For almost all cases where more than one spell in teaching was observed, the second spell had only just started by the time of the 1987 interview and contains therefore little information about subsequent decisions to leave teaching. Of those who left teaching

relation between these measures and current wages. This finding confirms the expectations of encountering such problems raised by Heckman and Walker (1990).

within the observation period, about 43 percent had returned to teaching before the 1987 interview date. However, only 8 percent of these teachers returned from a non-teaching job, while all others returned from a temporary departure from the labor force. This finding provides support for our position that analysis of job exit behavior requires the incorporation of information on destination and exit types. In the evaluation of alternative policies aimed at reducing teacher attrition it will be useful to evaluate their effectiveness both in retaining teachers who might have permanently switched careers and in retaining those teachers who are likely to have left the teaching force only temporarily.

Variable means for the total sample of 923 teachers are reported in the first column of Table 1. Of the 923 corresponding spells in teaching, 340 (37 percent) ended with exit from teaching with all other spells right censored (CENSOR) at the survey date in 1987. 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), had no postgraduate qualifications (ACA=0, NACA=0) and experienced about 3 months of unemployment (UNBJ1) before accepting the teaching job.

Of all teachers 71.5 percent are female, 7.5 percent obtained a certificate of education (CERT), 41 percent have a Bachelor's in education (BED) degree and 38 percent a postgraduate certificate of education (DPGCOE). Thus, of a total of 923 teachers, 124 (13 percent) have no teaching qualifications, i.e., neither a Bachelor's in education, nor a postgraduate teaching certificate nor a nondegree teaching certificate. Secondary school teachers (SECONDARY) outnumber primary school teachers 83.5 percent to 16.5 percent. Further, 6 percent of teachers obtained a postgraduate academic qualification (ACA) while 4 percent received a nonacademic professional qualification (NACA). Almost 10 percent of the teachers in our sample reported that they had started their first job rather reluctantly (RELC), mainly because they could not find anything better or more suitable at the time, and 13 percent taught in the Greater London area (LONDON).

In columns 2 and 3 those who were still teaching in 1987 are compared to those who had left teaching sometime before 1987. On average, male teachers, teachers with a Bachelor's degree in education, with high starting salaries (SWAGE) and teachers who started their first jobs in regions with relatively high unemployment rates (UNEM(1)) are more likely to continue teaching. Movers are more likely to be teachers with postgraduate academic or nonacademic qualifications, graduates with a university degree, teachers who went to an independent high school, who live in the Greater London area and those belonging to a higher social class (SCLASS)[5]. Movers are also more likely to have started in their first teaching job reluctantly.

Table 1 also gives variable means by type of exit: distinguishing between those who left teaching for a non-teaching job and those who left for the non-employment state. In total, 25 percent of those who exit from teaching leave for a non-teaching job with all others leaving employment altogether. In our sample 22 percent of the teachers who left for a non-teaching job found other employment in the education sector (as university teacher or in administration), 31 percent found work in the legal, welfare and health sectors or found jobs as social scientists, 14 percent found jobs in business or management and 7 percent were employed as engineers or technicians.

Comparing these two types of movers, we find that those leaving for a non-teaching job are more likely to be male, less likely to have a Bachelor's degree in education and more likely to have a postgraduate certificate of education or postgraduate academic qualifications than those who stop working. They also have higher average degree levels (DEGCLASS, ranked from 8 (first degree) to 2 (pass) and 1 for nondegree holders), are more likely to have gone to an independent secondary school, live in the Greater London area and have more pre-1980 work experience (PRE80EXP). Teachers who were awarded a degree by a university rather than a polytechnic, those with a degree in one of the sciences or engineering (SCIENG) and those living in regions with high average unemployment rates were also more likely to change careers instead of leaving the work force.

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 discuss in some detail the construction and measurement of these wage variables. First, we know for each teacher in our sample, his or her starting salary. Further, for teachers who have not left the profession by 1987, the "stayers", we observe the salary earned in 1987 (FWAGE in Table 1). 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. In particular, using the data on "stayers" we estimated the following growth-in-earnings equation:

$$\frac{(lnW_{it} - lnW_{i0})}{t} = Z'_{i0}\gamma_1 + \alpha_{10}t + \alpha_{11}t^2 + \sigma_1 S_{i1} + \omega_{i1}$$

[5] SCLASS is measured by the parents' occupation, ranked 1 to 6 with 6 representing professional occupations and 1 representing unskilled occupations.

where lnW_{it} and lnW_{i0} 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 ω_{i1} is an i.i.d. error term. A selection bias correction term, S_{i1}, was included to account for the fact that teachers who stayed in teaching are a self-selected subsample of teachers, with on average either greater wage growth or fewer opportunities in the non-teaching and non-employment sectors[6].

The vector of individual characteristics Z_{i0} includes several measures of human capital which may affect 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 t allow for a variety of nonlinear earnings-tenure profiles.

Given estimates of γ_1, α_{10} and α_{11}, we then predicted an individual teacher's salary at each point in time as: $ln\hat{W}_{it} = lnW_{i0} + (Z'_{i0}\hat{\gamma}_1) \cdot t + \hat{\alpha}_{10}t^2 + \hat{\alpha}_{11}t^3$. As mentioned earlier, teachers' annual salaries in the UK during the period of consideration were largely predetermined and followed fixed pay schedules negotiated by teacher unions, leaving local education authorities only some limited control over teacher salaries. The teacher earnings-tenure profiles estimated here can be interpreted as an estimate or approximation of these wage schedules. On an aggregate level these teacher wage profiles can be considered as fixed. On an individual level however, actual earnings growth can still be partly endogenous because teachers can increase their salaries through promotions and teaching job switches.

Estimates of the growth equation are reported in Table 2. Teachers with a higher degree class, with a postgraduate academic degree, with previous (pre-1980) work experience and those who graduated from a university experience greater salary growth. Note that because DEGCLASS has a value of zero for teachers with a certificate of education, they actually make less on average than teachers with a Bachelor's degree, whose average degree class index equals 4.6. Compared to female teachers, salaries of male teachers grow at a faster rate. Given the highly regulated wage structures in teaching in which the gender of the teacher is irrelevant, this finding is perhaps somewhat surprising. It is however consistent with the empirically established fact that male teachers have, on average, a greater probability of promotion and the fact that they are on average more mobile than female teachers and therefore more likely to react to better paying teaching jobs elsewhere.

[6] Heckman (1979)'s two stage procedure was used to correct for selection bias. In the first stage a Probit equation was estimated with the censoring indicator as dependent variable, which included as one of the explanatory variables the 'time of exposure', i.e., the length of time since starting the teaching job until 1987 (TIME). The inverse Mill's ratio, S_{i1}, was then calculated as usual. The Probit estimates are reported in Table A1 of the appendix.

Faster wage growth is also experienced by teachers who work in the Greater London area and in regions with relatively low unemployment rates. Further, the greater the starting salary, the lower the rate of growth.

The growth rate initially increases with tenure, but then decreases[7]. This gives rise to the usual concave earnings-tenure profile shown in Figure 1. The figure shows the average predicted log earnings profile for the total sample of teachers as well as those for all male and female teachers separately. Even though female teachers and male teachers have similar starting salaries in the teaching sector, male teachers experience greater earnings growth over time. The difference in wage growth becomes apparent after the first two years in teaching, after which it consistently continues to increase.

To obtain individual specific measures of (expected) starting salaries in the non-teaching sector, a (log) starting wage equation was estimated using two different sources of wage data[8]. First, we observed the starting wages of ex-teachers who had opted for a non-teaching 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 starting wage equation:

$$LnW^*{}_{it} = Z^{*\prime}_{it}\gamma_2 + \alpha_2 t + \sigma_2 S_{i2} + \sigma_3 S_{i3} + \omega_{i2}$$

where Z^*_{it} is a vector of individual characteristics valued in non-teaching 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 t again represents the accumulated work experience obtained as teacher, which is only positive for ex-teachers[9].

Restricting the sample to include only those individuals who had chosen for a non-teaching career (possibly after leaving a teaching job) may result in biased wage equation parameter estimates. To correct for the potential sample selection bias, two selection bias correction terms S_{i2} and S_{i3} were included, the first one for the sample of ex-teachers, the second for the sample of graduates who had chosen an alternative career upon graduation. The calculation of these terms is further discussed in the appendix.

[7] The small wage drop in the first year may reflect the high inflation rates in the early eighties, leading to an initial fall in real wages.

[8] We chose to use both data sources because of the relatively small number of non-missing observations (76) when only using starting wages of ex-teachers.

[9] In preliminary estimations of this equation we also included t^2 which was found to be not significantly different from zero.

Estimates of the non-teacher wage equation are shown in Table 3. Graduates who experienced a period of unemployment after graduation and before entering the first job earn on average less, while those with more work experience before graduation earn more. Those with teaching experience also earn more, as do graduates with a science or engineering degree. We further find that individuals with postgraduate academic qualifications, such as a Master's or Doctoral degree earn significantly more, while those with postgraduate professional qualifications, such as a secretarial degree, earn much less than others. Males earn significantly more than females. Individuals living in the Greater London area and in regions with lower than average unemployment also receive higher starting wages, as do graduates who obtained their degree at a university rather than a polytechnic.

The estimated starting wage equation was used to predict opportunity wages for all teachers in the sample as follows $ln\hat{W}^*_{it} = Z^{*\prime}_{it}\hat{\gamma}_2 + \hat{\alpha}_2 t + \phi_i$, where ϕ_i is an estimate of the expectation $E[\omega_{i2}|NONTCH = 0]$, the expected value of the disturbance term given that these individuals all (first) chose a teaching job. Figure 2 shows the average predicted starting salaries for teachers in our sample as an increasing function of work experience obtained as teacher. The figure also indicates that male teachers face significantly greater opportunity costs than female teachers.

In the estimation results reported in section 5, the individual specific and tenure and calender year dependent imputed values for the logarithm of teaching salaries and opportunity wages will be denoted by TWAGE and NTWAGE, respectively.

4. Econometric Specification and Estimation

To study teacher retention and attrition we will estimate reduced form specifications of the hazard function and transition intensities characterizing a teacher's first spell in the teaching profession, that were derived in section two.

The single risk model

To analyze the data on first durations of stay in teaching, we adopt a continuous time reduced form hazard specification with unrestricted baseline hazard (Cox, 1972):

$$h_i(t) = \underline{h}(t) exp(X_i(t)'\beta)$$

where $\underline{h}(t)$ is the baseline hazard at time t, $X_i(t)$ is a vector of possibly time dependent explanatory variables for individual i at time t (normalized by the sample averages at

$t = 0$) and β is a vector of unknown parameters. In our case $X_i(t)$ includes the predicted (log) earnings in the teaching sector, $Ln\hat{W}_{it}$ and in the nonteaching sector, $Ln\hat{W}^*{}_{it}$ and other individual characteristics influencing exit decisions[10]. Along the lines suggested by Moffitt (1985), Meyer (1990) and Han and Hausman (1990), the baseline hazard will be estimated jointly with the parameterized heterogeneity component. This semi-parametric 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 non-parametric estimate of the baseline hazard.

For interval data of the type analyzed here, where employment durations in teaching are measured in complete months[11], the probability or likelihood of observing a complete (uncensored) duration of t_i months for individual i with vector of characteristics $X_i(s), s = 1,..,t$ is equal to

$$Prob(t_i \leq T < t_i + 1) = Prob(\int_0^{t_i} h_i(u)du \leq \int_0^{T} h_i(u)du < \int_0^{t_i+1} h_i(u)du)$$

$$= Prob(-log \int_0^{t_i+1} \underline{h}(u)e^{X_i(u)'\beta}du \leq \epsilon_i < -log \int_0^{t_i} \underline{h}(u)e^{X_i(u)'\beta}du)$$

$$= exp(-\sum_{s=1}^{t_i} e^{X_i(s-1)'\beta} \int_{s-1}^{s} \underline{h}(u)du) - exp(-\sum_{s=1}^{t_i+1} e^{X_i(s-1)'\beta} \int_{s-1}^{s} \underline{h}(u)du) \qquad [1]$$

$$= \Big[1 - exp(-e^{X_i(t_i)'\beta}\gamma(t_i+1))\Big] exp(-\sum_{s=1}^{t_i} e^{X_i(s-1)'\beta}\gamma(s)) \qquad [2]$$

where $\gamma(s) = \int_{s-1}^{s} \underline{h}(u)du$, T is the actual (unobserved) duration and ϵ_i, minus the logarithm of the integrated hazard function, has (conditional on X_i) an extreme value distribution with distribution function $F(\epsilon) = exp(-exp(-\epsilon))$. Note that the value of X_i is assumed to be constant inside each $[s-1, s)$ interval[12]. In expression [1] the probability is written as the difference between $Prob(T \geq t_i)$ and $Prob(T \geq t_i + 1)$. The first term

[10] Identification of the wage effects is achieved through exclusion restrictions, where an individual's degree class, pre-graduation work experience, and institution type (UNIV) are assumed to affect an individual's propensity to leave only through their effect on wages.

[11] Durations are calculated by subtracting the starting date from the exit date (both reported in month and year). While individuals presumably start on the first day of a month, we do not know whether an individual left on the first, last or any other day of the reported exit month. Therefore, if the calculated duration is t months, then the actual duration is assumed to lie somewhere between t and $t + 1$ months.

[12] It is straightforward to allow for regressor variables that vary in a known way with time within each interval.

in [2] represents the probability of exit in the $[t_i, t_i+1)$ interval given that the spell has lasted until t_i and thus represents the discrete (grouped) interval hazard rate. The second term in [2] represents the probability of staying in teaching at least until time t_i, or the survival probability $Prob(T \geq t_i)$. Thus for right censored observations this second term will represent the probability of observing a censored spell of duration t_i. For the sample of N individuals the likelihood is

$$
\begin{aligned}
L^1(\underline{h}, \beta) &= \prod_{i=1}^{N} L_i(t_i, d_i) \\
&= \prod_{i=1}^{N} \Big[1 - exp(-e^{X_i(t_i)'\beta}\gamma(t_i+1))\Big]^{d_i} exp(-\sum_{s=1}^{t_i} e^{X_i(s-1)'\beta}\gamma(s))
\end{aligned} \qquad [3]
$$

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. Maximization of the log-likelihood, lnL, with respect to $\underline{h}$ (the $\gamma(s)$ terms) and β, under the constraint that the hazard pieces $\gamma(s)$ are non-negative, will provide us with consistent estimates of the baseline hazard pieces $\int_{s-1}^{s} \underline{h}(u)du$ and of the parameter vector β (see Meyer, 1990).

It is well known that the presence of omitted unobserved heterogeneity may lead to a dynamic selection bias in the estimate of the baseline hazard and in parameter estimates for the included explanatory variables. Introducing unobserved heterogeneity in the form of omitted variables, v_i, in the heterogeneity term: $exp(X_i(s)'\beta + v_i)$, with v independent of X, the unconditional likelihood then contains integrals of the individual likelihood terms $L_i(t_i, d_i)$. When $exp(v)$ has a gamma distribution with mean one (a normalization) and variance σ^2, these integrals have a convenient closed form solution (see Lancaster, 1979). In that case the likelihood is given by[13]

$$
L^2(\underline{h}, \beta, \sigma^2) = \prod_{i=1}^{N} \Big[1 + \sigma^2 \sum_{s=1}^{t_i} e^{X_i(s-1)'\beta}\gamma(s)\Big]^{-\frac{1}{\sigma^2}} - d_i\Big[1 + \sigma^2 \sum_{s=1}^{t_i+1} e^{X_i(s-1)'\beta}\gamma(s)\Big]^{-\frac{1}{\sigma^2}}
$$

Alternatively we can adopt a semi-parametric approach suggested by Heckman and Singer (1984), in which the unknown distribution of the unobserved heterogeneity term is approximated by a discrete multinomial distribution whose points of support and corresponding probabilities can be estimated jointly with $\underline{h}$ and β. The likelihood function can

[13] Note that $Prob(t_i \leq T < t_i + 1) = Prob(T \geq t_i) - Prob(T \geq t_i + 1)$ and that $Prob(T \geq t) = M(-\int_0^t h_i(s)ds)$, where $M(t)$ is the moment generating function of $exp(v)$ which is $M(t) = (1 - \sigma^2 t)^{-1/\sigma^2}$.

then be written as the product of weighted sums of terms similar to $L_i(t_i, d_i)$ in [3]:

$$L^3(\underline{h}, \beta, \lambda, \mu, J) = \prod_{i=1}^{N} \sum_{j=1}^{J} \lambda_j L_i(t_i, d_i | \mu_j)$$

where μ_j, $j = 1, ..., J$ are the J points of support with probabilities $\lambda_j = Prob(v_i = \mu_j)$ and $L_i(t_i, d_i|\mu_j)$ corresponds to the expression in [3] with $exp(X(t)'\beta)$ replaced by $exp(X(t)'\beta + \mu_j)$.

In addition to the baseline hazard segments and β, maximization of L^3 provides us with estimates of $J-1$ weights $\lambda_1, ..., \lambda_{J-1}$ ($\lambda_J = 1 - \sum_{j=1}^{J-1} \lambda_j$) and $J-1$ points of support $\mu_1, ..., \mu_{J-1}$ where μ_J is normalized to $\mu_J = 0$[14].

Estimation of the discrete number of mass points, J, is more complicated. A practical approach is to estimate the model for increasing values of J until the likelihood fails to increase[15]. Meyer (1986) has shown that the maximum likelihood estimates obtained for this mixed single risk proportional hazard model with Heckman-Singer type heterogeneity, are consistent estimates of the model parameters.

A competing risks model

Individuals leave the teaching force for different reasons and end up in different destination states. The single risk model above did not distinguish between different types of exit but instead analyzed the aggregate risk of leaving the teaching force. Now consider the case where individuals can leave for one of several destinations or reasons. In this case the observed exit time or duration t_i is not only characterized by a censoring indicator, but also by an exit type indicator. In the case of K mutually exclusive and exhaustive destination states or exit types, let the random variable C, $C = 1, ..., K$ represent the exit type. Then at each point in time we can describe the exit process in terms of K transition intensities defined as

$$h^k(t) = \lim_{dt->0} \frac{Prob(t \leq T < t + dt, C = k | T \geq t)}{dt}$$

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

14 In the discussion of the results, we will instead report estimates of $exp(\mu_j)$ with normalization $exp(\mu_J) = 1$.

15 This procedure will produce estimates conditional on the "optimal" value of J. The standard errors reported later do not take into account the fact that J was determined from the data.

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 duration or survival times. The actual exit time and exit type can then be interpreted as realizations of random variables T and C defined as

$$\begin{aligned} T =& min(T^k; k = 1, ..., K) \\ C =& argmin_k(T^k; k = 1, ..., K) \end{aligned}$$

where the independent random variables $T^1, T^2, ..., T^K$ are the latent durations, representing the length of stay before an exit of type k occurs in the absense of all other types of exit risks. With only C and T being observed, this model is often referred to as an independent competing risks model. We will assume that each of the transition intensities are of the proportional hazard type with

$$h_i^k(t) = \underline{h}^k(t) exp(X_i(t)'\beta_k), \qquad k = 1, ..., K$$

Consider the case of 2 exit types (K=2) and the grouped interval data analyzed here. Then under the assumption that the durations T^1 and T^2 are independent (conditional on X), it is possible by applying monotonic transformations of the variables to show that for censored obervations

$$\begin{aligned} & Prob(T^1 \geq t_i, T^2 \geq t_i) = \\ & \qquad Prob\Big(\epsilon_{1i} \geq -log \int_0^{t_i} e^{X_i(u)'\beta_1} \underline{h}^1(u) du, \ \epsilon_{2i} \geq -log \int_0^{t_i} e^{X_i(u)'\beta_2} \underline{h}^2(u) du\Big) \end{aligned} \qquad [5]$$

where ϵ_1 and ϵ_2 are independently distributed extreme value errors (see Han and Hausman, 1990). Similarly, the probability of observing a complete duration t_i with exit type c for individual i is

$$\begin{aligned} & Prob(t_i \leq T < t_i + 1, C_i = c) = Prob(t_i \leq T^c < t_i + 1, \ T^k \geq T^c) = \\ & Prob\Big(-log \int_0^{t_i+1} \underline{h}^c(u) e^{X_i(u)'\beta_c} du \leq \ \epsilon_{ci} \ < -log \int_0^{t_i} \underline{h}^c(u) e^{X_i(u)'\beta_c} du, \ \epsilon_{ki} \geq m(\epsilon_{ci})\Big) \end{aligned} \qquad [6]$$

for $c, k = 1, 2$ and $c \neq k$, where $m(\epsilon_{ci})$ represents the value of ϵ_{ki} such that the duration T^k implied by that ϵ_k through $\epsilon_k = -log \int_0^{T^k} \underline{h}^k(u) e^{X_i(u)'\beta_k} du$ equals the duration T^c similarly implied by ϵ_c.

Notice that the probability in [6] is bounded between $Prob(t_i \leq T^c < t_i + 1, \ T^k \geq t_i)$ and $Prob(t_i \leq T^c < t_i + 1, \ T^k \geq t_i + 1)$. In the case of continuous duration data (ie. not grouped by interval), the relevant probability will be $Prob(t_i \leq T^c < t_i+\Delta,\ T^k \geq t_i)$ which is equal to the product of the probability of an exit of type c in interval $(t_i, t_i + \Delta)$ times the probability that the duration T^k was censored at time t_i. Accordingly the likelihood consisting of terms like [5] and [6] can be factored into separate components for each risk where failures of the alternative type are treated as censored observations for exit of other types. This implies that both hazard functions $h_1(t)$ and $h_2(t)$ can be estimated in the same way single risk models are estimated, by treating exits of other types as censored observations.

In the case of grouped interval data we can not factor the likelihood in this way. Further, even though it is straightforward to find the two bounds given above, to be able to calculate the joint probability in [6] it is necessary to make an assumption about the shape of the hazard within each interval. It is not possible to estimate the hazard shapes within intervals because the exact completed durations inside the intervals are not known.

A convenient assumption to make is that the two density functions of T^1 and T^2 are uniform within each interval because in that case we have[16]

$$Prob(t_i \leq T^c < t_i + 1,\ T^k \geq T^c) =$$
$$=0.5\ Prob(t_i \leq T^c < t_i + 1,\ T^k \geq t_i) + 0.5\ Prob(t_i \leq T^c < t_i + 1,\ T^k \geq t_i + 1)$$

Given that T^1 and T^2 are independent, these probabilities can be calculated as a product of the univariate probabilities found for the single risk model and which can be calculated as in [2] with $\underline{h}(u)$ replaced by $\underline{h}^{c_i}(u)$.

With this additional assumption, the baseline hazard is no longer left completely unspecified and cannot be estimated nonparametrically. Instead a very flexible baseline hazard is estimated in which the (unidentified) hazard shape within intervals has been fixed, as is for example the case in a piecewise constant hazard function. The sensitivity of the estimates of the model to alternative specifications of the within interval distribution was tested and was found to be very low. In particular, using the upper bound above gives almost identical results. Note that in this case we can factor out the likelihood (as in the continuous time case), so that the cause specific hazard functions can be estimated in the same manner as the single risk model discussed earlier, but where exits of other types are now treated as censored durations.

[16] Han and Hausman (1990) and Sueyoshi (1992) instead assume that the log of the integrated hazard function is a linear function in t within each interval. Note that any assumption along these lines is arbitrary and not testable, fixing the joint probability somewhere in between the two bounds.

The likelihood function for the sample of N individuals is defined as

$$L^4((\underline{h}_k, \beta_k), k = 1, .., K) = \prod_{i=1}^{N} L_i^4(t_i, c_i, d_i)$$

$$= \prod_{i=1}^{N} \prod_{k=1}^{2} Prob(t_i \leq T^k < t_i + 1, T^j \geq T^k)^{I(c_i = k) \cdot d_i} \; Prob(T^1 \geq t_i, T^2 \geq t_i)^{1-d_i}$$

where the indicator function $I(.) = 1$ if the argument is true, and $I(.) = 0$ if not and $j \neq k$.

As in the single risk model, it is also possible to allow for unobserved heterogeneity in a competing risks setting. Consider K latent durations $T^1, ..., T^K$ with hazard functions

$$h_i^k(t) = \underline{h}^k(t) exp(X_i(t)'\beta_k + v_i^k), \qquad k = 1, ..., K$$

Thus there is an unobserved heterogeneity term for each of the K risks. These terms might be correlated. Therefore, even though the latent durations are again independent conditional on the K heterogeneity terms $v^1, ..., v^K$, 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 Han and Hausman (1990) and by Heckman and Honore' (1989) that all parameters of the model, including the joint heterogeneity distribution, are identified under fairly weak conditions which 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 (in case of 2 risks only) as a discrete multinomial distribution with J mass points $\mu^j = (\mu_{1j}, \mu_{2j}),\ j = 1, ..., J$, with probabilities $Prob(v^1 = \mu_{1j}, v^2 = \mu_{2j}) = \lambda_j$. Then the marginal likelihood function is

$$L^5((\underline{h}^k, \beta^k),\ k = 1, ..., K,\ (\mu^j, \lambda_j),\ j = 1, ..., J, J) = \prod_{i=1}^{N} \sum_{j=1}^{J} \lambda_j L_i^4(t_i, c_i, d_i | \mu^j)$$

Again one of the weights λ_J has to be normalized so that the probabilities sum up to one and for each risk type, we impose the same normalization as before on the mass points with $\mu_{kJ} = 0,\ k = 1, .., K$. Maximization of the likelihood L^5 will result in consistent parameter estimates, both when the regressor variables are constant over time and when they are time-dependent[17].

[17] This can easily be shown by extending the analysis of Sueyoshi (1992) along the lines by Meyer (1986).

5. Estimation Results

Before discussing the estimates of the hazard models, it will be useful to take a look at the raw duration data (see Table 4). The distribution of the reported completed and censored durations reveals that many exits occur at 12 months intervals at tenure levels corresponding to the end of each academic year. Clearly this is the result of fixed-term contracts. However, the table and the Kaplan-Meier estimate of the sample hazard function (shown in Figure 3)[18] also indicate that the risk of leaving teaching at other tenure levels is often quite considerable. In fact, in our sample approximately 61 percent of all exits did not occur at the two peak exit months in each year. Typically there are two smaller spikes between the bigger yearly spikes, suggesting that many teachers may also leave at the end of each school term. A second feature of the Kaplan-Meier estimate is that while the risk of leaving at tenure levels associated with the end of each academic year appears to be falling over time, the exit rate at other tenure levels shows the opposite pattern and increases with tenure. Overall the hazard rate exhibits positive duration dependence[19].

Single risk model estimates

We will first report the estimates of the single risk model. As shown in Table 5, teacher earnings have a negative and significant effect on the exit rate. The estimated elasticity of the hazard with respect to teacher salaries is -1.48. Potential earnings in the non-teaching sector on the other hand have a positive but insignificant effect, with a corresponding estimated hazard elasticity of 1.46. The estimates imply that an equal increase in both types of (log) earnings has almost no effect on the exit rate. This implies that as a response to a given percentage increase in salaries offered in the non-teaching sector, educational agencies must increase teacher salaries by the same percentage in order to avoid losing more teachers.

Teachers with a Bachelor's of education degree have (all else equal) a significantly lower exit rate at each tenure level than those with a postgraduate certificate of education or those qualified teachers without an education degree. Compared to all other teachers, those with a BED are probably the most specialized in teaching and have the most occupation

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[18] The Kaplan-Meier estimate of the monthly hazard rate equals the fraction of spells ongoing at the start of each month which end during that month. Thus the estimate given at tenure level t represents an estimate of the risk of leaving sometime during the $(t+1)$-th month in teaching.

[19] Fitting a Weibull hazard $h(t) = \alpha t^{\alpha-1} e^{c}$ resulted in an estimate of α equal to 1.152 with standard error 0.074, implying positive duration dependence.

specific education. Those with postgraduate professional qualifications have a much greater attrition rate than those who do not, even after controlling for associated differences in both predicted earnings levels. Such qualifications may indicate that the individual has some preference for or interest in a professional non-teaching career, or a greater non-teaching job offer rate.

Teachers who did attend an independent secondary school have a greater than average exit rate and so do teachers with a higher social class background. As is to be expected, graduates who started their first teaching job rather reluctantly, mainly because they could not find anything better or more suitable at the time, are much more inclined to leave teaching than others[20]. Finally, the region's unemployment rate has a negative significant effect on the hazard rate of leaving teaching. A higher unemployment rate may imply that there are fewer outside job opportunities (a lower outside job offer rate). This effect appears to dominate the likely positive effect on the exit rate caused by an increased risk of layoff.

The last two sets of estimates shown in Table 5 correspond to the same hazard model but now when we allow for either Gamma unobserved heterogeneity or heterogeneity of the Heckman-Singer type. In both cases introducing a mixing distribution has little effect on the covariates' coefficient estimates. The variance of the gamma distribution is estimated to be 1.085. Both the asymptotic t statistic and the likelihood ratio statistic indicate that gamma heterogeneity does not improve the model fit significantly. The third column estimates indicate that the unmeasured heterogeneity distribution can be best described by a two-point distribution of the mover-stayer type, with about 23 percent of the teachers having a zero exit rate. The data did not support a third mass point[21]. Given that $exp(\mu_1) = 0$ lies on the boundary of the parameter space, no standard error is reported. Ignoring the boundary problem, the LR test statistic for $H_0 \; : \; exp(\mu_1) = exp(\mu_2)$ (or $exp(\mu_1) = 1$) has an asymptotic χ_1^2 distribution under the null hypothesis, even though under the null hypothesis λ_1 is not identified while it is under the alternative (see Ridder, 1990). The LR statistic is 5.08, so H_0 is rejected at the 95 percent level, implying that we can reject the hypothesis of no unobserved heterogeneity. At the same time, however,

[20] Because the information on RELC was gathered retrospectively, it is possible that the reported RELC was affected by the actual exit decision, implying that it may be endogenous. Leaving this variable out of the specification, has no effect on the other parameter estimates, suggesting the potential endogeneity of RELC does not bias the other estimates.

[21] In the estimation with three mass points, the added mass point also coverged to zero.

ignoring its presence did not appear to have led to dramatic biases in the parameter estimates.

As pointed out earlier, non-parametric estimation of the baseline hazard avoids potential biases caused by a misspecification of the baseline hazard. When we constrain the baseline hazard to be of the commonly adopted Weibull type, we obtain the estimates reported in Table 5-A. Comparing these estimates with those in Table 5, we find that most coefficient estimates corresponding to the time-invariant explanatory variables are quite similar but that those corresponding to the opportunity wages and the regional unemployment rate change considerably.

The non-parametric estimate of the baseline hazard corresponding to the estimates in the first column of Table 5 is shown in Figure 4 (the corresponding estimated hazard function for a ficticious "average teacher"[22], are shown in Figure A1 in the appendix). In the same figure the Weibull baseline hazard estimate (corresponding to the estimates in column 1 of Table 5-A) is shown to be an increasing function of tenure. Comparing the baseline hazard shapes it is perhaps no surprise that the corresponding coefficient estimates discussed above were somewhat different. The flexible baseline estimate closely mimics the Kaplan-Meier estimate discussed earlier, while the Weibull baseline estimate is upward sloping. A LR test of the null hypothesis of a Weibull baseline hazard is strongly rejected[23].

Table 5-A also shows that when a Weibull baseline hazard is imposed, the parameter estimates are very sensitive to the inclusion and specification of the unobserved heterogeneity distribution. The parameter estimates in the second and third column differ substantially from each other as well as from those in the first column, especially those of covariates such as the (predicted) earnings in the teaching and nonteaching sectors, residence in the Greater London area and the possession a science or engineering degree. The coefficient estimates of these covariates and others also differ greatly from those in corresponding columns in Table 5. These results indicate that misspecification of the baseline hazard leads to biases in most of the covariates' coefficient estimates, while neglected unobserved heterogeneity only appears to affect the estimates in the misspecified parametric baseline hazard case.

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[22] The latter represents the estimated hazard function evaluated at the time-invariant covariate means and at the monthly average values of the time-varying covariates.

[23] The chi-square statistic with 73 degrees of freedom is 217.6, with a critical value at the 95 percent level being 93.66.

The variance of the gamma distribution is now 1.890 and significant, and we find support for three mass points in the discrete multinomial distribution[24]. The mass point estimates suggest that the distribution of unobserved heterogeneity can be adequately described by dividing the population into three groups, one of which encompasses 58 percent of teachers with very low attrition rates, one of 30 percent of teachers with somewhat larger attrition rates and the remaining group of 13 percent with relatively high exit rates from teaching. In both cases a LR test of the null hypothesis of no unobserved heterogeneity is clearly rejected. Comparing the specifications in Table 5-A with those in Table 5, for both mixing distributions the Weibull baseline hazard specification is rejected.

Independent competing risk models

To obtain a better understanding of the exit process we estimated an independent competing risks model that distinguished between exits into the non-teaching sector and exits to the non-employment state (either unemployment or out of the labor force). Estimates of the propensity to leave for a non-teaching job are shown in the first part of Table 6. The main differences from the single risk model estimates are related to the two wage effects. The negative effect of teacher salaries is now much larger, although it is now only significant at the 10 percent level. Further, the positive effect of higher expected opportunity wages is now large and significant.

The possession of postgraduate professional qualifications increases the propensity of leaving teaching for an alternative career. Graduates with a science or engineering degree are, holding potential wages and other characteristics constant, estimated to be *less* likely to exit from the teaching profession for another career. Taking the corresponding wage differentials into account, having a SCIENG degree rather than another degree has a small negative effect on the probability of a career switch. Given that shortages of teachers exist in these areas, the estimates here seem to indicate that the problem may be more one of recruitment than of retention. We find the gamma variance estimate not to be significantly different from zero, while the LR statistic for $H_0 : exp(\mu_{11}) = exp(\mu_{12})$ for the binomial heterogeneity distribution in the exit to non-teaching hazard equals 3.52, implying that H_0 can not be rejected.

As can be seen from the first part of Table 6-A, imposing a Weibull baseline hazard on the exit rate into the non-teaching sector has in this case little effect on the parameter

[24] The likelihood fails to improve when an additional mass point is added.

esimates, except for a small decrease in the estimate of the opportunity wage parameter. A LR test of the null hypothesis of a Weibull baseline specification is only barely rejected, with the chi-square statistic, χ^2_{73} equal to 98.45, with a critical value at the percent level of 93.66. Considering the impact of introducing unobserved heterogeneity, in comparison to the single model case, here we do not find the same dramatic impacts on the coefficient estimates. The gamma variance estimate is not significantly different from zero, and we also accept the null hypothesis $H_0 \;:\; exp(\mu_{11}) = exp(\mu_{12})$, with a χ^2_1 statistic of 2.32.

Estimates of the transition intensity to the non-employment state are shown in the second part of Table 6. Teacher salaries reduce the propensity of leaving teaching for the non-employment state, while starting salaries in the non-teaching sector have virtually no effect on this exit probability. These estimates together with those in the first part of Table 6, clearly indicate that both wage levels play an important but different role in the decision to change careers and in the decision to leave the labor force.

Female teachers have a higher propensity to leave and become unemployed or leave the labor force than men, suggesting that their is a greater demand for their time at home. Having a BED degree still has a negative, but somewhat less pronounced effect on the hazard rate and those with postgraduate professional qualifications are more likely to leave the work force than others, possibly representing a temporary exit to unemployment.

As in the single risk model with flexible baseline hazard, our estimates of the heterogeneity distribution imply a mover-stayer type model with 32 percent of all teachers remaining in teaching with probability one. We again do not observe large changes in the coefficient estimates when either a gamma or multinomial heterogeneity distribution is adopted. The gamma variance estimate is not significantly different from zero, but we do reject the null hypothesis $H_0 \;:\; exp(\mu_{21}) = exp(\mu_{22})$, with a χ^2_1 statistic of 4.67.

Comparing these estimates with those of a specification with a Weibull baseline hazard (second part of Table 6-A), we find that most parameter estimates change considerably. Especially the magnitude of the negative opportunity wage and unemployment effects have increased. This shows that the estimates are quite sensitive to misspecification of the baseline hazard. A LR test of the null hypothesis of a Weibull baseline specification for the exit to non-employment hazard is strongly rejected, with the chi-square statistic, χ^2_{73} equal to 190.78 and a critical value at the percent level of 93.66. We also find the Weibull specification estimates to change considerably when we include unobserved heterogeneity. The hypothesis of no unobserved heterogeneity can be rejected for both the gamma and multinomial distribution specifications. These and the previous estimates for the non-teaching exit hazard show that the misspecification biases caused by imposing a Weibull hazard in the single risk model are primarily due to the misspecification of the non-employment baseline hazard.

When we compare the baseline hazard estimates for both exit types in Figures 5 and 6 (for the flexible baseline specification without unobserved heterogeneity), the baseline hazard for exits into the non-teaching sector appears to have no clear time trend, while that for exits to the non-employment state seems to increase with length of tenure on the job[25]. Another interesting aspect of both graphs is that the peaks present at tenure dates corresponding to the end of an academic year are much less pronounced in the baseline hazard for exit to non-teaching jobs than for exit to any other destination state, suggesting that many teachers who switch careers are more prone than others to quit their teaching jobs at miscelaneous dates during an academic year. The Weibull baseline estimates show the same pattern of duration dependence with only the increasing exit rate to the non-teaching sector not being significantly different from a constant hazard.

Additional insight into the patterns of teacher attrition can be obtained by distinguishing exits by reason for leaving rather than by destination state[26]. Table 7 gives the parameter estimates for transition rates corresponding to two mutually exclusive reasons for leaving the teaching job: involuntary departures and exits for family or health reasons on the one hand and voluntary exits (for reasons other than family or health) on the other. The latter category includes exits about which the respondent stated that he or she had left the job to obtain a better job or because of other career motives. The first includes those who were dismissed from their job, those who left because a contract had ended and those who left for family, domestic or health reasons.

The results are striking, but are those that could have been expected. While a higher salary earned as a teacher in the two cases has an almost equal effect discouraging teacher attrition, the expected wage in the non-teaching sector only has a strong effect on the exit rate in the case of voluntary exit. Female teachers are more likely to leave for family reasons and those who started their first job reluctantly are both more likely to leave

[25] The estimated hazards for an average teacher, on the other hand, as shown in Figures A2 and A3 look very different. The average trends in the wage measures leads to positive duration dependence in the risk of leaving for a non-teaching job and a non-monotone pattern of duration dependence in the risk for leaving the labor force.

[26] Means of all variables by reason for leaving and a cross-tabulation of the two exit type distinctions are presented in Tables A3 and A4 of the appendix.

voluntarily and to be dismissed or to leave for family or health reasons. Those with academic postgraduate qualifications are more likely to leave voluntarily, but less likely to leave for other reasons. A higher regional unemployment rate has a stronger negative effect on the voluntary exit rate than on the involuntary/family related exit rates.

As before, for the semiparametric specification with flexible baseline hazard we do not find any large changes when we allow for unobserved heterogeneity. In fact, for both voluntary and other exits, we only find support for one mass point (in the voluntary exit case the second mass point converged to the first).

The estimates corresponding to the Weibull baseline specifications (Table 7-A) are qualitatively similar, except for considerable differences in the parameter estimates of the opportunity wage effect, becoming much smaller in both hazards, and the gender coefficient now being much greater and significant in the voluntary exit hazard. For both voluntary and other exits the Weibull baseline specification is rejected. With regard to the effects on estimates of introducting unobserved heterogeneity in the Weibull models, we find results similar to those for the flexible baseline specification. For both exits we accept the hypothesis of no gamma unobserved heterogeneity, while we accept the hypothesis of having a degenerate heterogeneity distribution for the voluntary exit hazard only.

When we compare the baseline hazard estimates for both exit types in Figures 7 and 8 (for the flexible baseline specification without unobserved heterogeneity), the baseline hazard for voluntary exits appears to be much less affected by length of tenure in teaching than is true of the hazard of exits for involuntary reasons, which appears to increase with tenure[27].

In summary, the above estimates show that distinguishing between different types of exits could shed more light on the attrition process. During our sample period only 14 percent of teachers who had left the teaching force for a non-teaching job did return to teaching. Of those who had left for the non-employment state 53 percent returned. Similarly, of those who left teaching voluntarily, 28 percent returned to teaching while for all other exits this percentage was 52 percent. On the basis of these statistics it could be argued the if one is concerned primarily with the permanent attrition of teachers, then a study of its causes should perhaps devote more attention to exits to the non-teaching

[27] The corresponding estimated hazards for the "average" teacher, shown in Figures A4 and A5, show again very different patterns. The hazard for voluntary exits exhibits positive duration dependence, while that for involuntary exits first increases and then decreases with tenure.

sectors and to voluntary exits than to other exits.

The above estimates also indicated that misspecification of the baseline hazard generally biases the estimates of all parameters, especially those corresponding to time-varying explanatory variables, and that a flexible specification, such as the non-parameteric specification adopted here, will solve this problem. In addition, we found that neglecting or misspecifying the unobserved heterogeneity distribution has almost no consequences in the case of a flexible baseline specification. Unobserved heterogeneity was however found to affect the estimates considerably when an incorrect parametric form of the baseline hazard was imposed.

Dependent competing risks models

In the competing risks models estimated above, we did not allow for any dependence between the two unobserved heterogeneity components. Therefore all tests for unobserved heterogeneity in the independent competing risks model were conditional on the assumption that any pair of such heterogeneity components were independent. In Tables 8, 8-A, 9 and 9-A we report estimates when the independence assumption is relaxed. Considering first the competing risks model with exits by destination state, we find that the results are very similar to those reported in Table 6 for the independence case. The estimates of the heterogeneity distribution imply that the unobservables are positively correlated with correlation coefficient 0.46[28], but a likelihood ratio test of the independence assumption accepts the hypothesis that (conditional on the presence of unobserved heterogeneity in both hazards) the correlation is zero.

Similarly in Table 9 we find the estimates of the competing risks model distinguishing voluntary exits from others, not to be very different from those of the independent model reported in Table 7. The heterogeneity components in both hazards are estimated to be perfectly correlated, with estimated correlation coefficient equal to 1, but this correlation estimate is not statistically significant at the 5 percent level ($\chi_1^2 = 3.78 < 3.84$), though it is at the 10 percent level.

The estimates corresponding to the Weibull baseline specifications are quite different from those obtained under the independence assumption in case of the destination specific

[28] As shown by Van den Berg et al. (1993) the correlation between the unobservables equals $\left(\lambda_1\lambda_4 - \lambda_2\lambda_3\right)/\left(\sqrt{(\lambda_1+\lambda_3)(\lambda_2+\lambda_4)(\lambda_1+\lambda_2)(\lambda_3+\lambda_4)}\right)$. A test of independence corresponds to a test of this expression being equal to zero. We calculate the LR test statistic which under the null has asymptotically a χ_1^2 distribution, and ignore the boundary problem that arises when $exp(\mu)$ converges to zero.

competing risks model. The coefficients on teacher salaries, the unemployment rate, having a science or engineering degree or a postgraduate academic degree all change considerably, especially for the non-employment hazard. A likelihood ratio test of independence is now rejected[29]. The estimated correlation coefficient of the two unobserved heterogeneity terms in the case of six mass points is somewhat harder to calculate. Van den Berg et al. (1993) show that the covariance between both error terms (in our case between the $exp(\mu_{ij})$ terms) equals $(e^{\mu_{11}} - e^{\mu_{12}}) \cdot \Big[(\lambda_1\lambda_5 - \lambda_2\lambda_4) \cdot (e^{\mu_{21}} - e^{\mu_{22}}) + (\lambda_1\lambda_6 - \lambda_3\lambda_4) \cdot (e^{\mu_{21}} - e^{\mu_{23}}) + (\lambda_2\lambda_6 - \lambda_3\lambda_5) \cdot (e^{\mu_{22}} - e^{\mu_{23}})\Big]$. The covariance thus depends on the actual values of the mass points, the $e^{\mu_{ij}}$. The covariance and correlation coefficient calculated in this way equal 0.051 and 0.369 respectively.

The estimates in Table 9-A for the reason-for-leaving specific hazards are very similar to those obtained under the independence assumption. The estimated correlation coefficient between the two unobserved heterogeneity components is 1, but it is not statistically significant at the 5 percent level.

In summary, allowing for dependence in the competing risks model has virtually no impact on our estimates, except for the destination specific competing risks model with Weibull baseline hazards, where the estimates change considerably.

6. Conclusions and Economic Policy Implications

The economic policy implications of our estimates should not be understated. Most obvious are the results which point to the importance of teacher salaries and foregone earnings in turnover decisions. These results suggest at the most simplistic level that the lower the wage on offer to teachers and the higher the earnings on offer in non-teaching professions, the more likely they are to leave teaching.

The importance of relative wages in teacher turnover decisions is illustrated in Figures 9 to 11. These figures show the predicted survival probability at each tenure level for our sample of teachers. For example, in Figure 9, the percentage of teachers still in teaching after 5 years is about 66 percent. A uniform increase in teacher salaries of 10 percent is predicted to increases this percentage to 69 percent (a 9 percent increase), while an

[29] In the dependent competing risks model with 6 mass points, a test for independence corresponds to a test for both $\lambda_1 \cdot \lambda_6 = \lambda_3 \cdot \lambda_4$ and $\lambda_2 \cdot \lambda_6 = \lambda_3 \cdot \lambda_5$. This test asymptotically has a χ^2_2 distribution.

increase in expected non-teacher earnings by 10 percent is predicted to decrease it to 62 percent (a 12 percent decrease).

When we consider the survivor function corresponding to exit to non-teaching positions only, i.e., in absence of any other type of exit, we find that the percentage of teachers predicted to leave leaving for a non-teaching job within the first five years to increase by 45 percent and decrease by 18 percent after a 10 percent increase in opportunity wages and a 10 percent increase in teacher salaries, respectively. The corresponding figures for exits to the non-employment state are respectively a decrease of 1 percent and a decrease of 9 percent.

However these results are only the immediate implications. The results have more far-reaching potential policy implications. We discuss only a few of them briefly.

A natural finding of empirical work of this kind is that there are differential propensities for turnover for teachers of different educational background, gender, social class and ability. Some of these differences are due to their different opportunity wages in other jobs. This will have implications for the potential number of trainee teachers which need to be recruited with a certain education or personal background or in a particular geographic region.

The corollary to the above is that if the link between relative wages and turnover are well established then it is clear that the educational authorities would need to have some contingency planning regarding: numbers of new trainees required according to the wage settlement which could be imposed. In addition, the educational authorities face the potential problem of having to devise a tenure-wage profile which retains the right numbers of staff of the appropriate experience and qualifications (see Bartholemew, 1973). Clearly a school needs a balance of senior and junior teachers in order to effectively discharge all the duties involved in running such an educational unit. 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 educational unit would emply no senior qualified staff. Therefore what is needed is a wage profile in the career which induces the right number of people to stay in the job.

Another area in which our results could have important implications is in the appropriate treatment for women teachers. Many women teachers will leave their teaching job, not necessarily to go to another 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. One important issue here is for example: what wages provide the appropriate incentive structure for women to quit and then return to teaching at the appropriate time?

An additional problem which faces schools or educational administrators is what level of training to provide for the teachers it employs. Such costly investment requires careful planning and this planning should take into account which categories of teachers have the highest propensity to quit the profession and therefore either waste that investment or incur the highest depreciation on the acquisition of those human capital skills.

Although our discussion of the policy implications has, of necessity, been brief it should be clear that the consequences of appropriate modelling of teacher turnover and its link to relative wages is of central importance for educational manpower planning and the effective administration of education.

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APPENDIX

Sample selection correction in the non-teaching starting wage regression

To correct for a potential sample selection bias caused by the non-random nature of our estimation sample, a two stage procedure was adopted as suggested in Heckman(1979) and Lee (1982). As discussed in section 3, to estimate the starting wage equation we make use of wage information on ex-teachers who left teaching for an alternative career, and of starting wage information on those graduates whose first job was in the non-teaching sector.

For this latter group, we first estimated a Probit equation with as dependent variable the occupation choice indicator, NONTCH, which equals 1 if the graduate's first full-time job was outside teaching and 0 if not. Estimation results are reported in Table A2. An inverse Mill's ratio, S_{i3}, was then calculated as usual. This variable, an estimate of $E[u_{it}|NONTCH = 1]$, was then included into the wage regression for all individuals who had chosen their first job in the non-teaching sector.

For the sample of ex-teachers a similar approach was adopted. For an ex-teacher with tenure t, the correction term equals $E[u_{i2}|(NONTCH = 0 \ and \ exit \ to \ non-teaching \ job \ at \ tenure \ T = t)]$. To estimate this term, a 'reduced form' version (i.e., without the imputed wage variables) of the proportional hazard model was estimated to obtain tenure specific probabilities of exit to the non-teaching sector, within each one-month interval. These probabilities, which are conditional on entering the teaching profession, were then multiplied with the probability $Prob(NONTCH = 0)$ to obtain the joint probability $Prob(NONTCH = 0 \ and \ exit \ to \ non-teaching \ sector \ at \ T = t)$. The selection bias term was then calculated as in Lee (1982) for non-normal selection probabilities.

DATA APPENDIX

The survey of 1980 UK graduates was carried out by the Department of Employment, Employment Market Research Unit (EMRU) in association with the Department of Education and Science. The respondents were sampled once at the end of 1986 and asked detailed questions about the nature of their: degree, periods of training and further education, qualifications undertaken at the postgraduate level, jobs and spells of unemployment as well as information about social and family background.

The 1980 survey of graduates was a successor to those undertaken in 1970 by the Unit for Manpower Studies, and in 1960 by Professor Kelsall at Sheffield University. The aim of the 1980 survey was to collect information about the early work histories of graduates after they have had enough time to become established in their careers. Respondents were asked for details of their 1980 qualification, up to three qualifications which they have attempted since 1980 and up to four jobs which they may have held in the period up to the beginning of 1987. In addition, questions were asked about the school attended, A- level results, parental background and present family circumstances. These personal and social factors are known to be important in the determination of labour market experiences.

The fieldwork for the survey was undertaken by Social and Community Planning Research (SCPR) who contacted 46 universities, 27 polytechnics, and 96 colleges to sample a total of 8,948 graduates and diplomates. This fieldwork was conducted between October 1986 and Spring 1987 with a corresponding variation in the timing of the return of the questionnaires. The survey sampled one in six university graduates, one in four polytechnic graduates and a random sample of college graduates. The survey excluded overseas students and dental and medical graduates. The sample also included all Scottish electronic engineering graduates.

The overall response rate was approximately 50%. However this proportion includes those who were known definately not to have received the questionnaire in the post since it was returned. Therefore, amongst those who were eligible and received the questionnaire the response rate was 65%. The differential responses from different groups is reported in Field and Meadows (1988). It seems that response was higher from: university graduates than those who attended polytechnics and colleges; women respondents rather than men; and those reading sciences than other subjects. It is also likely that those who were in work at the time of the survey and those who had been more successful in the labour market were more likely to respond. The Field and Meadows (1988) report also details the sampling procedure and the possible statistical bias in the sample by comparison of the sample with the survey of the First Destination of Graduates.

There are 3978 male and 3163 female graduates in our original sample. 67.3% of the men and 56.5% of the women were awarded a degree from a university and 95.4% of men and 96.8% of women described themselves as of white ethnic origin. This sample size is reduced by ommitting 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 6098 of whom 3484 were men and 2614 were women. In this sample 923 individuals were school teachers in their first job.

The variables reviewed can be grouped into:
i) social and personal variables including ethnic background, social class, school type, age, marital status and fertility;
ii) educational variables including highest level of qualification obtained before degree, A level score, degree class, degree subject, and postgraduate qualifications;
iii) work information including current employment status, current sector and type of work, current occupation, earnings, number of jobs and years of work experience.

This appendix gives a detailed description of the variables used in the analysis in the main body of the text. The description illustrates how these variables are constructed and the values which they take.

Variable Definitions

LFWAGE: The logarithm of (full-time) salary in sterling at the end of 1986. All salary information used in this analysis has been indexed with April 1976 as the base period.
SCHTYPE: A dummy variable taking the value 1 if the respondent attended an independent high school and 0 otherwise.
INSTTYPE: An indicator variable taking the value 1 if the respondent was awarded his or her degree from a university and 0 otherwise.
LSWAGE: The logarithm of the (indexed) starting salary in the first job after graduation.
DEGRCLASS: An ordinal variable for the first degree class. The values are allocated according to the following scale: 8 for a First, 7 for an Upper Second, 6 for an Undivided Second, 5 for a Lower Second, 4 for a Third, 3 for an Ordinary, 2 to a Pass or Fourth and 1 for Others. This variable takes the value 0 for non-degree holders (those with CERT=1).
SCLASS: An ordinal variable for the social class of parents, as determined by the nature of their Socio-Economic Group. A value between 1 and 6 is assigned to each social class as follows: 6 for professional occupation, 5 for an intermediate occupation 4 for a skilled (non manual) occupation, 3 for a skilled (manual) occupation, 2 for a partly skilled occupation and 1 for an unskilled occupation.
MALE: A dummy variable with a value 1 if the respondent is male and 0 if female.

UNBJ1: The number of months unemployed following graduation and prior to the respondents first job. Where this spell was less than 4 months UNBJ1 is given a value of 0.
NACA: A dummy variable taking a value 1 if the respondent has successfully completed a postgraduate professional or secretial qualification awarded by a professional body, and 0 if not.
ACA: A dummy variable taking a value 1 if the respondent has successfully achieved a postgraduate academic qualification, such as a Masters Degree or a PhD degree, and 0 if not.
LONDON: A dummy variable taking the value 1 if the respondents main region of employment during the spell in teaching job was the greater London area, and 0 if located elsewhere.
CENSOR: A dummy variable taking the value 1 if the respondents length of time in the teaching profession was right censored.
DURAT: The total duration of employment in the teaching sector (possibly right censored).
SECONDARY: A dummy variable taking the value 1 if the respondent was a secondary rather than a primary school teacher.
CERT: A dummy variable taking the value 1 if the teacher had received a (non-degree) certificate of education, 0 if not.
BED: A dummy variable taking the value 1 if the teacher had a Bachelors degree in education, 0 if not.
DPGCOE: A dummy variable taking the value 1 if the respondent had succesfully achieved a postgraduate certificate of education.
SCIENG: A dummy variable taking the value 1 if the respondent's Bachelors degree was in a science or engineering subject.
PRE80EXP: The number of months of work experience accumulated before graduating in 1980.
LSNWAGE: The (log) average starting salary in the non-teaching sector, for those teachers who left teaching for a non-teaching job and for those whose first job was in the non-teaching sector.
NONTCH: A dummy variable taking the value one if the respondent's first job after graduation was not a teaching job and 0 otherwise.
RELC: A dummy variable taking the value 1 if the respondent accepted the first job mainly because he or she could not find better or more suitable work at the time, rather than any other main reason for accepting the first job.
UNEM: The average unemployment rate by year, region and sex. The regions were: Greater London, South East, Midlands, North, Wales, Scotland and East Anglia.
TWAGE: Each individual's, age and tenure dependent imputed teaching salary, $\hat{ln} W_{it}$. See section 3 for the derivation of this variable.
NTWAGE: Each individual's, age and tenure dependent imputed non-teaching salary, $\hat{ln} W_{it}^*$. See section 3 for the derivation of this variable.

TABLE 1 : SAMPLE MEANS

Variable	Total Sample	Stayers	Movers	Exit to Non-teaching job	Exit to Non-employment
DURAT	54.12	67.39	31.37	38.14	29.12
CENSOR	0.632	1.000	0.000	0.000	0.000
SECONDARY	0.835	0.847	0.815	0.835	0.808
CERT	0.075	0.069	0.085	0.082	0.086
BED	0.414	0.441	0.368	0.318	0.384
DPGCOE	0.382	0.374	0.397	0.447	0.380
SCIENG	0.148	0.142	0.159	0.153	0.161
DEGCLASS	4.556	4.580	4.515	4.635	4.475
UNIV	0.412	0.386	0.456	0.518	0.435
ACA	0.062	0.053	0.076	0.082	0.075
NACA	0.040	0.019	0.076	0.071	0.078
MALE	0.285	0.316	0.232	0.376	0.184
UNBJ1	2.970	2.921	3.053	3.212	3.000
SCHTYPE	0.063	0.045	0.094	0.106	0.090
RELC	0.099	0.079	0.132	0.141	0.129
SCLASS	4.506	4.412	4.668	4.600	4.690
LONDON	0.127	0.122	0.135	0.153	0.129
PRE80EXP	0.735	0.740	0.725	1.300	0.533
UNEM(1)	8.960	9.336	8.314	9.055	8.067
LSWAGE	7.804	7.815	7.784	7.800	7.779
SWAGE	2488	2517	2438	2481	2424
LFWAGE[1]	–	7.913	–	–	–
FWAGE[1]	–	2754	–	–	–
LSNWAGE[1]	–	–	–	7.654	–
SNWAGE[1]	–	–	–	2428	–
Number of obs.	923	583	340	85	255

For a definition of the variables see the Data appendix.

[1] Calculated for non-missing wage observations only. All wages are deflated into 1976 pounds.

TABLE 2 : WAGE GROWTH EQUATION ESTIMATES

Dep. Var.: $\frac{(LnW_i(t)-LnW_i(0))}{t} \cdot 1000$

Variable	Estimate	Standard Error
Constant	91.289*	3.945
CERT	1.051*	0.430
BED	0.306	0.287
DPGCOE	0.134	0.256
DEGCLASS	0.272*	0.045
ACA	0.614	0.327
NACA	0.541	0.593
MALE	0.836*	0.211
UNBJ1	-0.001	0.019
LSWAGE	-12.396*	0.442
LONDON	0.836*	0.220
PRE80EXP	0.164*	0.032
SECONDARY	0.096	0.193
UNIV	0.448*	0.186
SCIENG	0.012	0.208
UNEM(1)	-0.090*	0.031
DURAT	0.223*	0.054
DURAT-sq/100	-0.189*	0.051
S_{i1}	-1.128	0.632

Number of non-missing wage growth observations: 554
Adj. R^2: 0.64

TABLE 3 : STARTING SALARIES IN THE NON-TEACHING SECTOR

Dep. Var.: $LnW_i^*(t)$

Variable	Estimate	Standard Error
Constant	7.447*	0.021
CERT	0.117	0.065
BED	0.036	0.061
DPGCOE	-0.081	0.042
DEGCLASS	0.014*	0.003
ACA	0.038*	0.012
NACA	-0.090*	0.011
MALE	0.125*	0.012
UNBJ1	-0.007*	0.001
LONDON	0.113*	0.011
PRE80EXP	0.026*	0.003
UNIV	0.035*	0.009
SCIENG	0.127*	0.009
DURAT	0.008*	0.002
UNEM	-0.006*	0.001
S_{i2}	-0.057*	0.025
S_{i3}	0.057	0.051

Number of non-missing starting wage observations: 5248
Adj. R^2: 0.172

TABLE 4 : EMPIRICAL DURATION DISTRIBUTION

TENURE	AT RISK	FAIL	CENS	TENURE	AT RISK	FAIL	CENS
1	923	0	0	39	699	3	1
2	923	0	0	40	696	3	0
3	923	6	0	41	693	3	0
4	917	2	0	42	690	4	0
5	915	2	0	43	686	5	0
6	913	6	0	44	681	5	0
7	907	8	0	45	676	2	0
8	899	7	0	46	674	13	0
9	892	6	0	47	658	12	3
10	886	25	0	48	646	2	0
11	861	15	0	49	643	3	1
12	846	8	0	50	634	4	6
13	838	7	0	51	622	7	8
14	831	4	0	52	613	5	2
15	825	4	2	53	608	3	0
16	821	3	0	54	605	5	0
17	818	0	0	55	599	3	1
18	818	3	0	56	596	6	0
19	815	9	0	57	586	6	4
20	806	3	0	58	577	0	3
21	802	4	1	59	564	8	13
22	798	20	0	60	548	3	8
23	778	9	0	61	509	0	36
24	769	2	0	62	466	2	43
25	767	1	0	63	350	1	114
26	766	2	0	64	323	1	26
27	761	9	3	65	320	2	2
28	752	2	0	66	317	2	1
29	750	1	0	67	315	1	0
30	749	2	0	68	314	3	0
31	747	3	0	69	307	2	4
32	744	3	0	70	296	3	9
33	741	3	0	71	275	2	18
34	738	14	0	72	262	1	11
35	723	11	1	73	219	1	42
36	712	4	0	74	172	0	46
37	706	5	2	75	0	0	172
38	701	1	0				

TABLE 5 : ESTIMATES SINGLE RISK PROPORTIONAL HAZARD MODEL

			Unobserved Heterogeneity			
			Gamma		HS	
Variable	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
TWAGE	-1.480*	0.502	-1.616*	0.678	-1.622*	0.586
NTWAGE	1.458	1.000	1.254	1.262	1.138	1.122
MALE	-0.182	0.216	-0.186	0.271	-0.185	0.241
CERT	-0.247	0.290	-0.134	0.378	-0.149	0.333
BED	-0.593*	0.229	-0.616*	0.298	-0.566*	0.260
DPGCOE	0.042	0.176	0.051	0.225	0.034	0.198
ACA	0.307	0.200	0.551	0.299	0.616*	0.262
NACA	1.332*	0.236	1.814*	0.442	1.677*	0.329
UNBJ1	0.016	0.012	0.023	0.015	0.022	0.013
SCHTYPE	0.527*	0.202	0.667*	0.295	0.590*	0.250
RELC	0.426*	0.167	0.611*	0.237	0.482*	0.205
SCLASS	0.177*	0.061	0.212*	0.081	0.209*	0.070
SECONDARY	0.017	0.161	0.046	0.212	0.073	0.190
LONDON	-0.106	0.198	-0.062	0.255	-0.066	0.228
SCIENG	-0.120	0.210	-0.015	0.264	-0.078	0.235
UNEM	-0.050*	0.025	-0.062*	0.031	-0.057*	0.027
σ^2			1.085	0.692		
$exp(\mu_1)$					0.000	-.—
λ_1					0.225*	0.080
$exp(\mu_2)$					1.000	-.—
λ_2					0.775	-.—
Log-Likh	-1870.91		-1869.15		-1868.26	

Number of spells: 923

TABLE 5-A : ESTIMATES SINGLE RISK PROPORTIONAL HAZARD MODEL

Weibull Baseline Hazard: $\underline{h}(t) = \alpha\ t^{\alpha-1}e^{c}$

			Unobserved Heterogeneity			
			Gamma		HS	
Variable	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
α	1.372*	0.158	1.698*	0.222	2.726*	0.288
c	-6.327*	0.491	-7.238*	0.658	-7.748*	0.750
TWAGE	-1.463*	0.485	-1.584*	0.695	-2.386*	0.944
NTWAGE	-0.234	0.792	0.126	0.998	1.898	1.312
MALE	0.059	0.193	-0.020	0.268	-0.139	0.347
CERT	-0.062	0.266	0.102	0.393	0.481	0.493
BED	-0.428*	0.206	-0.501	0.309	-0.390	0.361
DPGCOE	0.038	0.165	0.075	0.248	0.305	0.304
ACA	0.397*	0.190	0.747*	0.330	1.942*	0.334
NACA	1.102*	0.209	1.908*	0.482	2.592*	0.458
UNBJ1	0.007	0.011	0.024	0.016	0.021	0.021
SCHTYPE	0.539*	0.189	0.770*	0.336	0.714	0.408
RELC	0.444*	0.160	0.745*	0.263	1.204*	0.312
SCLASS	0.167*	0.056	0.217*	0.083	0.326*	0.100
SECONDARY	0.048	0.147	0.079	0.225	-0.416	0.269
LONDON	0.054	0.180	0.045	0.260	-0.715*	0.341
SCIENG	0.078	0.190	0.213	0.263	1.315*	0.330
UNEM	-0.068*	0.022	-0.085*	0.031	-0.110*	0.041
σ^2			1.890*	0.759		
$exp(\mu_1)$*100					0.049	0.029
λ_1					0.576*	0.030
$exp(\mu_2)$*100					3.115*	0.930
λ_2					0.297*	0.030
$exp(\mu_3)$					1.000	-.–
λ_3					0.127	-.–
Log-Likh	-1979.73		-1974.16		-1968.58	

Number of spells: 923

TABLE 6 : INDEPENDENT COMPETING RISKS MODEL
by Destination State

Exit to non-teaching sector

			Unobserved Heterogeneity			
			Gamma		HS	
Variable	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
TWAGE	-2.475	1.481	-3.207	2.225	-2.801	2.248
NTWAGE	5.117*	2.178	6.260	3.889	5.139	3.896
MALE	0.121	0.468	0.234	0.635	0.585	0.725
CERT	-0.808	0.777	-0.836	1.048	-0.378	1.129
BED	-1.199*	0.605	-1.353	0.848	-1.241	0.892
DPGCOE	0.276	0.443	0.347	0.600	0.297	0.675
ACA	0.327	0.607	0.428	0.946	0.397	1.166
NACA	1.950*	0.655	2.428*	1.186	2.521	1.545
UNBJ1	0.044	0.030	0.066	0.047	0.065	0.045
SCHTYPE	0.599	0.505	0.780	0.755	1.183	0.993
RELC	0.357	0.421	0.509	0.608	0.633	0.665
SCLASS	0.179	0.162	0.240	0.231	0.326	0.247
SECONDARY	-0.045	0.513	-0.015	0.704	0.103	0.772
LONDON	-0.317	0.499	-0.255	0.688	0.016	0.798
SCIENG	-0.784	0.558	-0.826	0.810	-0.532	0.843
UNEM	-0.045	0.061	-0.065	0.077	-0.096	0.080
σ^2			3.668	5.196		
$exp(\mu_{11})$					0.000	-.—
λ_{11}					0.724*	0.096
$exp(\mu_{12})$					1.000	-.—
λ_{12}					0.276	-.—

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TABLE 6 CONTINUED

Exit to non-employment state

Variable	Estimate	S.E.	Unobserved Heterogeneity Gamma Estimate	S.E.	HS Estimate	S.E.
TWAGE	-1.221*	0.585	-1.150*	0.821	-1.338	0.704
NTWAGE	-0.145	1.348	-0.958	1.665	-0.751	1.482
MALE	-0.315	0.289	-0.357	0.367	-0.332	0.321
CERT	-0.040	0.354	0.142	0.485	0.010	0.415
BED	-0.383	0.274	-0.410	0.374	-0.385	0.321
DPGCOE	-0.044	0.212	-0.062	0.287	-0.089	0.248
ACA	0.325	0.237	0.694	0.366	0.737*	0.310
NACA	1.116*	0.287	1.723*	0.525	1.448*	0.385
UNBJ1	0.004	0.015	0.008	0.021	0.008	0.018
SCHTYPE	0.516*	0.241	0.669	0.370	0.614*	0.306
RELC	0.449*	0.201	0.738*	0.298	0.538*	0.249
SCLASS	0.180*	0.071	0.219*	0.097	0.212*	0.082
SECONDARY	0.050	0.186	0.079	0.259	0.130	0.223
LONDON	0.020	0.258	0.076	0.340	0.062	0.298
SCIENG	0.146	0.264	0.329	0.348	0.193	0.300
UNEM	-0.050	0.030	-0.063	0.040	-0.058	0.034
σ^2			1.799	1.131		
$exp(\mu_{21})$					0.000	-.—
λ_{21}					0.323*	0.106
$exp(\mu_{22})$					1.000	-.—
λ_{22}					0.677	-.—
Log-Likh	-2004.77		-2002.38		-2000.75	

Number of spells: 923

Table 6-A : Independent competing risks model
by Destination State

Weibull Baseline Hazard: $\underline{h}(t) = \alpha \ t^{\alpha-1}e^{c}$

Exit to non-teaching sector

Variable	Estimate	S.E.	Unobserved Heterogeneity Gamma Estimate	S.E.	HS Estimate	S.E.
α	1.242*	0.330	1.428*	0.415	1.502*	0.401
c	-8.253*	1.167	-9.032*	1.449	-7.975	1.297
TWAGE	-2.364*	1.158	-3.151	1.742	-2.731	1.618
NTWAGE	3.802*	1.421	4.987*	2.306	4.514*	1.957
MALE	0.267	0.313	0.406	0.431	0.616	0.431
CERT	-0.677	0.542	-0.674	0.806	-0.280	0.806
BED	-1.059*	0.440	-1.200	0.660	-1.132	0.618
DPGCOE	0.290	0.328	0.389	0.469	0.333	0.474
ACA	0.413	0.413	0.552	0.661	0.496	0.681
NACA	1.749*	0.468	2.343*	0.978	2.507*	1.032
UNBJ1	0.038	0.022	0.066*	0.032	0.064	0.027
SCHTYPE	0.605	0.376	0.841	0.613	1.159	0.624
RELC	0.404	0.341	0.561	0.533	0.614	0.535
SCLASS	0.164	0.119	0.239	0.168	0.315	0.163
SECONDARY	-0.018	0.325	0.030	0.467	0.127	0.467
LONDON	-0.185	0.339	-0.054	0.460	0.068	0.478
SCIENG	-0.635	0.388	-0.627	0.542	-0.416	0.513
UNEM	-0.049	0.042	-0.068	0.059	-0.089	0.056
σ^2			4.785	4.545		
$exp(\mu_{11})$					0.000	-.—
λ_{11}					0.731*	0.068
$exp(\mu_{12})$					1.000	-.—
λ_{12}					0.269	-.—

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TABLE 6-A CONTINUED

Exit to non-employment state

			Unobserved Heterogeneity			
			Gamma		HS	
Variable	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
α	1.476*	0.193	1.924*	0.281	2.868*	0.366
c	-6.664*	0.573	-7.827*	0.789	-7.934*	0.914
TWAGE	-1.216*	0.557	-0.947	0.853	-1.722	1.072
NTWAGE	-1.928	0.997	-1.924	1.227	-0.940	1.577
MALE	-0.041	0.256	-0.238	0.366	-0.340	0.474
CERT	0.159	0.311	0.418	0.484	0.304	0.575
BED	-0.216	0.236	-0.364	0.389	-0.577	0.432
DPGCOE	-0.053	0.193	-0.047	0.313	-0.079	0.365
ACA	0.412	0.220	0.913*	0.410	1.358*	0.406
NACA	0.878*	0.241	1.950*	0.580	2.370*	0.561
UNBJ1	-0.007	0.013	0.010	0.021	0.000	0.025
SCHTYPE	0.524*	0.226	0.742	0.427	0.691	0.482
RELC	0.458*	0.187	0.957*	0.328	1.298*	0.383
SCLASS	0.173*	0.065	0.230*	0.099	0.356*	0.115
SECONDARY	0.077	0.169	0.098	0.280	-0.426	0.328
LONDON	0.182	0.219	0.109	0.337	-0.492	0.413
SCIENG	0.357	0.227	0.530	0.333	1.323*	0.417
UNEM	-0.073*	0.027	-0.090*	0.039	-0.115*	0.050
σ^2			3.109*	1.265		
$exp(\mu_{21}) * 100$					0.058	0.045
λ_{21}					0.640*	0.037
$exp(\mu_{22}) * 100$					3.748*	1.379
λ_{22}					0.255*	0.037
$exp(\mu_{23})$					1.000	-.—
λ_{23}					0.105	-.—
Log-Likh	-2149.39		-2142.96		-2136.50	

Number of spells: 923

TABLE 7 : INDEPENDENT COMPETING RISKS MODEL
by Reason for Leaving

Voluntary Exits

			Unobserved Heterogeneity			
			Gamma		HS	
Variable	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
TWAGE	-1.498	1.074	-1.674	1.233	-1.498	1.074
NTWAGE	3.882*	1.580	4.259*	1.966	3.882*	1.580
MALE	0.535	0.351	0.572	0.410	0.535	0.351
CERT	-0.911	0.600	-0.986	0.698	-0.911	0.600
BED	-1.079*	0.423	-1.140*	0.503	-1.079*	0.423
DPGCOE	0.230	0.340	0.266	0.397	0.230	0.340
ACA	1.033*	0.308	1.208*	0.470	1.033*	0.308
NACA	1.625*	0.444	1.823*	0.690	1.625*	0.444
UNBJ1	0.028	0.020	0.035	0.024	0.028	0.020
SCHTYPE	0.453	0.374	0.522	0.455	0.453	0.374
RELC	0.355	0.317	0.382	0.376	0.355	0.317
SCLASS	0.211	0.122	0.230	0.146	0.211	0.122
SECONDARY	-0.031	0.351	0.026	0.416	-0.031	0.351
LONDON	-0.244	0.340	-0.223	0.389	-0.244	0.340
SCIENG	-0.521	0.414	-0.591	0.488	-0.521	0.414
UNEM	-0.075	0.041	-0.083	0.048	-0.075	0.041
σ^2			1.001	1.783		
$exp(\mu_{11})$					1.000	-.—
λ_{11}					1.000	-.—

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Table 7 continued

Involuntary / Family Related Exits

			Unobserved Heterogeneity			
			Gamma		HS	
Variable	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
TWAGE	-1.458*	0.641	-1.415	0.806	-1.362	0.777
NTWAGE	-0.999	1.686	-1.669	1.910	-1.764	1.849
MALE	-0.865*	0.360	-0.897*	0.397	-0.861*	0.381
CERT	0.167	0.391	0.368	0.484	0.459	0.467
BED	-0.262	0.322	-0.255	0.379	-0.254	0.366
DPGCOE	-0.103	0.242	-0.145	0.287	-0.179	0.279
ACA	-0.514	0.400	-0.437	0.429	-0.411	0.423
NACA	1.090*	0.334	1.360*	0.482	1.315*	0.438
UNBJ1	0.001	0.017	0.001	0.020	-0.001	0.019
SCHTYPE	0.599*	0.269	0.718*	0.360	0.706*	0.354
RELC	0.507*	0.226	0.663*	0.299	0.588*	0.283
SCLASS	0.164*	0.085	0.199	0.105	0.230*	0.099
SECONDARY	0.072	0.211	0.033	0.256	0.002	0.249
LONDON	0.101	0.327	0.120	0.389	0.114	0.377
SCIENG	0.227	0.300	0.426	0.362	0.425	0.341
UNEM	-0.026	0.036	-0.030	0.041	-0.029	0.040
σ^2			1.042	1.076		
$exp(\mu_{21})$					0.000	-.—
λ_{21}					0.326*	0.130
$exp(\mu_{22})$					1.000	-.—
λ_{22}					0.674	-.—
Log-Likh	-2013.99		-2013.33		-2012.55	

Number of spells: 923

TABLE 7-A : INDEPENDENT COMPETING RISKS MODEL
by Reason for Leaving

Weibull Baseline Hazard: $\underline{h}(t) = \alpha\ t^{\alpha-1}e^{c}$

Voluntary Exits

			Unobserved Heterogeneity			
			Gamma		HS	
Variable	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
α	1.258*	0.255	1.511*	0.328	1.381*	0.273
c	-7.476*	0.865	-8.358*	1.086	-7.399*	0.879
TWAGE	-1.570	0.891	-2.074	1.154	-1.778	0.974
NTWAGE	2.154	1.124	2.764	1.456	2.164	1.207
MALE	0.754*	0.269	0.933*	0.377	0.757*	0.300
CERT	-0.715	0.478	-0.926	0.661	-0.726	0.530
BED	-0.859*	0.328	-1.019*	0.462	-0.851*	0.367
DPGCOE	0.219	0.265	0.315	0.369	0.269	0.297
ACA	1.140*	0.258	1.577*	0.490	1.363*	0.328
NACA	1.366*	0.371	1.769*	0.744	1.716*	0.514
UNBJ1	0.017	0.018	0.030	0.024	0.028	0.020
SCHTYPE	0.466	0.309	0.661	0.461	0.519	0.359
RELC	0.396	0.264	0.486	0.386	0.375	0.301
SCLASS	0.192*	0.095	0.244*	0.125	0.207*	0.104
SECONDARY	0.020	0.269	0.143	0.366	0.152	0.302
LONDON	-0.057	0.277	0.106	0.374	-0.050	0.310
SCIENG	-0.326	0.308	-0.443	0.422	-0.389	0.342
UNEM	-0.087*	0.033	-0.109*	0.044	-0.094*	0.036
σ^2			4.785	4.545		
$exp(\mu_{11})$					0.000	-.—
λ_{11}					0.388*	0.152
$exp(\mu_{12})$					1.000	-.—
λ_{12}					0.612	-.—

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TABLE 7-A CONTINUED

Involuntary / Family Related Exits

			Unobserved Heterogeneity			
			Gamma		HS	
Variable	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
α	1.502*	0.225	1.705*	0.286	1.621*	0.235
c	-7.012*	0.654	-7.567*	0.821	-6.948*	0.665
TWAGE	-1.396*	0.610	-1.257	0.808	-1.281	0.731
NTWAGE	-2.179	1.201	-2.186	1.321	-2.257	1.260
MALE	-0.655*	0.316	-0.820*	0.368	-0.734*	0.338
CERT	0.310	0.334	0.560	0.437	0.585	0.402
BED	-0.157	0.278	-0.202	0.356	-0.197	0.318
DPGCOE	-0.097	0.221	-0.127	0.289	-0.162	0.261
ACA	-0.455	0.371	-0.354	0.415	-0.351	0.395
NACA	0.931*	0.273	1.462*	0.461	1.261*	0.357
UNBJ1	-0.004	0.015	0.004	0.018	-0.000	0.017
SCHTYPE	0.594*	0.247	0.760	0.366	0.717*	0.333
RELC	0.508*	0.214	0.735*	0.300	0.587*	0.256
SCLASS	0.159*	0.074	0.208*	0.097	0.234*	0.086
SECONDARY	0.085	0.181	0.018	0.239	-0.001	0.212
LONDON	0.192	0.254	0.103	0.322	0.127	0.291
SCIENG	0.372	0.254	0.561	0.314	0.493	0.283
UNEM	-0.047	0.031	-0.047	0.038	-0.046	0.035
σ^2			1.607	1.030		
$exp(\mu_{21})$					0.000	-.—
λ_{21}					0.343*	0.104
$exp(\mu_{22})$					1.000	-.—
λ_{22}					0.657	-.—
Log-Likh	-2165.99		-2163.05		-2163.09	

Number of spells: 923

TABLE 8 : DEPENDENT COMPETING RISKS MODEL
by Destination State

Variable	Exit to Non-teaching Sector Estimate	S.E.	Exit to Non-working State Estimate	S.E.
TWAGE	-3.232	2.034	-1.408*	0.705
NTWAGE	6.153	3.469	-0.544	1.504
MALE	0.237	0.631	-0.305	0.325
CERT	-0.675	0.991	0.048	0.416
BED	-1.355	0.819	-0.358	0.316
DPGCOE	0.282	0.602	-0.074	0.244
ACA	0.593	1.045	0.663*	0.300
NACA	2.737*	1.230	1.446*	0.388
UNBJ1	0.067	0.042	0.010	0.018
SCHTYPE	1.027	0.822	0.602	0.309
RELC	0.642	0.595	0.528*	0.244
SCLASS	0.311	0.227	0.215*	0.081
SECONDARY	0.074	0.707	0.121	0.223
LONDON	-0.190	0.704	0.083	0.299
SCIENG	-0.716	0.765	0.222	0.302
UNEM	-0.075	0.073	-0.058	0.034
$exp(\mu_{11})$	0.000	-.—		
$exp(\mu_{12})$	1.000	-.—		
$exp(\mu_{21})$			0.000	-.—
$exp(\mu_{22})$			1.000	-.—
λ_1		0.257*	0.084	
λ_2		0.357	0.211	
λ_3		0.000	-.—	
λ_4		0.386	-.—	
$CORR(e^{\mu_1}, e^{\mu_2})$		0.466		

Log-Likh: -1999.92
Number of spells: 923

TABLE 8-A : DEPENDENT COMPETING RISKS MODEL
by Destination State
Weibull Baseline Hazard: $\underline{h}(t) = \alpha\ t^{\alpha-1}e^{c}$

Variable	Exit to Non-teaching Sector Estimate	S.E.	Exit to Non-working State Estimate	S.E.
α	1.764*	0.398	3.252*	0.371
c	-9.219*	1.271	-8.281*	0.907
TWAGE	-1.734	1.371	-0.812	1.018
NTWAGE	4.405*	1.865	-1.760	1.547
MALE	0.638	0.421	-0.151	0.433
CERT	0.129	0.803	0.900	0.516
BED	-1.215*	0.598	-0.525	0.428
DPGCOE	0.350	0.452	0.204	0.352
ACA	0.442	0.607	1.215*	0.405
NACA	2.720*	0.779	1.535*	0.464
UNBJ1	0.067*	0.026	0.026	0.024
SCHTYPE	1.195	0.569	0.719	0.426
RELC	0.869	0.482	1.383*	0.358
SCLASS	0.343*	0.158	0.415*	0.116
SECONDARY	0.074	0.444	0.032	0.294
LONDON	0.019	0.453	0.702	0.377
SCIENG	-0.182	0.495	0.758	0.406
UNEM	-0.111*	0.053	-0.156*	0.048
$exp(\mu_{11})$	0.000	-.—		
$exp(\mu_{12})$	1.000	-.—		
$exp(\mu_{21}) * 100$			0.039	0.027
$exp(\mu_{22}) * 100$			2.299*	0.831
$exp(\mu_{23})$			1.000	-.—
λ_1		0.556*	0.041	
λ_2		0.000	-.—	
λ_3		0.000	-.—	
λ_4		0.116*	0.041	
λ_5		0.242*	0.030	
λ_6		0.087	-.—	
CORR(e^{μ_1}, e^{μ_2})		0.369		

Log-Likh: -2133.09
Number of spells: 923

TABLE 9 : DEPENDENT COMPETING RISKS MODEL
by Reason for Leaving

Variable	Exit Voluntary Estimate	Exit Voluntary S.E.	Exit Involuntary / Fam. Reasons Estimate	Exit Involuntary / Fam. Reasons S.E.
TWAGE	-1.675	1.202	-1.618*	0.746
NTWAGE	3.755*	1.749	-1.039	1.820
MALE	0.475	0.392	-0.909*	0.385
CERT	-0.805	0.666	0.223	0.440
BED	-1.053*	0.472	-0.279	0.361
DPGCOE	0.249	0.379	-0.143	0.275
ACA	1.263*	0.377	-0.185	0.447
NACA	2.069*	0.607	1.425*	0.416
UNBJ1	0.040	0.022	0.007	0.019
SCHTYPE	0.547	0.440	0.711*	0.342
RELC	0.381	0.363	0.557*	0.275
SCLASS	0.241	0.135	0.201*	0.096
SECONDARY	0.073	0.410	0.091	0.243
LONDON	-0.228	0.376	0.114	0.374
SCIENG	-0.517	0.461	0.297	0.336
UNEM	-0.083	0.044	-0.029	0.039
$exp(\mu_{11})$	0.000	-.—		
$exp(\mu_{12})$	1.000	-.—		
$exp(\mu_{21})$			0.000	-.—
$exp(\mu_{22})$			1.000	-.—
λ_1		0.238*	0.082	
λ_2		0.000	–.—	
λ_3		0.000	–.—	
λ_4		0.762	–.—	
CORR(e^{μ_1}, e^{μ_2})		1.000		

Log-Likh: -2010.66
Number of spells: 923

TABLE 9-A : DEPENDENT COMPETING RISKS MODEL
by Reason for Leaving
Weibull Baseline Hazard: $\underline{h}(t) = \alpha\ t^{\alpha-1}e^{c}$

	Exit Voluntary		Exit Involuntary / Fam. Reasons	
Variable	Estimate	S.E.	Estimate	S.E.
α	1.440*	0.269	1.621*	0.232
c	-7.737*	0.872	-7.049*	0.663
TWAGE	-1.839	0.950	-1.559*	0.698
NTWAGE	2.164	1.168	-2.040	1.245
MALE	0.685	0.292	-0.695*	0.336
CERT	-0.613	0.535	0.382	0.371
BED	-0.836*	0.359	-0.160	0.308
DPGCOE	0.260	0.289	-0.122	0.253
ACA	1.406*	0.316	-0.075	0.402
NACA	1.889*	0.480	1.286*	0.333
UNBJ1	0.033	0.019	0.006	0.016
SCHTYPE	0.595	0.358	0.745*	0.307
RELC	0.435	0.294	0.565*	0.249
SCLASS	0.235*	0.102	0.198*	0.081
SECONDARY	0.156	0.301	0.115	0.205
LONDON	-0.051	0.307	0.188	0.286
SCIENG	-0.339	0.330	0.433	0.279
UNEM	-0.095*	0.035	-0.050	0.034
$exp(\mu_{11})$	0.000	-.—		
$exp(\mu_{12})$	1.000	-.—		
$exp(\mu_{21})$			0.000	-.—
$exp(\mu_{22})$			1.000	-.—
λ_1		0.274*	0.068	
λ_2		0.000	-.—	
λ_3		0.000	-.—	
λ_4		0.726	-.—	
CORR(e^{μ_1}, e^{μ_2})		1.000		

Log-Likh: -2160.65
Number of spells: 923

Table A1 : Probit Estimates

Dep. Var.: CENSOR

Variable	Estimate	Standard Error
Constant	-3.769	2.139
CERT	0.005	0.273
BED	0.238	0.172
DPGCOE	0.036	0.153
DEGCLASS	0.015	0.031
ACA	-0.210	0.180
NACA	-0.892*	0.228
MALE	0.005	0.144
UNBJ1	0.003	0.011
LSWAGE	0.506	0.263
LONDON	0.058	0.142
PRE80EXP	-0.022	0.021
UNIV	-0.148	0.117
SCIENG	-0.013	0.136
SECONDARY	0.047	0.122
SCHTYPE	-0.405*	0.180
TIME	0.003	0.009
RELC	-0.334*	0.146
SCLASS	-0.133*	0.045
UNEM(1)	0.057*	0.018

Number of Observations: 923
Log-Likh: -568.6

Table A2 : Probit Estimates

Dep. Var.: NONTCH

Variable	Estimate	Standard Error
Constant	1.979*	0.190
CERT	-2.100*	0.172
BED	-2.408*	0.092
DPGCOE	-1.853*	0.067
DEGCLASS	-0.024	0.019
ACA	0.344*	0.094
NACA	0.700*	0.100
MALE	0.642*	0.081
UNBJ1	-0.004	0.004
LONDON	0.233*	0.081
PRE80EXP	-0.013	0.014
UNIV	-0.145*	0.067
SCIENG	0.143*	0.069
SCHTYPE	0.055	0.101
SCLASS	0.027	0.028
UNEM(1)	-0.059*	0.010

Number of Observations: 6098

Log-Likh: -1287.5

TABLE A3 : SAMPLE MEANS BY REASON FOR LEAVING

Variable	Total Sample	Stayers	Movers	Voluntary exits	Invol./Fam. exits
DURAT	54.12	67.39	31.37	34.82	29.19
CENSOR	0.632	1.000	0.000	0.000	0.000
SECONDARY	0.835	0.847	0.815	0.848	0.793
CERT	0.075	0.069	0.085	0.061	0.101
BED	0.414	0.441	0.368	0.326	0.394
DPGCOE	0.382	0.374	0.397	0.455	0.361
SCIENG	0.148	0.142	0.159	0.167	0.154
DEGCLASS	4.556	4.580	4.515	4.841	4.308
UNIV	0.412	0.386	0.456	0.523	0.413
ACA	0.062	0.053	0.076	0.144	0.034
NACA	0.040	0.019	0.076	0.068	0.082
MALE	0.285	0.316	0.232	0.409	0.120
UNBJ1	2.970	2.921	3.053	2.977	3.101
SCHTYPE	0.063	0.045	0.094	0.098	0.091
RELC	0.099	0.079	0.132	0.144	0.125
SCLASS	4.506	4.412	4.668	4.621	4.697
LONDON	0.127	0.122	0.135	0.159	0.120
PRE80EXP	0.735	0.740	0.725	1.216	0.413
UNEM(1)	8.960	9.336	8.314	9.005	7.876
LSWAGE	7.804	7.815	7.784	7.812	7.767
SWAGE	2488	2517	2438	2503	2397
LFWAGE[1]	–	7.913	–	–	–
FWAGE[1]	–	2754	–	–	–
LSNWAGE[1]	–	–	–	7.794	7.064
SNWAGE[1]	–	–	–	2630	1577
Number of obs.	923	583	340	132	208

[1] Calculated for non-missing wage observations only

[2] Calculated for non-missing wage observations with exits to non-teaching only.
All wages are deflated into 1976 pounds.

TABLE A4 : CROSS-TABULATION DESTINATION STATE *vs* REASON FOR LEAVING

Destination State	Reason for Leaving		
	Voluntary	Invol./Fam	Total
Non-teaching sector	66	19	85
Non-employment sector	66	189	255
Total	132	208	340

FIG. 1 : The Earnings–Tenure Profile of Teachers

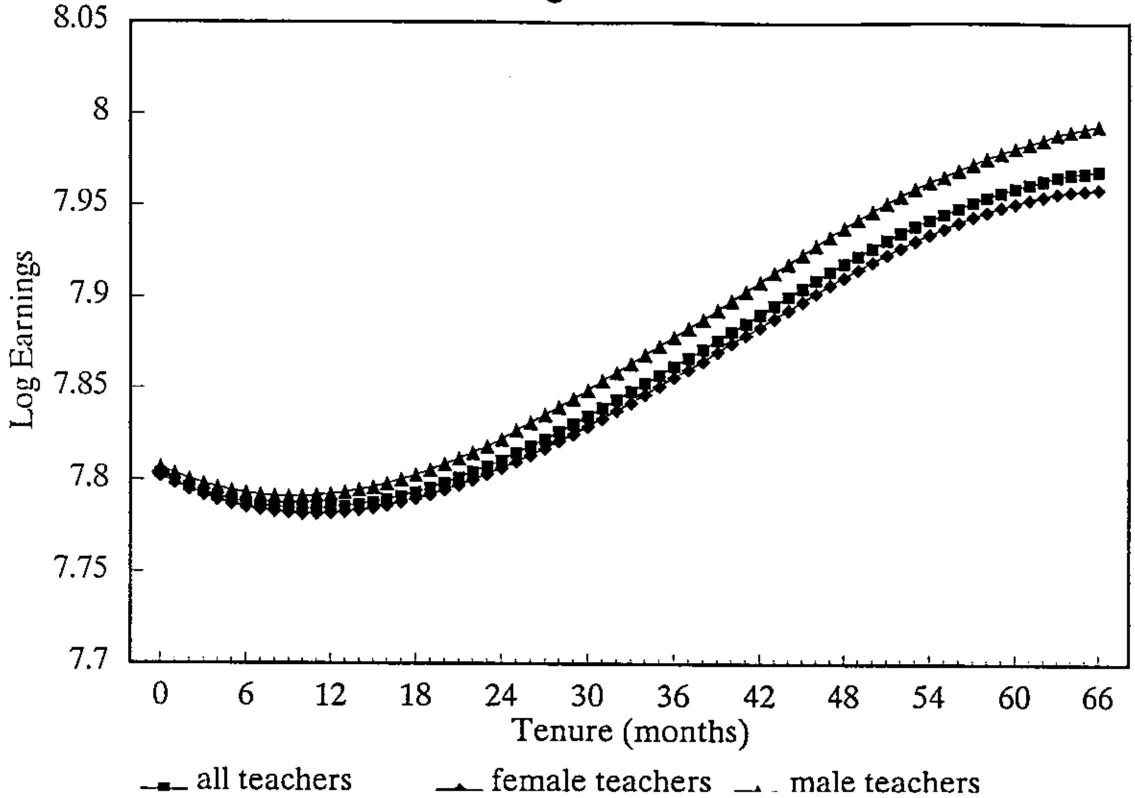

FIG. 2 : Predicted Starting Wages in Non–Teaching Sector

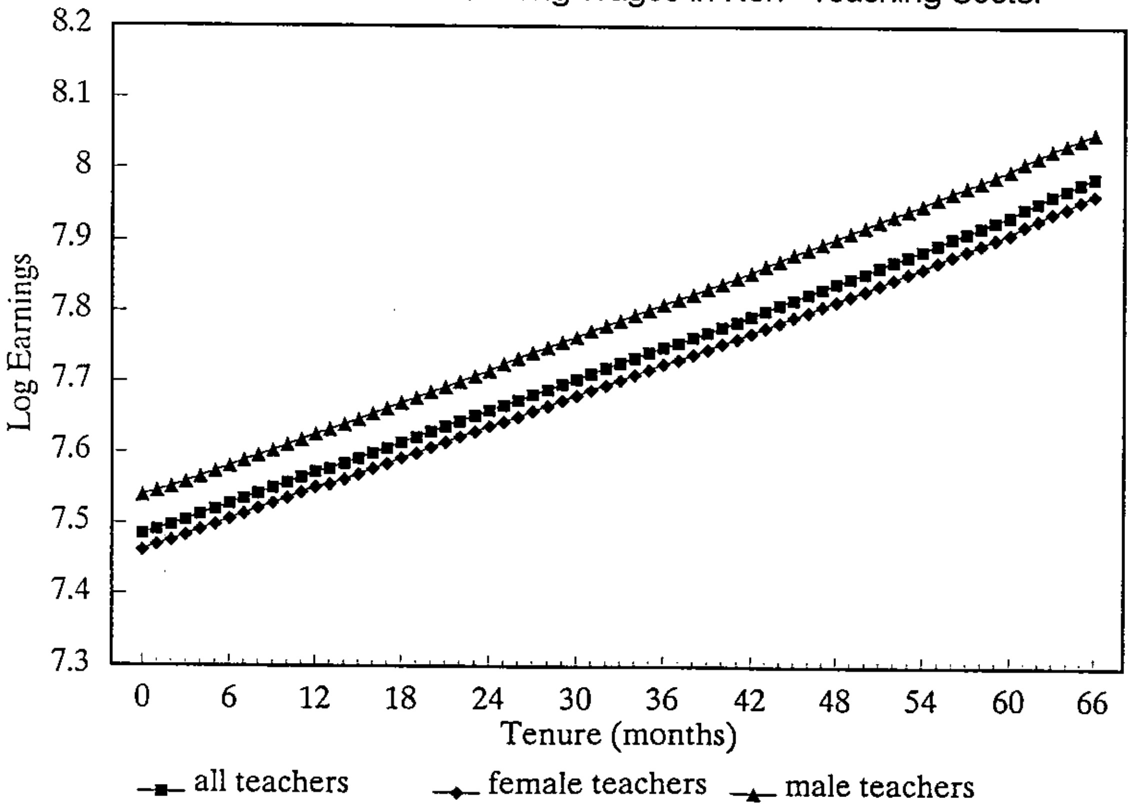

FIG. 3 : Kaplan–Meier Estimate of Hazard Function

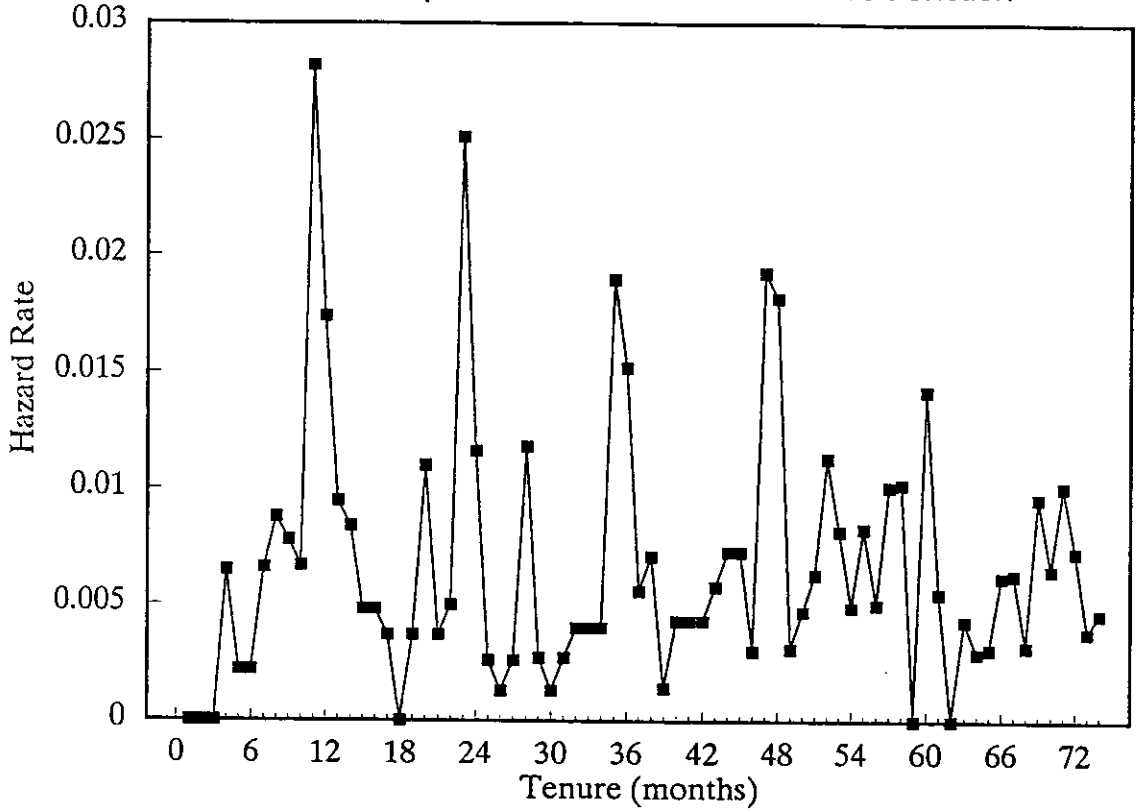

FIG. 4 : Baseline Hazard Estimate (Single Risk Model)

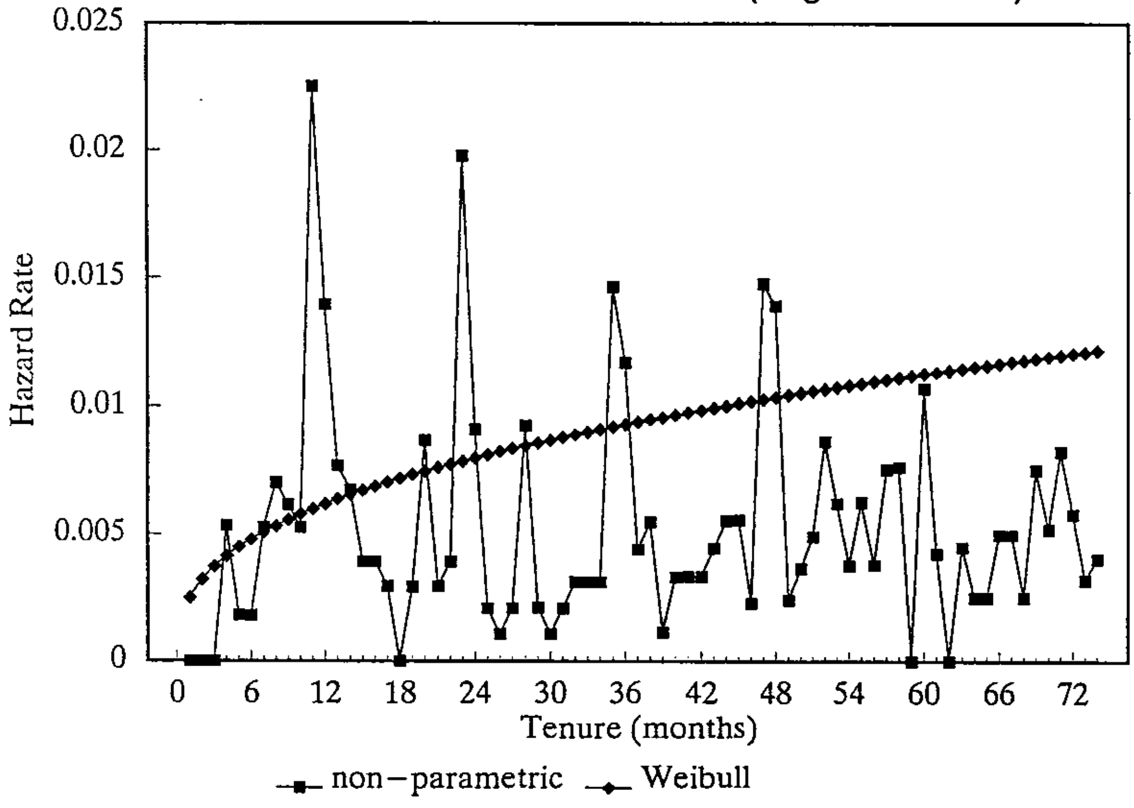

FIG. 5 : Baseline Hazard – Exit to Non–Teaching Sector

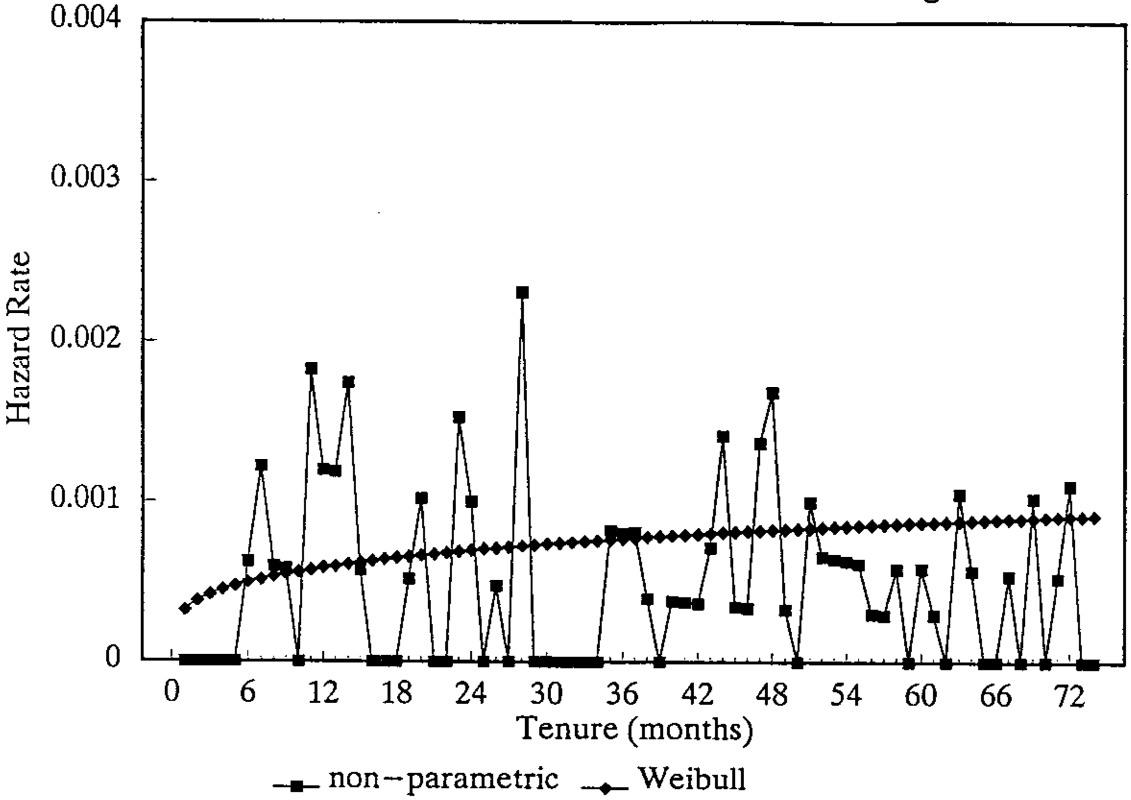

FIG. 6 : Baseline Hazard – Exit to Non–Employment State

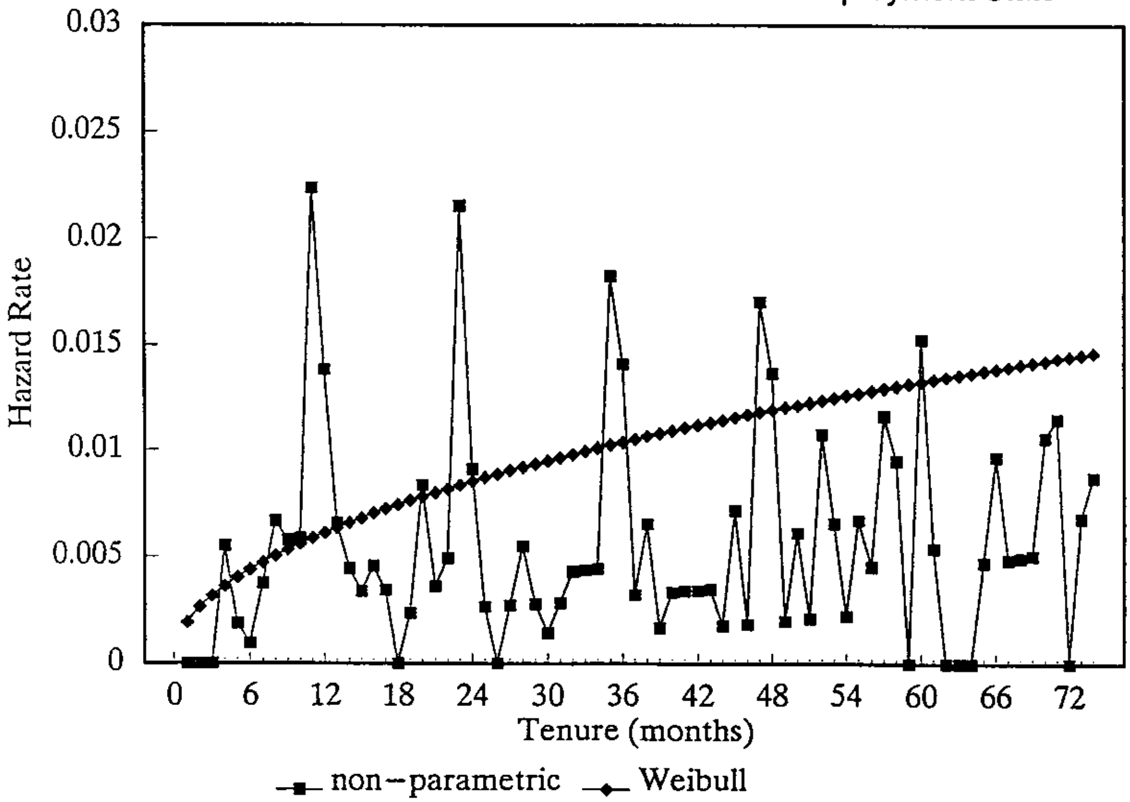

FIG. 7 : Baseline Hazard – Voluntary Exits

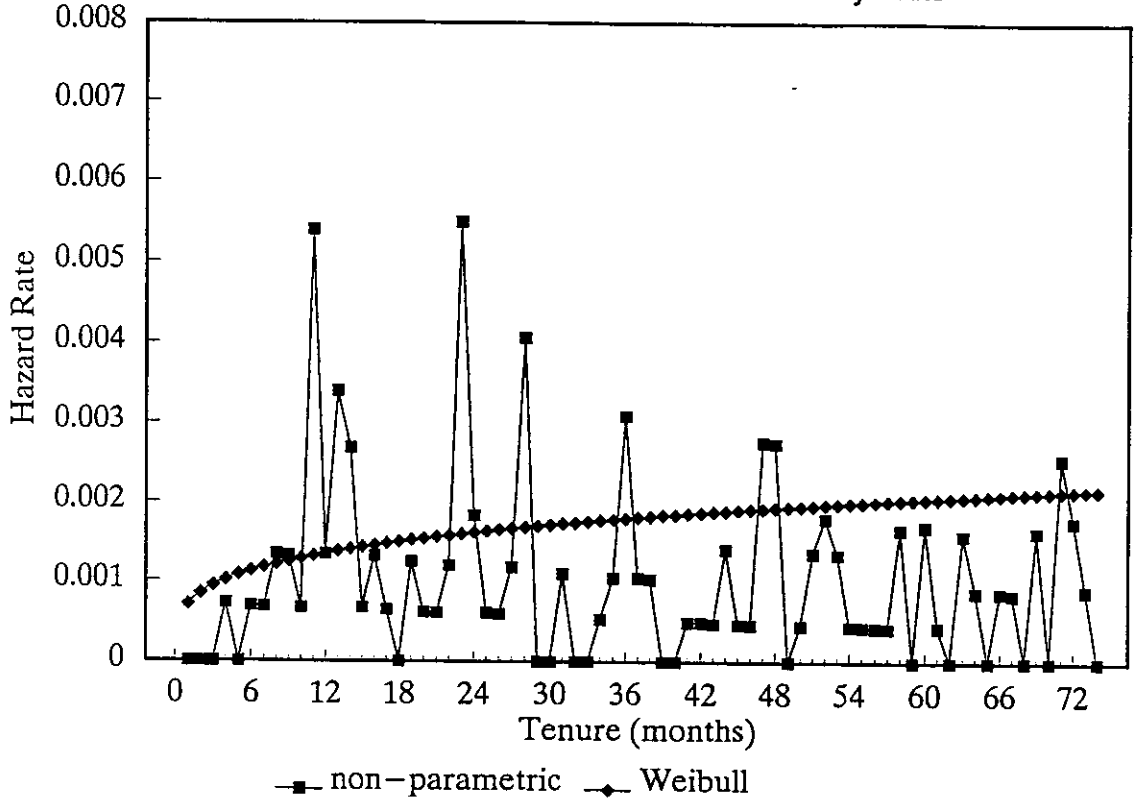

FIG. 8 : Baseline Hazard – Involuntary/Family related Exits

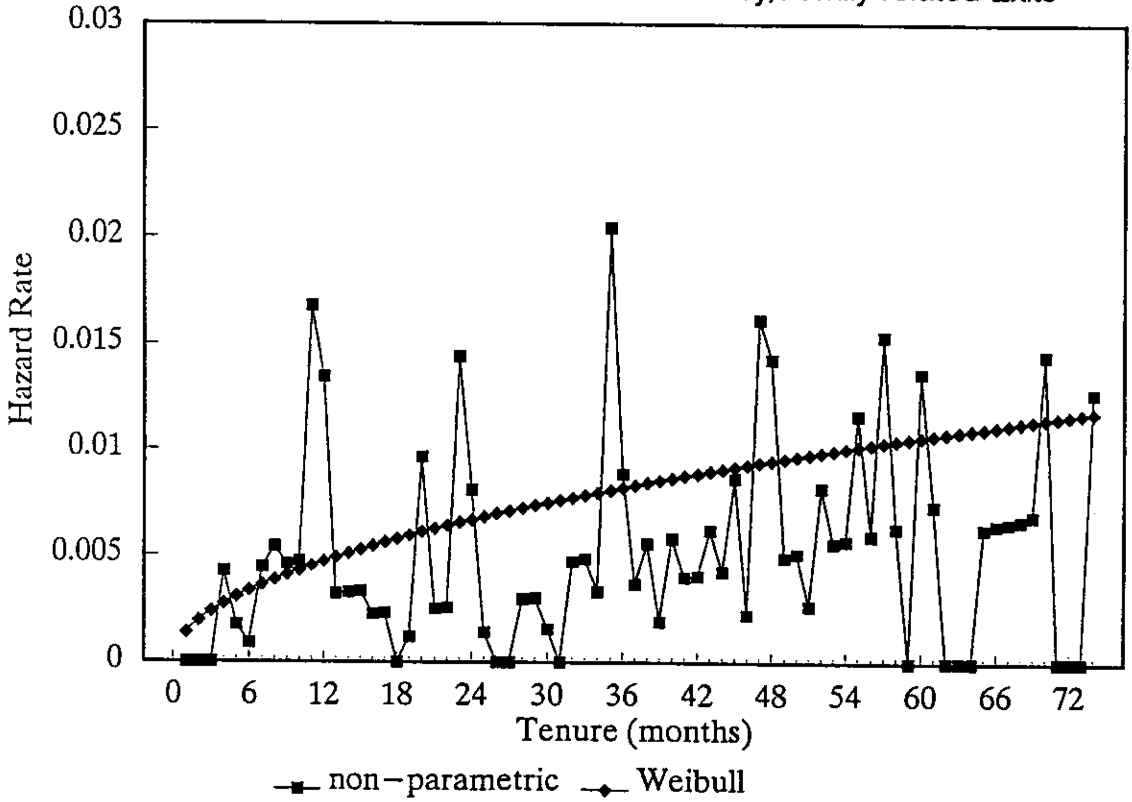

FIG. 9 : Survivor Function – Duration in Teaching
All Exits out of Teaching

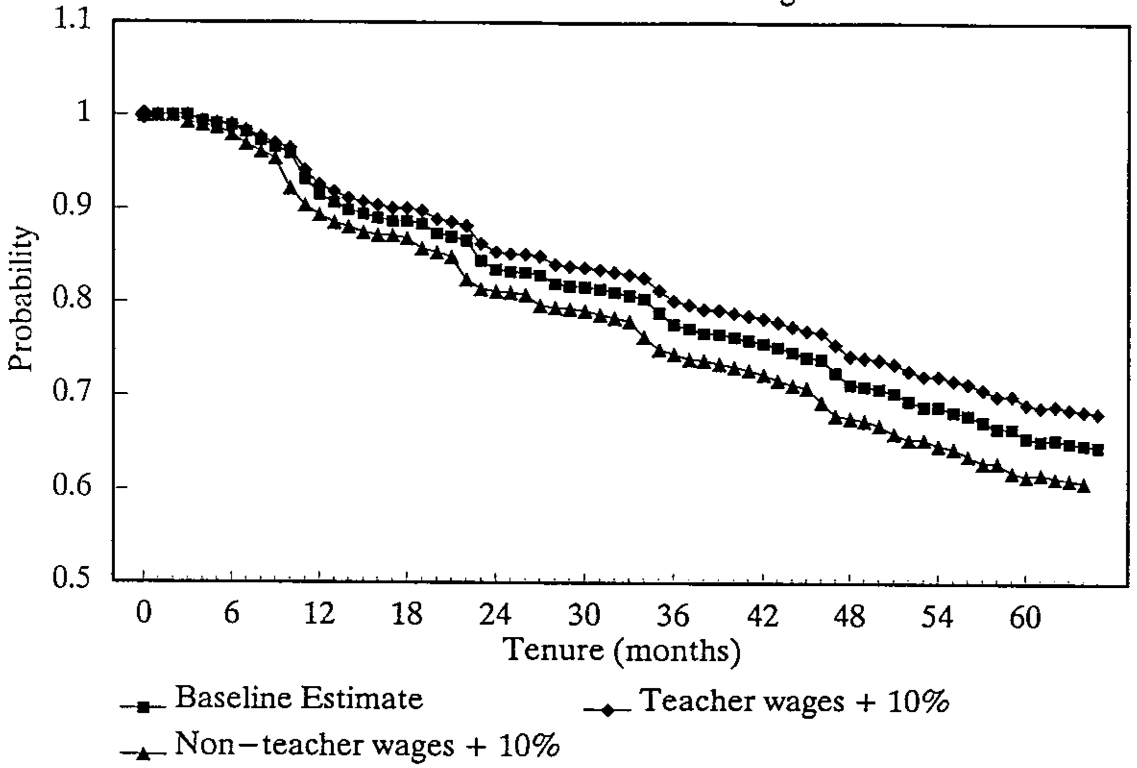

FIG. 10 : Survivor Function – Duration in Teaching
Considering only exit to the non–teaching sector

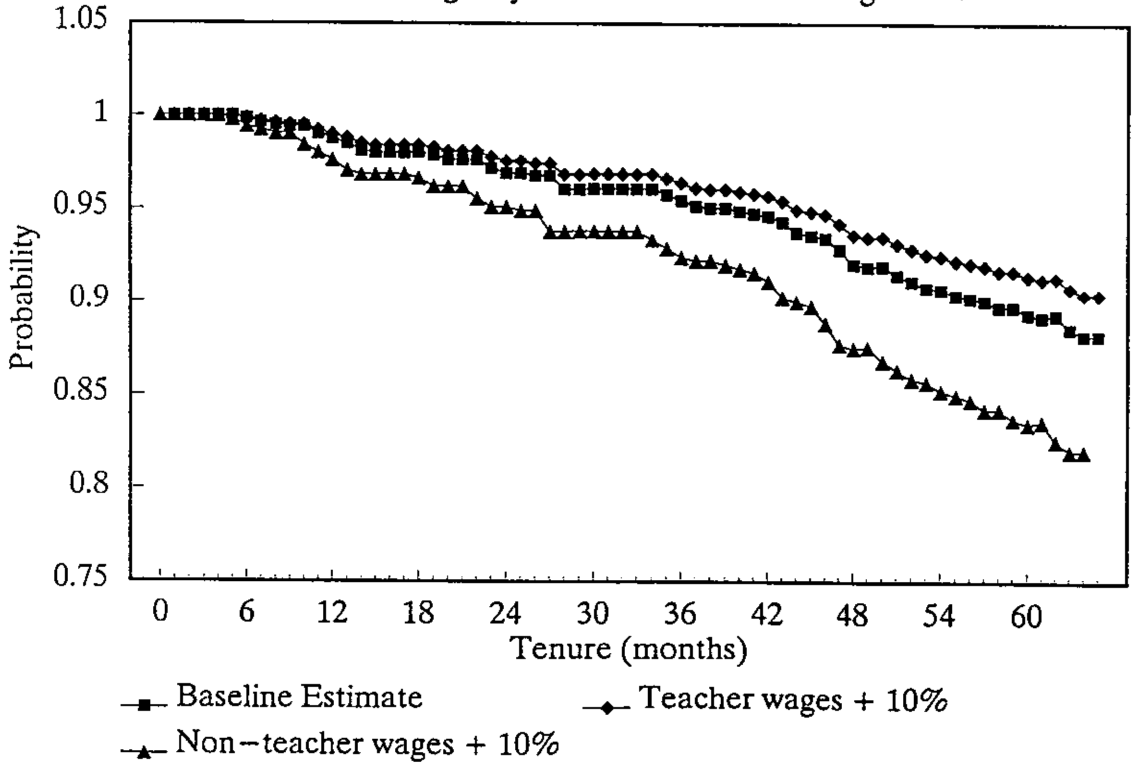

FIG. 11 : Survivor Function – Duration in Teaching
Considering only exit to the non–employment state

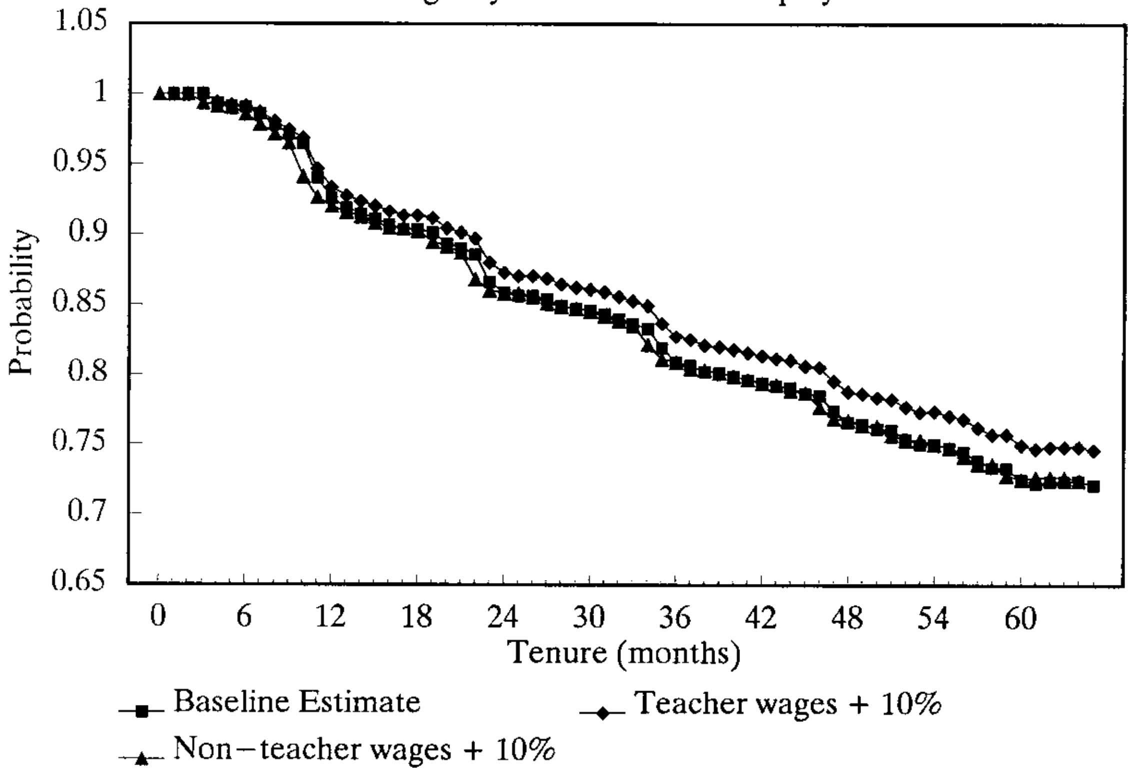

FIG. A1 : Estimated Hazard for Average Teacher

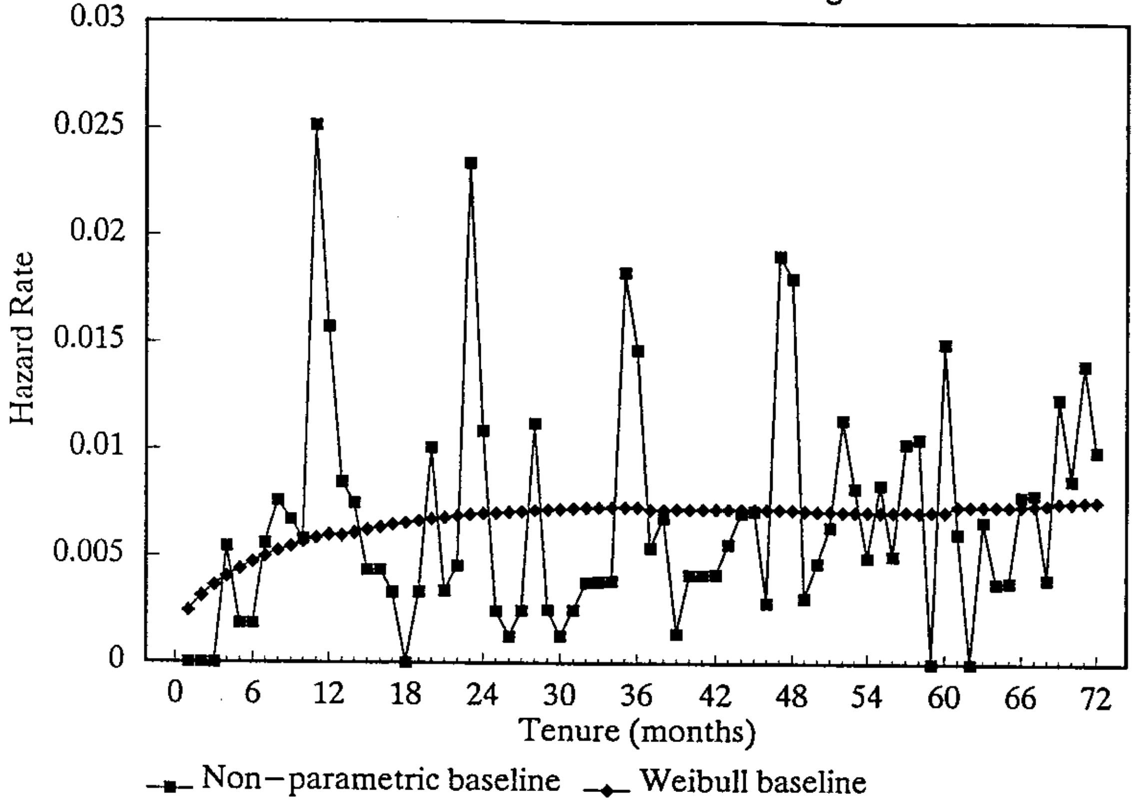

FIG. A2 : Estimated Hazard for Average Teacher
Exit to Non−teaching Sector

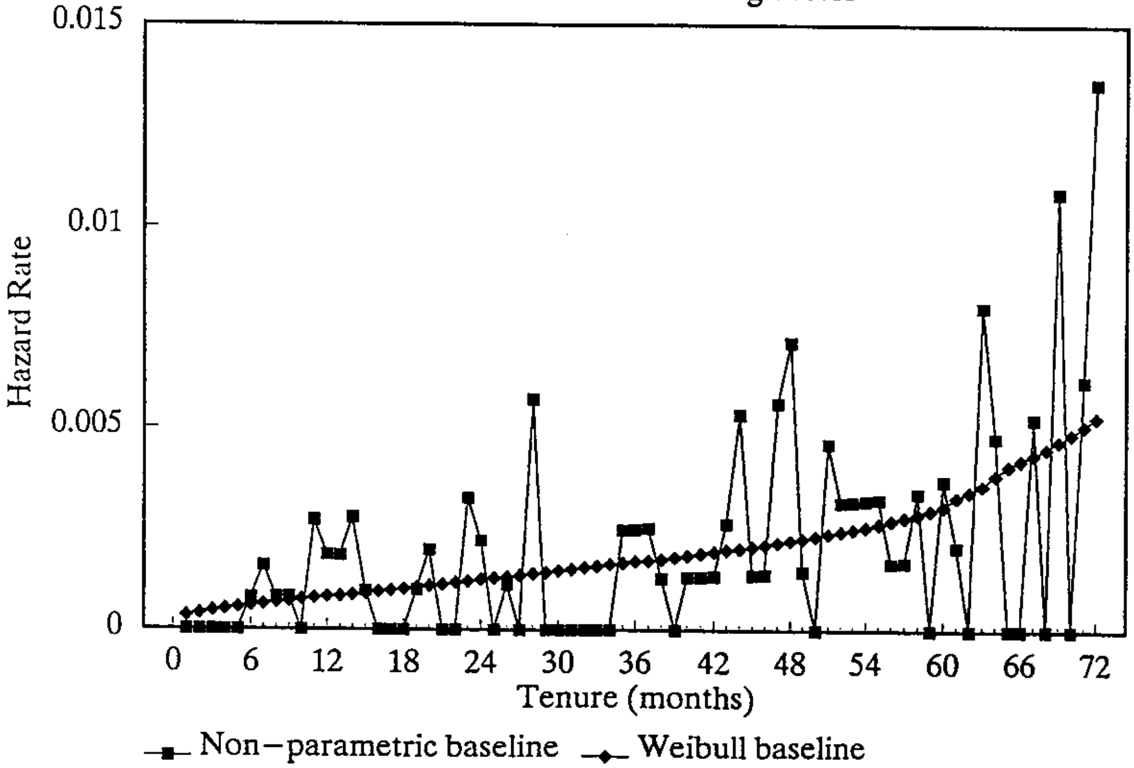

FIG. A3 : Estimated Hazard for Average Teacher
Exit to Nonemployment State

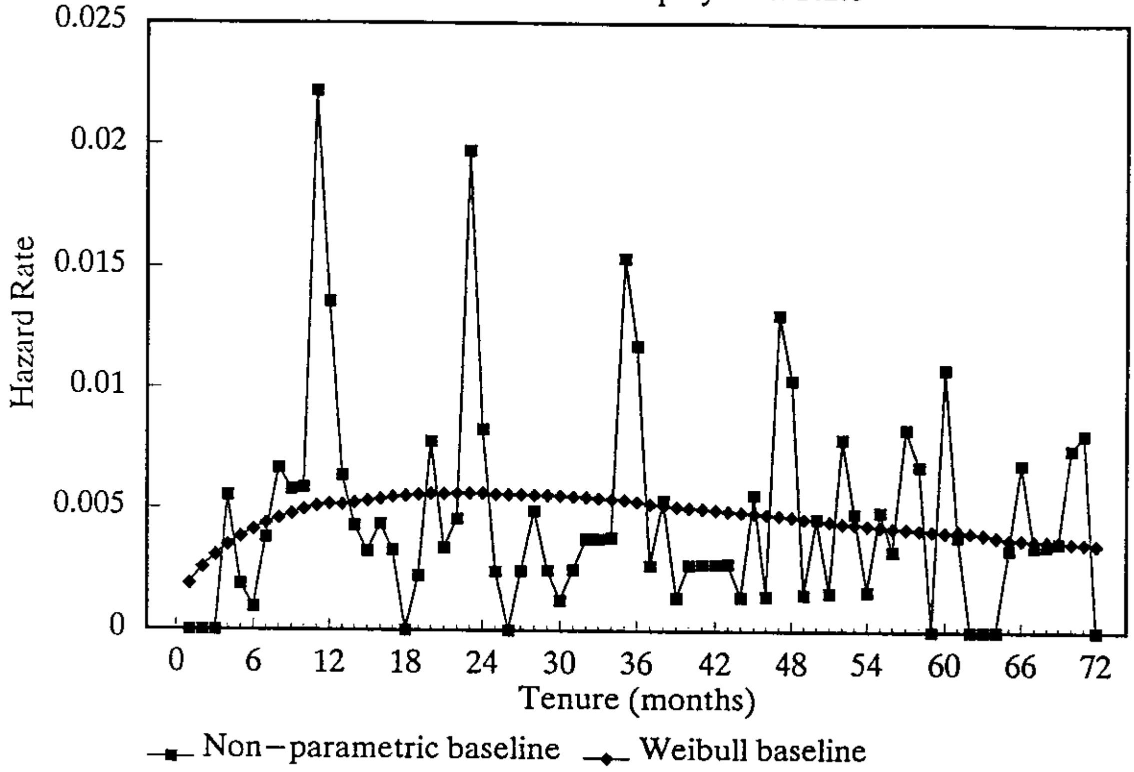

FIG. A4 : Estimated Hazard for Average Teacher
Voluntary Exits

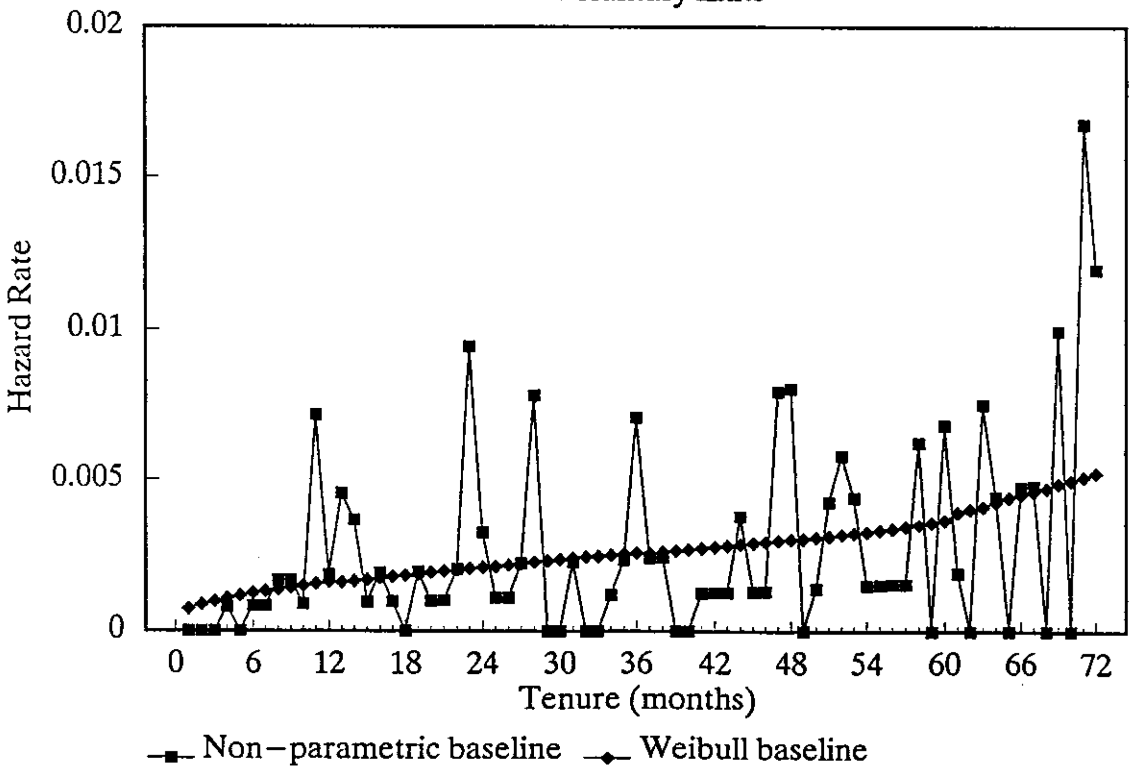

FIG. A5 : Estimated Hazard for Average Teacher
Involuntary/Family related Exits