Dropping out of post-compulsory education in the UK: An analysis of determinants and outcomes[1]

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Abstract We analyse the decision to drop out of post-compulsory education over the period 1985-94 using data from the Youth Cohort Surveys. We show that the drop out rate declined between 1985 and 1994, in spite of the rising participation rate in education, but is still substantial. Dropping out is more or less constant over the period of study, though the risk of drop out does vary with young people's prior attainment, ethnicity, family background and the state of the labour market. The course of study has a substantial effect on the risk of the drop out.

JEL classification I21, J24

Keywords Drop outs, competing risks, employment

[1] All correspondence should be sent to Steve Bradley. We would like to thank two anonymous referees and the Editor of the journal for helpful comments, which have greatly improved our paper. The authors are also grateful to Social and Community Planning Research for providing the Youth Cohort Surveys and for information that enabled us to combine several data sets. We are grateful to Anna Vignoles and participants at the Human Resource Economics Study Group (Lancaster) for helpful comments, and in particular Rob Crouchley, Geraint Johnes, Anh Nguyen, Dave Stott and Jim Taylor. The authors accept responsibility for remaining errors and omissions.

1 Introduction

In this paper we analyse the determinants, timing and outcomes of dropping out of post-compulsory education.[1] This is an important policy issue because educational success between the ages of 16 and 18 increases the likelihood of participation in higher education, which the UK government is seeking to increase. Increasing the proportion of young people who successfully complete post-compulsory education has also been seen as one means of reducing the so-called 'skills gap' (Keep and Mayhew 1999; Prais 1995). A high drop out rate may militate against the achievement of these objectives. Furthermore, young people who drop out of post compulsory education may have missed opportunities for acquiring skills in the labour market, via apprenticeships and government-sponsored training programmes. Consequently, dropouts may be forced into dead end jobs or unemployment, including long term unemployment, all of which is likely to lead to lower lifetime earnings (Markey 1988).

In the US there has been considerable debate regarding the problem of high school dropouts (Toby 1989; Finn and Toby 1989; Toby and Armor 1992) but very little research has been conducted for the UK. In fact, what research has been conducted for the UK has either been descriptive (e.g. Hodkinson and Bloomer 2001) or has focused on dropouts from higher education (Arulampalam, Naylor and Smith 2004 and 2005; Johnes and McNabb 2004; Booth and Satchell 1995; Johnes and Taylor 1991). An exception is the work of Payne (2001), insofar as she uses the same data, albeit for a single cohort of young people. However, like almost all previous studies of drop outs, Payne (2001) ignores the timing and subsequent destination of dropouts, choosing to estimate cross-sectional binary choice models.

There are at least three reasons why it is important to model the timing of the decision to drop out, or more precisely, why the appropriate methodology is a duration model rather than a cross-sectional binary choice model. First, if the probability of dropping out is not constant throughout the period of post-compulsory education then estimating a cross-sectional binary choice model will fail to detect changes in this probability. Figures 1 and 2 clearly show that in the raw data the probability of drop out is not constant, but rather exhibits peaks and troughs. Second, by estimating a duration model we are able to control for the effect of time varying covariates, and in particular the unemployment and vacancy rates in the 'local' labour market, in which we have a particular interest. These effects are allowed to vary by month and by Local Authority District (LAD).[2] Third, our approach allows us to sweep out the effects of unobserved heterogeneity, such as attitudes to education and motivation to study, on the decision to drop out, which are likely to be important. Finally, knowing when young people are at the highest risk of drop out is important if policy makers and practitioners are to develop appropriate ameliorative policies.

FIGURES 1 AND 2 HERE

In view of the above, we seek to answer the following questions. What is the magnitude of the drop out rate from post-compulsory education in Britain and how has this changed over time? How does the decision to dropout vary over the period of study, and is there any relationship between the type of course studied and the decision to drop out? Third, what are the determinants of the decision to drop out, and in particular does the state of the local labour market have any effect? Fourth, do young people drop out for jobs, or are they more likely to become unemployed? To answer these questions we pool data from several Youth Cohort Surveys (YCS), that is, waves 1 to 3 of cohorts 2 to 6, which contains data for 16-19 year olds. The time period covered by these data is 1985-94, a period of rapid increase in post-compulsory participation rates in the UK.[3] We estimate single risk and competing risk hazard models of the decision to drop out, where in the latter case the risks are assumed to be independent of each other. For both sets of models, the baseline hazard and unobserved heterogeneity are estimated non-parametrically.[4] Clearly, the estimates obtained from our duration models will tell us how the probability of drop varies over time and with observed covariates, conditional on entering post-compulsory education. The decision to stay on in post-compulsory education may be non-random, and hence we also estimate multinomial logit models of this decision to identify possible selection effects, which in turn aids the interpretation of the estimates from the hazard models.[5]

The remainder of this paper is structured as follows. In the next section we briefly discuss the standard theoretical framework used to describe the decision to drop out and review the existing literature. Section 3 describes the data and discusses the non-parametric duration modeling techniques that we adopt to model the decision to dropout. In section 4 we discuss our findings in relation to the questions raised above, which is combined with a discussion of the multinomial estimates of the decision to stay on. This section also addresses the potential problem of attrition that exists in most panel data sets, and presents some evidence for the YCS. This is followed by our conclusions and a discussion of the implications for policy.

2 Literature review

The theoretical framework that has traditionally been used as a framework for understanding the decision to invest in, and subsequently drop out from, education is the human capital model (Becker 1964).[6] According to the human capital model, an individual will enroll in post-compulsory education as long as the discounted expected returns to education to the individual are greater than or equal to the costs of the investment, given available information. The return to the investment in education is measured by the increase in lifetime earnings, whereas the costs of continued education include foregone earnings and the direct costs of tuition and learning materials. Having made the initial decision to invest in post-compulsory education, it is therefore likely that the young person had calculated that the benefits outweighed the costs. Why then would they subsequently drop out of education? One possibility is that the young person perceives that they have reached the optimal amount of education and thus drop out before graduation (Jakobsen and Rosholm 2003). A second possibility is that they may have either over-estimated the wage premium associated with education or may have under-estimated the costs and, with the arrival of 'new' information (e.g. job offers with high wages), subsequently adjust their calculation of the net return to investment in education. Since some young people may be better able to make the initial calculation, it is expected that any over-estimation of the returns to education will vary with individual and family characteristics, hence leading to variation between young people in their propensity to drop out. A third possibility is that the psychic, or non-pecuniary, costs of continuing in education may rise which then leads a young person to drop out.

These costs could include a change in tastes towards education or simply a loss of interest in the course of study. These factors are typically unobserved in the data, hence the need to control for them in the econometric modeling.

As suggested earlier, there has been very little empirical work on drop out behaviour for the UK, which contrasts with the US where concern focuses on drop out rates from high school. However, since high school graduation in the US occurs at age eighteen, and post-compulsory education in the UK occurs between the ages of 16 to 18, we argue that the findings from US studies are relevant to our own work. One important caveat is that, whereas education up to the age of 18 is compulsory in some states of the US, this is not the case in the UK.[7] Thus being 'forced' to participate in education will be reflected in the US studies, but this is irrelevant in the UK context.

The existing literature on drop out behaviour has analysed the influence of personal, family, peer group, schooling, local labour market and prior attainment variables. In terms of prior attainment, more able individuals are most likely to stay-on in education because the expected benefits are much higher and risks of failure (a cost) are lower (McElroy 1996; Chuang 1997; Ashenfelter and Rouse 1998; Eckstein and Wolpin 1999; Light and Strayer 2000; Bishop and Mayne 2001; Payne 2001). For the UK, Payne (2001) finds that the odds of drop out decline with prior exam performance; young people in the highest decile of prior attainment are more likely to graduate (by a factor of six) compared to those young people in the lowest decile. Evans and Schwab (1995), Sander and Krautman (1995) and Nguyen, Taylor and Bradley (2002) emphasise the effects of school background on the probability of high school graduation and the decision to enter college. Catholic (private) school pupils are less likely to drop out and they are more likely to enter college (Nguyen, Taylor and Bradley 2006).

Ethnic differences in the decision to drop out are also found. Young people of black and Hispanic background are more likely to graduate from high school (Evans and Schwab 1995; Nguyen *et al* 2006). A similar finding is observed for the UK insofar as all ethnic groups, and especially Afro-Caribbeans, are less likely to drop out of post-compulsory education. One explanation for this finding may be that the opportunity cost of investing in education is lower if the individual perceives that this will lead to discrimination in the labour market.

There is a large literature on the effect of family background on schooling decisions (Hanushek 1992; Becker and Lewis 1973; Becker and Tomes 1976; Behrman and Taubman 1986; Manski *et al* 1992; Sander and Krautmann 1995; Neal 1997). Eckstein and Wolpin (1999) and Payne (2001) find that the probability of dropping out is increased for those pupils with less educated parents. A large number of siblings, low family income and living alone or with a single parent also increases the risk of drop out. Parental occupation is also likely to reflect attitudes to investment in education and the ability to cover the costs of education (Carpenter and Hayden 1987; Koshal, Koshal and Marino 1995; Armor 1992).

The state of the local labour market may also affect the decision to remain in education. Chuang (1994) finds that labour market factors exert a strong influence on the decision to re-invest in education. Young people invest in education when the labour market is slack (Card and Lemieux 2000), especially in the case of males (Markey 1988; Cohany 1986). This is a classic discouraged worker effect.

3 Data and econometric methods

3.1 The data and institutional background

In the UK young people can leave formal education at the end of the academic year following their sixteenth birthday, and proceed to post-compulsory full-time education or they can enter the labour market. During the period 1985-94, the youth labour market in Britain had a highly structured recruitment cycle, with entry to many employer apprenticeship training schemes and the ‘good’ Youth Training Schemes (YTS) commencing before the start of courses in post compulsory education. Other young people entered YTS programmes that had less formal training content or they became unemployed. Those young people who did proceed to post compulsory education could study at a sixth form college (sometimes attached to their school), or attend a college of further education. In both cases it was possible to pursue either an academic route (e.g.

A levels) or a vocational route (e.g. business, engineering, etc.), the former route typically regarded as the stepping stone to higher education.

The data used in this analysis are the Youth Cohort Surveys of England and Wales, versions 2 to 6, which refer to the 1985-94 period.[8] Each YCS is comprised of three sweeps, conducted at the ages 17, 18 and 19, and for each sweep the young person is asked to reflect back on their educational and labour market activities in the previous year. In addition, in the first sweep of the survey young people are asked about their experiences and achievements at school, and their personal and family characteristics.[9] For young people proceeding to post-compulsory education, the Survey also collects information on the type of course taken, whether the young person sits their exams and the grades achieved. Another important feature of the YCS, which allows us to compute the length of stay in post-compulsory education, is the diary information. This records the educational and labour market status of all young people in each of 36 months since the completion of compulsory education.[10]

We take October following the end of compulsory schooling as our starting point for the analysis of drop out behaviour, even though most courses begin in mid-September. Unfortunately, the YCS does not record whether a young person has dropped out or not. This has to be computed from two pieces of information, as follows: (1) a respondent is recorded as a dropout if she leaves full-time post-compulsory education and does not return in the same academic year; *and* (2) the respondent does not sit for the exam or gain the qualification for which she was originally enrolled. Young people can undertake courses that last either one or two academic years and this is the period in which they are 'at risk' of prematurely ending their education. Note that this time period includes the Easter vacation and the summer break between academic years. Examinations are typically taken in the period May-July, whereas coursework assessment is continuous.

In Tables 1 and 2 we report the sample sizes and the probability in the raw data of dropping out for each covariate. The raw data show that 12% of males and 13% of females drop out of their courses, although this rate has decreased over time in spite of the rapid expansion in the proportion of young people proceeding to post-compulsory education between 1985 and 1994. For instance, for males the percentage dropping out decreased from 16.5% for those who entered post-compulsory education in October 1985 to 10.1% for those who entered in October 1991. The equivalent figures for females were 16.3% and 11.0%, respectively. These figures are broadly similar to those produced by the Audit Commission (1993), which showed that for England 13 per cent of young people on academic courses dropped out, whereas the equivalent figure for vocational courses was 18 per cent. This is reassuring since the Audit Commission's study refers to the population of young people in post-compulsory education, implying that our measure of dropping out is reasonably accurate. Figures 1 and 2 show how dropping out varies over the period of study in post-compulsory education. It is clear that this is not constant, exhibiting large peaks in April (periods 6 and 18) of each year with a smaller peak in July (period 9).

TABLES 1 AND 2 HERE

Table 3 presents some descriptive statistics on the destination of dropouts. A substantial percentage of dropouts actually enter employment, and there is very little difference between males and females in this propensity. There are also very few differences between drop outs in terms of their prior attainment, except for the least qualified where a larger proportion become unemployed, especially in the case of females. The quality of the jobs taken by the employed is uncertain; dropping out to a dead-end job is clearly worse than dropping out for a job with training. However, we do not know the occupation of those young people who drop out to employment because this data is only collected annually by which time some of our young people have moved from employment to unemployment.

TABLE 3 HERE

3.2 Modelling the decision to enter post-compulsory education

As suggested earlier, young people can proceed to post-compulsory education or they can enter the labour market. Thus, rather than focus purely on the probability of dropping out, conditional on entry to post-compulsory education, we estimate a multinomial logit model that distinguishes between those who do stay on and those who do not. Those who enter the labour market are further split into the states of employment, youth training and unemployment. Moreover, following previous research, which suggests that drop out rates vary by the type of course undertaken (Payne, 2001; Jakobsen and Rosholm, 2003), we also sub-divide those who enter post-compulsory education into four states: low/high academic/vocational further education.[11] We therefore estimate a 7 state multinomial logit model, which allows us to examine non-random selection into post-compulsory education, and aids the interpretation of the marginal effects of dropping out.

3.3 Modelling the hazard of drop out of post-compulsory education

We model the decision to drop out of post-compulsory education as a hazard model following the approaches of Stewart (1996) and Andrews *et al* (2002). The length of time from entering post-compulsory education to dropping out is represented by the non-negative random variable T. Here T is measured in discrete time intervals since our data are recorded at monthly intervals. The hazard rate is a measure of the probability that an event, dropping out, occurs at time t, conditional on it not having occurred before time t.

A young person either drops out or they graduate (a small proportion of the sample – 8% of females and 10% of males - are censored i.e. they remain in post compulsory education). We adopt a single risk and a competing risks framework, in the latter case distinguishing between dropping out to unemployment (r_i = 1) and dropping out to employment (r_i = 2). We assume that the hazards for each competing risk are mutually independent, which enables us to estimate a separate model for each risk or exit state.[12] For each model the data are organised into sequential binary response form (Prentice and Gloecker 1978; Meyer 1990) where all observations are zero except for the period in which a dropout to the risk in question occurs. Thus, young people who exit to unemployment, (r_i = 1), for instance, are treated as censored at the point they exit in the hazard of exit to employment, (r_i = 2). For each risk, a panel of individuals is constructed with the i-th individual contributing j = 1, 2, …, t_i observations. The maximum number of periods (months) that an individual can be at risk is 20.[13] Assuming proportional hazards we have:

$$h_{rj}(\boldsymbol{x}_i') = \hat{h}_{rj} \exp(\boldsymbol{x}_i'\boldsymbol{\beta}) \qquad (1)$$

where h_{rj} is the hazard of exit for each j and to each state, $\hat{h}_{rj}$ is the baseline hazard for each exit state and x_i' is a vector of observable covariates. [14]

The likelihood for the i-th individual is then given as:

$$L_{ri} = \prod_{j=1}^{t_i} h_{rj}(x_i')^{y_{it}} [1 - h_{rj}(x_i')]^{1-y_{it}} \qquad (2)$$

The explanatory variables affect the hazard by the complementary log-log link function:

$$h_{rj}(x_i') = 1 - \exp[-\exp(x_i'\boldsymbol{\beta} + \gamma_j)] \qquad (3)$$

An issue that also has to be resolved is how to control for the presence of unobserved heterogeneity. There may be unobserved differences between graduates and dropouts that are not recorded in the data, for example the level of motivation and attitudes to education. Failure to control for unobserved differences between individuals may cause severe bias in the estimation of the baseline hazard (Heckman and Singer 1984, Lancaster 1990). Vandenberghe (2000) notes that the presence of unobserved heterogeneity leads to over-estimated coefficients for negative duration dependence and under-estimated coefficients for positive duration dependence. Standard practice suggests that it is possible to control for unobserved heterogeneity by including a positive-valued random variable (v), or mixture, into our model (suppressing the r subscripts) as follows:

$$h_j(x_i', v_i) = \hat{h}_j \exp(x_i'\boldsymbol{\beta}) v_i \qquad (4)$$

where v represents the unobserved heterogeneity. The above model can be written as follows:

$$h_j(x_i') = \hat{h}_j \exp(x_i' \boldsymbol{\beta} + u) \qquad (5)$$

where $u = \log v$ with density $f_u(u)$. The amended likelihood can then be written as

$$L_i(\beta) = \int \prod_{j=1}^{t_i} h_j(x_i', u_i)^{y_{it}} [1 - h_j(x_i', u_i)^{1-y_{it}}] \int (u_i) du_i \qquad (6)$$

where $h_j(x_i', u_i) = 1 - \exp[-\exp(x_i' \boldsymbol{\beta} + \gamma_j + u_i)]$.

Two approaches have been used to model the unobserved heterogeneity. The first is to assume a particular parametric distribution for the heterogeneity term. In this case $f_u(u_i)$ in Equation (6) is replaced by parameters from, for instance, the Gamma or the Gaussian distribution. The Gaussian mixture model is considered superior where there are thought to be a large number of unobservables. However, there is a debate concerning the appropriate distributional form of the heterogeneity term. Since the heterogeneity is unobservable there is often no justification for the choice of either parametric distribution. Moreover, the problem with specifying a parametric distribution for the heterogeneity term is that the estimated parameters may be sensitive to the particular distribution adopted, especially where the baseline hazard is not sufficiently flexible (Meyer, 1990). An alternative approach suggested by Heckman and Singer (1984) is to use the mass point technique, which approximates a continuous distribution by a finite discrete distribution of unrestricted form. In this case, u_i and $f_u(u_i)$ are replaced by a discrete mass point approximation. We adopt the mass point method in this paper.

For the single risk model we report the estimated coefficients and the odds ratios, the latter being easier to interpret. In the competing risks model the effect of a covariate on the probability of exit via risk r are not easy to interpret because they are dependent on both hazards $h_{1j},\ldots,h_{2j}$ via the overall survivor function (see Andrews *et al*, 2002 equation 5). But, when proportional hazards are assumed, it is easier to focus on the probability of exit via state r conditional on exiting during the interval j, denoted P_{rj}:

$$P_{rj} = \frac{h_{rj}}{\sum_r h_{rj}}, r = 1,\ldots,2. \tag{7}$$

The baseline hazards used to compute equation (7) set $\bar{x}$ and $\bar{\gamma}$ at their mean values.[15] The marginal effect of x on the conditional exit probability, is then given by

$$\delta_r \equiv \frac{\partial P_{rj}}{\partial x} = \frac{h_{rj}\sum_{k \neq r} h_{kj}(\boldsymbol{\beta}_r - \boldsymbol{\beta}_k)}{[\sum_{r=1}^{2} h_{rj}]^2} \tag{8}$$

These marginal effects sum to zero across all r because the summed conditional probabilities of exit equal one.

4 Results

4.1 Staying on and dropping out

So that we can better interpret the conditional marginal effects of the decision to drop out, we combine the discussion of the multinomial logit models of the decision to enter post-compulsory education (Tables 4 and 5) with that of the estimates from the single risk and competing risk models (Tables 6 and 7). The single risk estimates in Tables 6 and 7 allow us to say what 'type' of young person is more likely to drop out, whereas the results of the competing risk model indicate which exit state is most likely, conditional on having entered post-compulsory education and then having dropped out.

TABLES 4 AND 5 HERE

Qualifications achieved during compulsory schooling are a major determinant of post-school destination and are an obvious mechanism for sorting young people into different post-compulsory education courses.[16] Females who achieve 5 or more GCSEs graded A-C are 83 percentage points more likely than their counterparts with no qualifications to proceed to post-compulsory education for 'high academic' courses, such as A levels (see Table 4). The marginal effect for the next most qualified group, 1-4 GCSE A-C, is also very large (0.49) but still represents a 34 percentage point decrease in the risk of proceeding to these courses. A general trend is that the less qualified the young person the more likely it is that they will be sorted into 'low' level academic and vocational courses. Table 5 shows that a very similar picture emerges for males. The estimates from the single risk model also show that a higher level of qualification obtained at school is associated with a lower risk of dropping out from post-compulsory education. This is over and above any effect from the type of course studied, although some of the estimated coefficients are insignificant, perhaps because of a correlation with the course variables. Nevertheless, the odds ratios indicate that females in the highest attainment category (5+ GCSE A-C) are 35 percent less likely to drop out, compared to the base group, whereas the equivalent figure for males is 38 percent (see Tables 6 and 7). Furthermore, the competing risks models show that dropouts with GCSE qualifications are less likely to become unemployed. These effects are generally stronger for males, but there is no clear pattern of effects between the different qualification groups. For instance, females in the highest attainment category are 7 percentage points less likely to become unemployed (Table 6) whereas for their male counterparts this rises to 23 percentage points (Table 7).

TABLES 6 AND 7 HERE

Young people who enroll on 'low' level courses are substantially more likely to drop out when compared to their counterparts on 'high' academic courses. However, conditional on drop out, they are more likely to find a job rather than become unemployed. Low level vocational courses offer a particular advantage for males, where the marginal effect is six times larger than the equivalent for 'high' vocational courses. For females, low level academic or vocational courses provide almost equivalent advantage in the labour market. This suggests that the knowledge obtained on these low level courses is sufficient to enhance the human capital of young people and hence make them more employable.

Turning to the effect of ethnicity on the decision to enter post-compulsory education, in general, young people from ethnic minority groups enter academic courses, with some variation between groups with respect to whether it is ‘high’ or ‘low’ academic course. For instance, Indians and Bangladeshi’s enroll on ‘high’ academic courses, whereas Pakistanis are equally likely to proceed to either ‘low’ or ‘high’ academic courses. Afro-Caribbeans have a higher risk of entering ‘low’ academic courses. Males follow a broadly similar pattern, although Afro-Caribbean boys are more likely to enroll on ‘high’ academic courses, when compared to females, and boys from all ethnic groups are more likely to enroll on ‘low’ vocational courses. This pattern of course choice broadly follows the differences in their educational attainment at compulsory schooling (Bradley and Taylor, 2004), and may reflect an attempt to close the so-called ‘qualification gap’ between whites and non-whites that is observed at age 16. Tables 6 and 7 show that, conditional on continuing their education, young people from all ethnic backgrounds are less likely to drop out. However, in contrast to Payne (2001), we find that Indians are the least likely to drop out and there are some interesting differences between males and females. For instance, the odds ratios for Indian males and females are very similar - the risk of dropping out is reduced by 79 percent and 73 percent, respectively, whereas Afro-Caribbean male and female behaviour differs. Afro-Caribbean males are insignificantly different to whites, whereas Afro-Caribbean females are 57 percent less likely to drop out when compared to their white counterparts. The marginal effects from the competing risks models show that almost all ethnic groups who do drop out are less likely to become employed, especially in the case of males. The marginal effect on employment for Bangladeshi/Pakistani females is very large (-0.42), which compares with a larger effect (-0.49) for males, although we must be cautious about this result because it is based on a small number of observations. In sum, these findings imply that young people from an ethnic minority background remain in education to improve their qualifications to reduce the possibility of discrimination once they enter the labour market. An alternative view is that the differences between ethnic groups in their propensity to drop out are due to cultural factors.

Tables 4 and 5 show that young people who live on council estates (i.e. in social housing), where household incomes are relatively low, tend not to proceed to post compulsory education. In the case of males they are equally likely to become unemployed, employed or enter a government funded youth training programme. In contrast, females are twice as likely to enter employment as they are to become unemployed or enter training. There is also evidence that young people who live in social housing are more likely to drop out and become unemployed. The odds ratios on the social housing variable are also large, implying that males and females from council estates have a greater risk of dropping out than young people from the owner-occupied sector - between 33-35% (see Tables 6 and 7). Furthermore, not only do they fail achieve further qualifications, drop outs from council estates are more likely to become unemployed, though there is some difference in the outcome for males and females – the marginal effect is 0.12 for males compared to 0.04 for females.

Family background, reflected by parental occupation, has a statistically significant effect on the decision to stay on (Tables 4 and 5). Interestingly, the effect for a female of having a mother in a managerial/professional occupation outweighs the equivalent effect from the father's side (compare the marginal effects of 0.15 and 0.08, respectively). Similar effects are observed for females with parents in non-manual occupations, although these effects are roughly half those of the professional/managerial category. In contrast, the effects for males are similar in magnitude for fathers and mothers on both the managerial/professional and non-manual variables. A further noteworthy effect is that males from unskilled non-manual backgrounds have a higher probability than the base group of proceeding to 'high' academic courses. We find more limited evidence of family background effects on the conditional probability of drop out, insofar as the influence of parental occupation is only significant where either parent is in a managerial, professional or a skilled non-manual occupation. There are also different effects for males and females. Females with a mother or a father in a professional or managerial occupation are less likely to drop out, but if they do drop out they are less likely to become unemployed (Table 6). In comparison, for males there is no significant effect arising from a mother's occupation, whereas having a managerial/professional father reduces the probability of drop out (Table 7). These findings may reflect an income effect, insofar as parents in professional and managerial occupations are more able to support their children in education, or at least develop a taste for education in their children.

In contrast to the US literature, we do not find statistically significant effects of other family background factors, such as family size, single parenthood or household economic status.

In terms of the effect of labour market variables on the decision to stay on (Tables 4 and 5), we do not find a statistically significant effect of either the local unemployment or vacancy rates. This is consistent with the view that the supply constraint on the total number of places in post-compulsory education has been removed, although these may exist for specific courses. In contrast, as one would expect a higher unemployment rate does reduce the risk of employment and increase the probability of undertaking government funded training. Interestingly, the unemployment and vacancy variables are statistically significant with respect to the unemployment outcome and, although small in magnitude, are equal and opposite in sign. The state of the local labour market does, however, have a statistically significant effect on the hazard of dropping out but only in the competing risk models (Tables 6 and 7). Our evidence suggests that, if young people drop out, they are more likely to become unemployed the higher the local unemployment rate. The marginal effects imply that females have a slightly lower risk of becoming unemployed – 4 percentage points, compared to 10 percentage points for males.[17]

4.2 The timing of the dropout decision

Here we focus on the shape of the baseline hazards for each gender to each exit state (see Figure 3). Controlling only for observables, the shape of the baseline hazards reveal that the decision to dropout of post-compulsory education is not constant, but displays several spikes. There are large spikes towards the end of the period of study just before final examinations, which is a worrying finding. Students may be reluctant to sit examinations, preferring instead to search for work because job vacancies become available at the time of the peaks – April and July. Controlling for unobserved heterogeneity flattens the hazards and shifts them down, especially with respect to exits to employment. The spikes are more pronounced in the case of exits to unemployment (panels b and d), however, it is only for females that the spikes remain reasonably large towards the end of the period. Overall our evidence on the shape of the baseline hazards contrasts with previous evidence, which suggests positive duration dependence (Jakobsen and Rosholm, 2003). Controlling for observed and unobserved heterogeneity, the probability of drop out is constant over the duration of the course.

FIGURE 3 HERE

The baseline hazards are difficult to compare between the genders and between exit states, therefore we compute transition intensities, which are shown in Figure 4. Note that these conditional exit probabilities must sum to unity, helping to make it more obvious which exit state is most likely. Figure 4 shows that for both genders unemployment is the most likely outcome of dropping out, however males do better than females. Not only do they consistently have the highest probability of employment, they also have the lowest risk of unemployment for most of the period. The risk of unemployment for female drop outs is particularly acute.

FIGURE 4 HERE

4.3 Attrition from the YCS

Before we conclude, we turn to the problem of sample attrition, which can lead to biased estimates. This occurs where a non-random sample of respondents fail to respond to subsequent sweeps of the Survey. The YCS suffers from the problem of attrition, particularly between sweeps 1 and 2, however this problem is more severe for young people who enter the labour market at age 16. For instance, in our data 60% of 16 year olds proceed to post-compulsory education (18,796) and of these 60% (11,252) remain in the Survey throughout. In contrast, 40% (12,303) entered the labour market and of these only 47% remain in the Survey. Females are less likely to attrit than males. Of the 68% (23,240) who continued their education, 66% (15,339) remained in the Survey and the equivalent figure for labour market entrants was 54%. Since our analysis of dropping out is conditional on continuing to post-compulsory education, we argue that attrition is likely to be a much less serious problem than an analysis of labour market entrants.

Nevertheless, we take the possible effects of sample attrition seriously and pursue two modeling strategies to explore further the potential bias that could be present in our previous analysis. These strategies and the associated results are discussed in more depth in a previous version of this paper.[18] Our first modeling strategy is to estimate two binary logit models of the decisions to continue in post-compulsory education and attrition from the Survey, so that we can ascertain what 'type' of young person is most likely to stay in education and which 'type' is most likely to leave the survey. The results are reassuring insofar as we find that those types of young people who are more likely to enter post-compulsory education are less likely to exit from the Survey. The second modeling strategy is to estimate the Heckman and Singer models separately for each wave of the YCS, and then compare the estimates of these sub-models with the full model. If attrition bias is a big problem then we would expect the estimates from the sub-models to differ substantially from each other and from the full model. The results for the single risk models show very little evidence of attrition bias. Virtually all of the variables that are statistically significant in the full model are also significant in each of the sub-models. There is no evidence that estimates switch sign and in most cases the absolute value of the estimates are very similar in magnitude. The estimates for the competing risks sub-models exhibit more variation when compared with the full model, but the basic story presented above does not change. We are therefore reasonably confident that the results reported in Tables 6 and 7 do not suffer from a major problem of attrition bias.

5 Conclusion

In this paper we analyse the magnitude, timing, determinants and outcomes of dropping out of post-compulsory education in Britain for the period 1985-94. This is the first study of its kind for the UK and our findings are richer and different to the closest comparable study by Payne (2001). We use data from several cohorts of the YCS, and use duration modeling techniques, allowing for unobserved heterogeneity and incorporating time varying covariates.

Our main findings with respect to the magnitude and timing of the decision to drop out are that, in spite of a rapid increase in the number of 16 year olds proceeding to post-compulsory education over the period 1985-94, the drop out rate actually fell. This is an encouraging finding, but it is still the case that by 1994 1 in 10 young people failed to complete their chosen course of study. This is a substantial number and requires policy action, especially if the policy objectives are to increase the skills of the workforce and raise the participation rate in Higher Education.

The raw data show that dropping out is more likely in April and July, however, when we control for observable and unobservable differences between young people, we find that the baseline hazards of exit to employment and unemployment flatten and shift downwards. Thus, although there is some evidence of a spike in the unemployment baseline hazards, especially towards the end of the study period, the main conclusion with respect to the timing of drop out is that this probability is basically constant, which contrasts with other evidence in the literature of positive duration dependence. The calculation of transition intensities reveals that male drop outs fare better than female drop outs, the former having a higher risk of employment and the latter a higher risk of unemployment.

Our results clearly show how young people are sorted into different levels (high versus low) and types (academic versus vocational) of courses in post-compulsory education on the basis of their prior attainment. The most qualified enter 'high' academic courses and are less likely to drop out, implying optimal matches between course type and student. Conversely, the least qualified are more likely to enroll on 'low' level courses but are more likely to drop out, implying sub-optimal matches. However, the least qualified who do drop out are more likely to get jobs, which is good outcome but we are unable to determine the quality of those jobs. Studying 'low' level courses for a short spell may thus enhance their human capital sufficiently to improve their position in the labour market. It is likely, however, that dropouts miss out on other training opportunities in the youth labour market, since these tend to begin before courses in post-compulsory education. This implies that dropouts are likely to enter 'dead-end' jobs.

There are differences in outcomes for other sub-groups of young people. Young people from ethnic minority backgrounds are more likely to enroll on academic courses and their risk of dropping out is lower than their white counterparts, especially for Indians. There are some differences in the drop out behaviour of Afro-Caribbeans and Bangladeshi/Pakistani groups but only for males. In general, it would appear that young people from ethnic minority groups are more optimally matched with their courses when compared to their white counterparts. Our evidence is also consistent with the view that young people from ethnic minority groups seek to close the 'qualification gap' by staying on. We also find that young people from high income households (professional and managerial parents) are more likely to choose 'high' academic courses and are less likely to drop out, also implying good matches. If these young people do drop out they are more likely to get a job. The opposite is the case for young people from low income households (i.e. those from social housing). The state of the local labour market has no effect on the decision to stay on, or more specifically course choice, which contrasts with existing evidence, however, there is an effect on the decision to drop out. The single risk models suggest that a high local unemployment rate reduces the risk of drop out, whereas an increase in the vacancy rate encourages dropping out, emphasizing the close links between the education and labour markets for this age group.

In sum, the magnitude of the drop out problem is high and is concentrated on particular 'types' of young people, which does point to a need for policy maker and teacher intervention. One possible solution is that better vocational guidance should be given about college and course choice. Another is the provision of pastoral care for young people who are considering dropping out, or the development of a more 'proactive' approach to the early detection of dropouts. A final one is the provision of financial incentives to attend courses in post-compulsory education, an initiative that has recently been introduced in the UK.

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[1] Our data refer to England and Wales where young people complete their compulsory schooling at the age of 16, and may then proceed to a period of continued education, typically up to the age of 18, prior to entrance to the labour market or to university. The period of education between 16-18 is voluntary and is referred to throughout this paper as post-compulsory education.

[2] The Local Authority District is regarded in this study as a self-contained labour market because young people tend to be less geographically mobile than adults and they are therefore likely to respond to 'local' labour market conditions.

[3] In 1984 the staying on rate was comparatively low with only 41% of all 16 year olds entering post-compulsory education, whereas by 1994 this figure had risen to 71%.

[4] A potential limitation of the method we adopt is that the effects of unobservables are assumed to be uncorrelated with the observed covariates.

[5] As an aside, it is worth noting that the previous literature has typically estimated cross-sectional binary choice models of the decision to drop out, *conditional* on having stayed on. The few longitudinal models of dropout in higher education do not take into consideration the initial decision made by the individual to enter university.

[6] An alternative approach that has recently been applied to an investigation of drop outs by Jakobsen abd Rosholm (2003) is the screening/signaling model (e.g. Spence, 1974).

[7] In 1997, 11 states required the youth to attend school until age 18 (National Center for Education Statistics, 1998).

[8] YCS2-YCS6 are the only versions where sample members complete an annual survey. In YCS7-YCS9 respondents complete a retrospective diary covering a 2 year period (i.e. for the period of 16-18), which may exacerbate the problem of recall bias. Since this is the period in which young people pursue post-compulsory education, we decided not to use the more recent data. In addition, YCS10-YCS11 had only one sweep at the time of going to press, which means that it is not useful for our purposes.

[9] Specifically, young people are sent a postal questionnaire, which they are asked to complete and return.

[10] There is some concern about the quality of the retrospective diary information contained in the YCS, which may lead to measurement error in the dependent variable. To reduce the likelihood of measurement error we carefully examined the diary information and made the following assumptions. First, if a young person in post-compulsory education indicated that they had a spell of employment, for instance, between two spells of education, then the spell of employment was recoded to education. This occurred most frequently in the Christmas and Easter holiday period, which implies that the employment spell referred to a casual job. Since the young person returned to education it is safe to assume that their main activity is still as a student. Second, the imposition of two conditions for a young person to be a drop out (see the text above) also reduces measurement error because young people whose diaries are inaccurate but nevertheless sit the examination are counted as graduates. Of course, we cannot completely rule out the presence of measurement error in our data, however, this is unlikely to be any worse than the measurement error associated with many other longitudinal datasets, such as the BHPS and the NCDS, which are routinely used by researchers to estimate models similar to those estimated in this paper.

[11] 'High' academic education refers to young people taking A Levels, the traditional route to Higher Education, whereas 'low' refers to young people repeating their GCSE exams (see footnote 8). Similarly, a 'high' vocational education refers, for instance, refers to BTEC National Diplomas in Business Studies, Science, Engineering, which are 'equivalent' to A levels, and 'low' vocational education includes basic business, typing and similar courses.

[12] For the single risk model $r_i = 1$ and $r_i = 2$ are combined but the econometric methods are identical to the competing risks model discussed in the text.

[13] In the econometric analysis, since a young person cannot by definition be observed to start and quit post-compulsory education in the same month, we combine the months October and November thereby giving a total of 20 time periods.

[14] The baseline hazard is estimated non-parametrically, which means that the hazard can vary freely over time but is assumed to be constant within each time interval. This is equivalent to assuming an exponential survival in each time interval.

[15] The marginal effects are actually computed at $\gamma=12$ for females and $\gamma=10$ for males.

[16] Students sit the General Certificate of Secondary Examination (GCSE) at the end of their compulsory schooling, typically at age 16, in up to 10 subjects dictated by the National Curriculum. The grades that could be achieved at the time of this study were A (high) through to G (low).

[17] We also estimated a model with interaction effects between academic attainment and the local unemployment rate to see if their response to labour market conditions differed. For males there was no statistically significant effects and for females the model would not converge because of the small number of observations in some categories.

[18] This version of the paper is available at the following web address:
http://www.lancs.ac.uk/staff/ecasb/work.html.

Figure 1 The incidence of drop out from post-compulsory education, Females

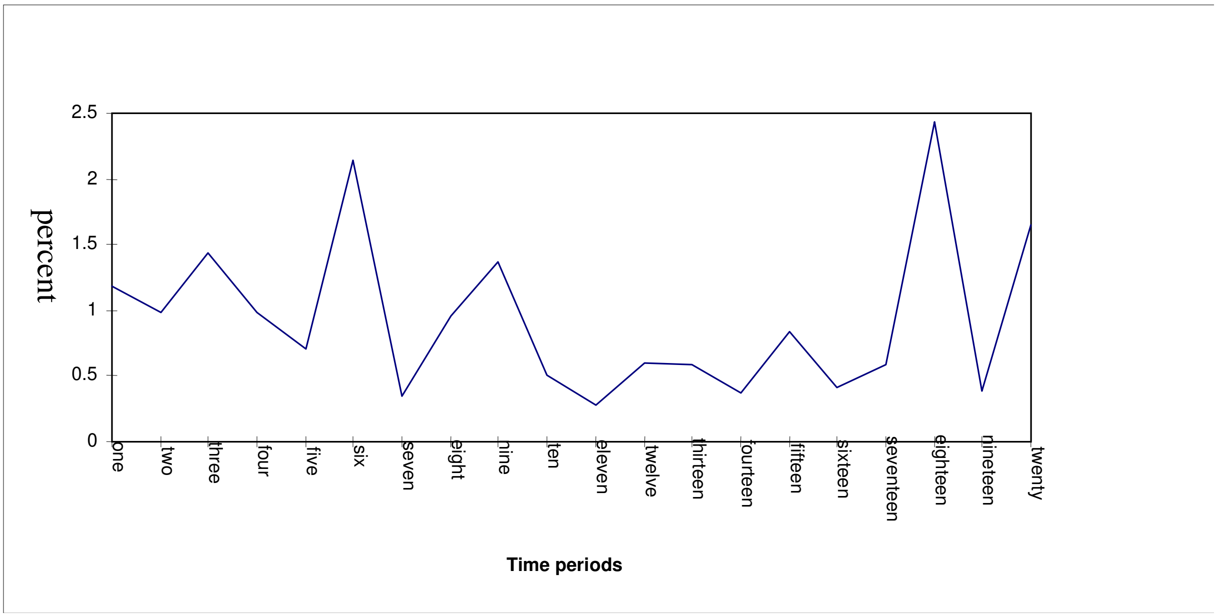
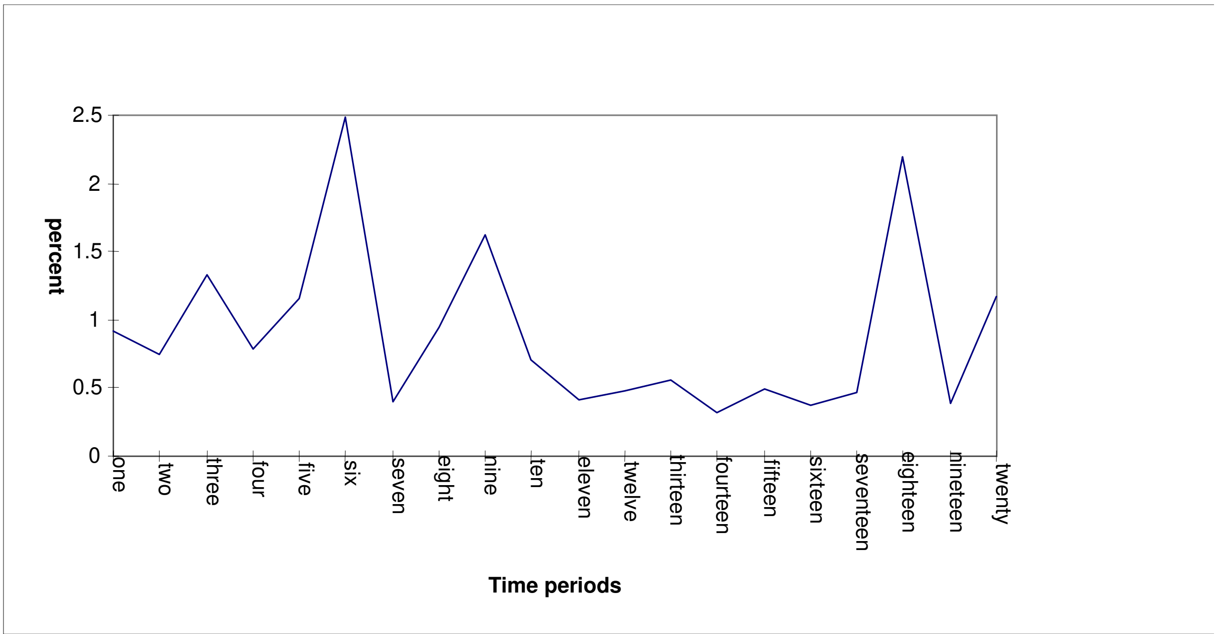


Figure 2 The incidence of drop out from post-compulsory education, Males



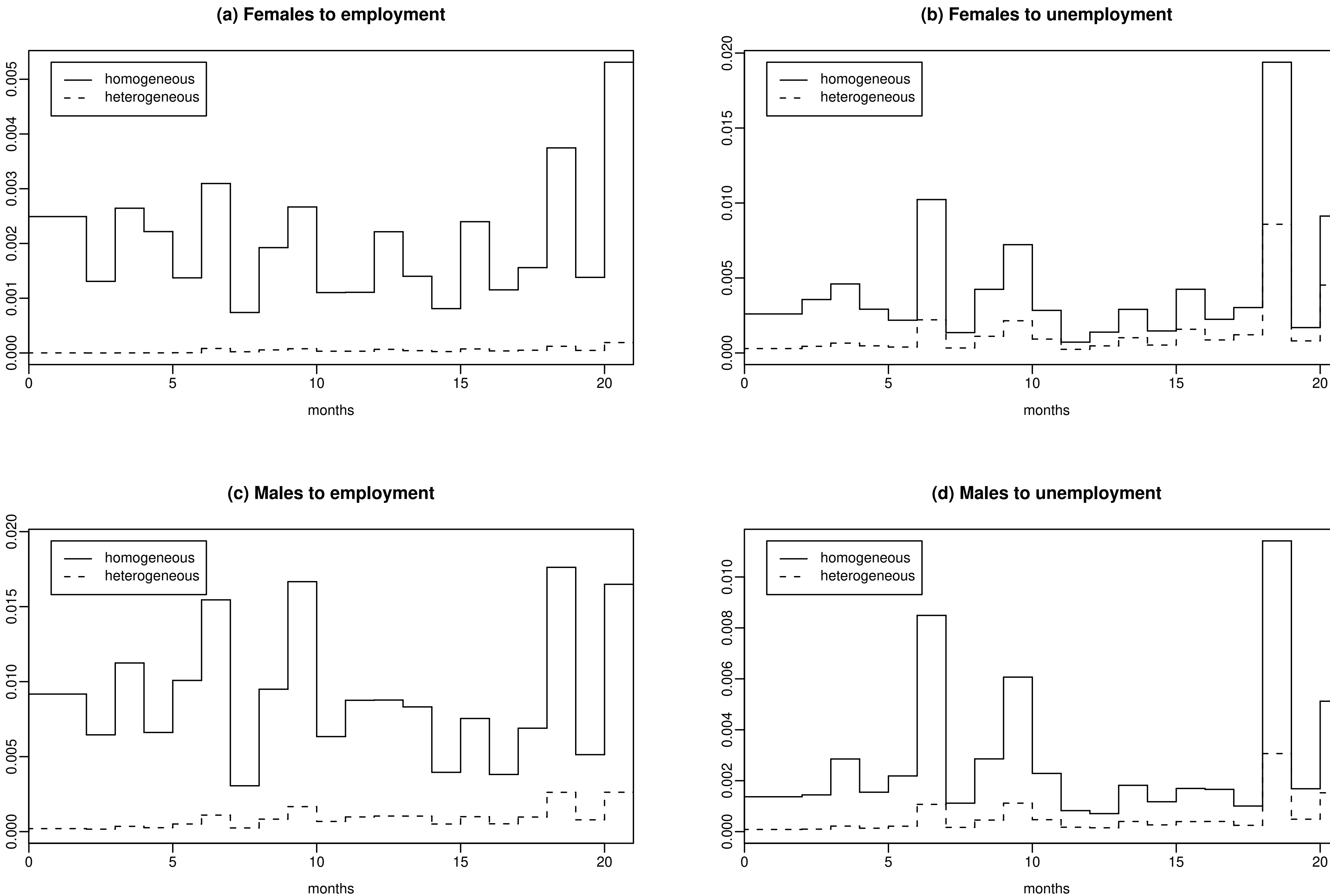


Fig. 3: Baseline hazards

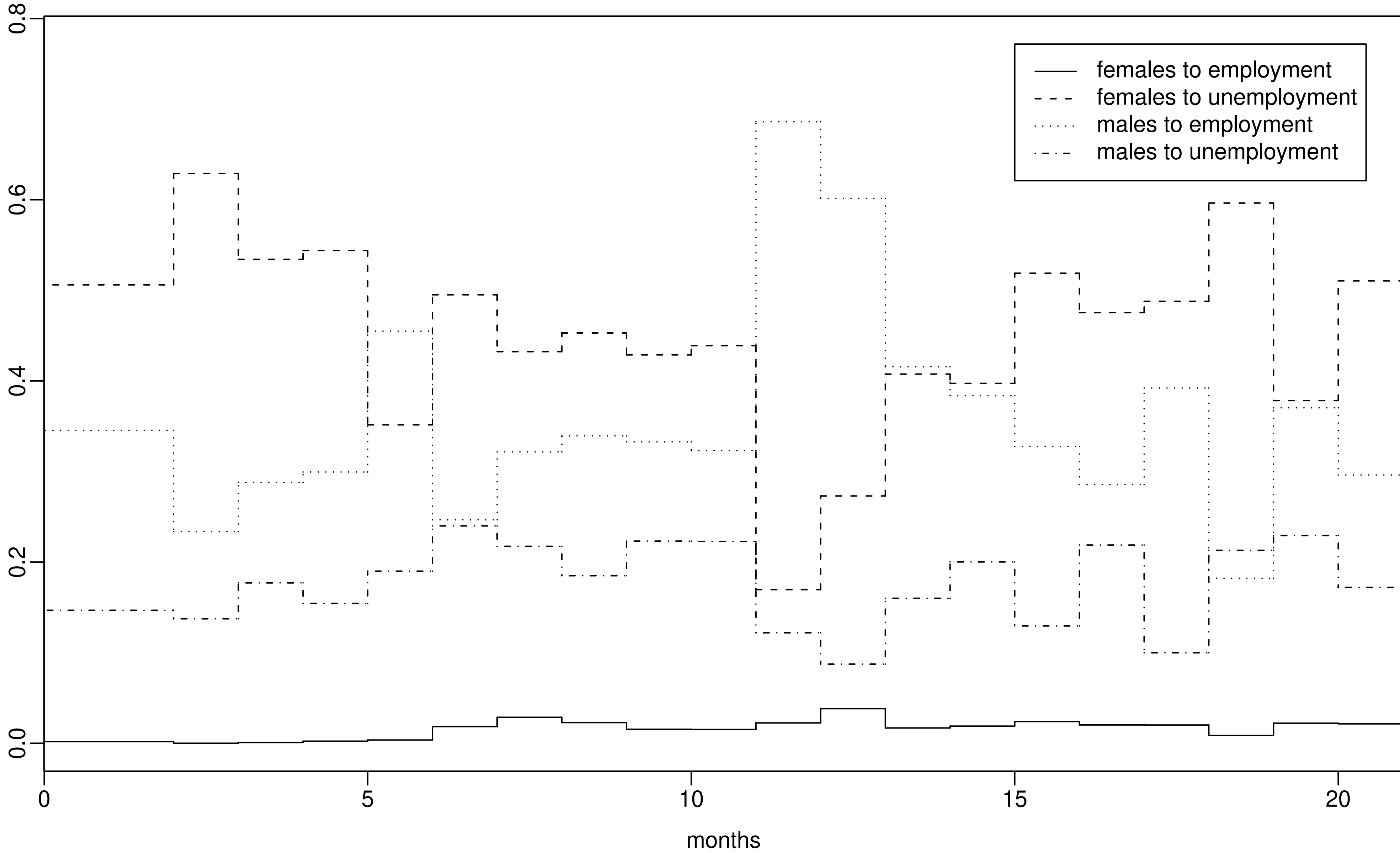


Fig. 4: Transition intensities, heterogeneous models

Table 1 The incidence of dropping out by characteristics, females

Characteristic	Sample size	Percentage who drop out	
		No	Yes
	School Background		
Comprehensive to age 16 (base)	7370	86.0	14.0
Comprehensive to age 18	16717	86.2	13.8
Secondary Modern	790	80.0	20.0
Grammar or Independent	3138	94.6	5.4
Other School	105	86.7	13.3
	Prior Attainment		
5+ GCSE grades A-C	14985	93.6	6.4
1-4 GCSE grades A-C	9074	82.1	17.9
5+ GCSE grades D-G	2149	77.1	22.9
1-4 GCSE grades D-G	1397	68.8	31.2
No GCSE grades (base)	515	65.4	34.6
	Ethnicity		
Black	515	89.1	10.9
Indian	684	92.1	7.9
Bangladeshi or Pakistani	415	88.9	11.1
Other race	565	87.8	12.2
White (base)	25596	86.7	13.3
	Family Structure		
no siblings (base)	4331	85.6	14.4
one sibling	13040	88.5	11.5
two siblings	6437	86.7	13.3
three siblings	2244	83.8	16.2
four siblings	1418	83.5	16.5
Social housing	3084	77.2	22.8
Private housing (base)	23307	88.3	11.7
Both parents in employment	11171	87.5	12.5
Neither parent in employment	2214	83.6	16.4
One parent in employment (base)	12169	87.6	12.4
Lives with both parents (base)	23709	87.7	12.3
Lives with mother only	3276	84.2	15.8
Lives with father only	535	82.6	17.4
No parents present	367	75.2	24.8
	Socio-economic status		
Father Managerial or Professional	6210	92.9	7.1
Father skilled non-manual	4551	90.0	10.0
Father skilled manual	7460	83.2	16.8
Father unskilled non-manual	2087	86.3	13.7
Father unskilled manual (base)	2589	84.7	15.3
Father occupation unknown	5223	83.7	16.3
Mother Managerial or Professional	2620	93.2	6.8
Mother skilled non-manual	6542	89.8	10.2
Mother skilled manual	2329	82.3	17.7
Mother unskilled non-manual	6982	84.7	15.3
Mother unskilled manual (base)	1369	82.7	17.3
Mother occupation unknown	8278	86.4	13.6

Table 1 (continued)

Characteristic	No in sample	Proportion dropout	
		No	Yes
Present in cohort 2 (base)	4071	83.7	16.3
Present in cohort 3	4291	83.8	16.2
Present in cohort 4	4418	85.8	14.2
Present in cohort 5	5287	88.8	11.2
Present in cohort 6	10053	89.0	11.0

Table 2 The incidence of dropping out by characteristics, males

Characteristic	Sample size	Percentage who drop out	
		No	Yes
	School Background		
Comprehensive to age 16 (base)	5524	86.6	13.4
Comprehensive to age 18	13124	86.7	13.3
Secondary Modern	516	80.2	19.8
Grammar or Independent	3354	94.8	5.2
Other School	124	83.9	16.1
	Prior Attainment		
5+ GCSE grades A-C	12838	94.4	5.6
1-4 GCSE grades A-C	6601	82.7	17.3
5+ GCSE grades D-G	1761	76.0	24.0
1-4 GCSE grades D-G	1015	66.4	33.6
No GCSE grades (base)	427	64.2	35.8
	Ethnicity		
Black	344	83.4	16.6
Indian	712	93.7	6.3
Bangladeshi or Pakistani	513	89.3	10.7
Other race	489	90.2	9.8
White (base)	20281	87.6	12.4
	Family Structure		
no siblings (base)	3606	87.4	12.6
one sibling	10570	88.7	11.3
two siblings	5087	87.6	12.4
three siblings	1764	86.5	13.5
four siblings	1064	85.0	15.0
Social housing	1958	78.1	21.9
Private housing (base)	19107	88.9	11.1
Both parents in employment	9310	88.3	11.7
Neither parent in employment	1653	84.8	15.2
One parent in employment (base)	9910	88.5	11.5
Resides with both parents (base)	19485	88.5	11.5
Resides with mother only	2260	84.6	15.4
Resides with father only	500	83.6	16.4
No parents present	257	75.5	24.5
	Socio-economic status		
Father Managerial or Professional	5523	93.3	6.7
Father skilled non-manual	4089	90.7	9.3
Father skilled manual	5321	83.2	16.8
Father unskilled non-manual	1819	87.2	12.8
Father unskilled manual (base)	1844	84.7	15.3
Father occupation unknown	4046	84.8	15.2
Mother Managerial or Professional	2311	92.9	7.1
Mother skilled non-manual	5564	90.5	9.5
Mother skilled manual	1543	84.0	16.0
Mother unskilled non-manual	5077	86.0	14.0
Mother unskilled manual (base)	833	83.9	16.1
Mother occupation unknown	7314	86.8	13.2

Table 2 (continued)

Characteristic	No in sample	Proportion dropout No	Proportion dropout Yes
	Cohort		
Present in cohort 2 (base)	3058	83.5	16.5
Present in cohort 3	3742	85.7	14.3
Present in cohort 4	3519	86.6	13.4
Present in cohort 5	4441	89.4	10.6
Present in cohort 6	7882	89.9	10.1

Table 3 The labour market destination of drop outs by prior attainment level

	Males			Females		
Prior attainment	Employed	Unemployed	N	Employed	Unemployed	N
5+GCSE A-C	45.8	54.2	605	49.6	50.4	809
1-4 GCSE A-C	48.8	51.2	899	49.2	50.8	1250
5+ GCSE D-G	53.3	46.7	319	47.9	52.1	382
1-4 GCSE D-G	48.1	51.9	233	47.4	52.6	323
No GCSE grades	43.6	56.4	110	30.6	69.4	111

Table 4 The school-to-work transition and course choice, multinomial logit model, females

	Unemployment		Employment		Training scheme		FE: Low academic		FE: High academic		FE Low vocational		FE High vocational	
	Marginal effect (SE)	Prob value	Marginal effect (SE)	Prob value	Marginal effect (SE)	Prob value	Marginal effect (SE)	Prob value	Marginal effect (SE)	Prob value	Marginal effect (SE)	Prob value	Marginal effect (SE)	Prob value
5+ GCSE A-C	-0.095	0.000	-0.235	0.000	-0.278	0.000	-0.055	0.000	0.831	0.000	-0.136	0.000	-0.032	0.001
	(0.004)		(0.007)		(0.007)		(0.008)		(0.021)		(0.008)		(0.010)	
1-4 GCSE A-C	-0.071	0.000	-0.220	0.000	-0.179	0.000	0.008	0.615	0.487	0.000	-0.050	0.000	0.025	0.175
	(0.004)		(0.010)		(0.008)		(0.016)		(0.050)		(0.013)		(0.018)	
5+ GCSE D-G	-0.037	0.000	-0.131	0.000	-0.091	0.000	0.079	0.001	0.033	0.565	0.065	0.003	0.082	0.002
	(0.002)		(0.009)		(0.008)		(0.024)		(0.057)		(0.022)		(0.026)	
1-4 GCSE D-G	-0.024	0.000	-0.071	0.000	-0.026	0.006	0.110	0.000	-0.155	0.000	0.091	0.000	0.074	0.003
	(0.002)		(0.010)		(0.009)		(0.025)		(0.039)		(0.020)		(0.025)	
Afro-Caribbean	-0.016	0.001	-0.153	0.000	-0.062	0.000	0.110	0.000	0.059	0.055	0.071	0.002	-0.009	0.642
	(0.005)		(0.009)		(0.014)		(0.024)		(0.031)		(0.023)		(0.018)	
Indian	-0.025	0.000	-0.167	0.000	-0.107	0.000	0.119	0.000	0.167	0.000	0.004	0.829	0.010	0.548
	(0.004)		(0.007)		(0.007)		(0.021)		(0.028)		(0.016)		(0.016)	
Pakistani	-0.008	0.238	-0.134	0.000	-0.107	0.000	0.157	0.000	0.146	0.001	0.011	0.643	-0.065	0.000
	(0.007)		(0.013)		(0.009)		(0.031)		(0.042)		(0.023)		(0.016)	
Bangladeshi	-0.024	0.000	-0.150	0.000	-0.099	0.000	0.127	0.007	0.215	0.002	-0.035	0.222	-0.034	0.250
	(0.006)		(0.016)		(0.018)		(0.047)		(0.071)		(0.029)		(0.030)	
Other race	-0.005	0.373	-0.059	0.000	-0.053	0.000	0.056	0.003	0.074	0.004	-0.001	0.929	-0.012	0.452
	(0.005)		(0.013)		(0.011)		(0.019)		(0.026)		(0.016)		(0.017)	
Social housing	0.025	0.000	0.058	0.000	0.024	0.000	-0.016	0.012	-0.074	0.000	-0.009	0.173	-0.009	0.189
	(0.003)		(0.008)		(0.006)		(0.006)		(0.009)		(0.006)		(0.007)	
Father's occupation:														
Managerial/professional	-0.014	0.000	-0.057	0.000	-0.054	0.000	0.045	0.000	0.080	0.000	-0.012	0.161	0.012	0.182
	(0.004)		(0.009)		(0.007)		(0.010)		(0.013)		(0.009)		(0.009)	
Skilled non-manual	-0.014	0.001	-0.018	0.101	-0.054	0.000	0.031	0.012	0.044	0.002	0.015	0.184	-0.002	0.811
	(0.004)		(0.011)		(0.008)		(0.012)		(0.014)		(0.011)		(0.010)	
Skilled manual	0.002	0.481	-0.003	0.695	-0.004	0.585	0.014	0.081	-0.016	0.120	-0.003	0.734	0.009	0.220
	(0.003)		(0.009)		(0.007)		(0.008)		(0.010)		(0.008)		(0.008)	
Unskilled non-manual	-0.007	0.119	-0.028	0.011	-0.032	0.000	0.029	0.015	0.021	0.146	0.012	0.276	0.004	0.690

	(0.004)		(0.011)		(0.009)		(0.012)		(0.014)		(0.011)		(0.010)	
Father unknown occupation	0.004	0.355	0.003	0.793	-0.015	0.046	0.012	0.223	-0.015	0.219	0.007	0.465	0.006	0.518
	(0.004)		(0.010)		(0.008)		(0.010)		(0.012)		(0.009)		(0.009)	
Mother's occupation:														
Managerial/professional	-0.019	0.000	-0.066	0.000	-0.048	0.000	0.023	0.108	0.151	0.000	-0.034	0.004	-0.008	0.470
	(0.004)		(0.013)		(0.011)		(0.015)		(0.022)		(0.012)		(0.011)	
Skilled non-manual	-0.015	0.001	-0.058	0.000	-0.047	0.000	0.054	0.002	0.096	0.000	-0.013	0.305	-0.017	0.152
	(0.004)		(0.013)		(0.011)		(0.017)		(0.021)		(0.013)		(0.012)	
Skilled manual	-0.007	0.079	0.003	0.810	-0.016	0.108	0.011	0.405	0.027	0.141	-0.020	0.075	0.001	0.899
	(0.004)		(0.013)		(0.010)		(0.013)		(0.018)		(0.011)		(0.012)	
Unskilled non-manual	-0.014	0.000	-0.024	0.025	-0.020	0.019	0.014	0.211	0.044	0.004	-0.006	0.515	0.006	0.505
	(0.003)		(0.011)		(0.009)		(0.011)		(0.015)		(0.010)		(0.010)	
Unknown occupation	-0.005	0.198	-0.039	0.000	-0.018	0.036	0.030	0.010	0.048	0.002	-0.006	0.545	-0.009	0.354
	(0.004)		(0.011)		(0.009)		(0.012)		(0.015)		(0.010)		(0.009)	
Log(unemployment rate)	0.010	0.009	-0.068	0.000	0.076	0.000	-0.003	0.736	0.001	0.931	-0.009	0.307	-0.007	0.382
	(0.004)		(0.009)		(0.009)		(0.008)		(0.011)		(0.008)		(0.008)	
Log(vacancy rate)	-0.013	0.001	0.033	0.002	-0.009	0.297	-0.012	0.175	-0.007	0.588	0.004	0.684	0.005	0.616
	(0.004)		(0.011)		(0.009)		(0.009)		(0.012)		(0.010)		(0.009)	
Outcome sample size	1656		4864		5325		2793		12687		3856		3125	
	Diagnostics													
Total Sample size	34306													
Log likelihood	-46083.69													
LR Chi2(300)	27796.04													
Prob > chi2	0.0000													
Pseudo R2	0.2317													

Note: The model also includes controls for type of school attended, number of siblings, household employment status, single parent family, region of residence and cohort.
SE = standard errors – in brackets.

Table 5 The school-to-work transition and course choice, multinomial logit model, males

	Unemployment		Employment		Training scheme		FE: Low academic		FE: High academic		FE Low vocational		FE High vocational	
	Marginal effect (SE)	Prob value	Marginal effect (SE)	Prob value	Marginal effect (SE)	Prob value	Marginal effect (SE)	Prob value	Marginal effect (SE)	Prob value	Marginal effect (SE)	Prob value	Marginal effect (SE)	Prob value
5+ GCSE A-C	-0.099	0.000	-0.285	0.000	-0.318	0.000	-0.041	0.000	0.822	0.000	-0.085	0.000	0.005	0.485
	(0.004)		(0.007)		(0.007)		(0.009)		(0.017)		(0.006)		(0.007)	
1-4 GCSE A-C	-0.073	0.000	-0.253	0.000	-0.209	0.000	0.053	0.002	0.431	0.000	-0.010	0.309	0.060	0.000
	(0.004)		(0.010)		(0.008)		(0.018)		(0.040)		(0.010)		(0.016)	
5+ GCSE D-G	-0.041	0.000	-0.152	0.000	-0.105	0.000	0.171	0.000	-0.030	0.452	0.077	0.000	0.081	0.001
	(0.002)		(0.010)		(0.008)		(0.028)		(0.041)		(0.017)		(0.023)	
1-4 GCSE D-G	-0.026	0.000	-0.085	0.000	-0.036	0.001	0.113	0.000	-0.100	0.008	0.067	0.000	0.068	0.004
	(0.002)		(0.013)		(0.011)		(0.025)		(0.038)		(0.017)		(0.023)	
Afro-Caribbean	-0.012	0.082	-0.145	0.000	-0.047	0.025	0.016	0.518	0.077	0.044	0.078	0.002	0.034	0.080
	(0.007)		(0.017)		(0.021)		(0.024)		(0.038)		(0.025)		(0.019)	
Indian	-0.027	0.000	-0.219	0.000	-0.150	0.000	0.110	0.000	0.221	0.000	0.060	0.001	0.005	0.678
	(0.004)		(0.007)		(0.007)		(0.022)		(0.030)		(0.017)		(0.012)	
Pakistani	-0.024	0.000	-0.209	0.000	-0.159	0.000	0.145	0.000	0.192	0.000	0.042	0.035	0.013	0.435
	(0.004)		(0.009)		(0.007)		(0.030)		(0.040)		(0.020)		(0.016)	
Bangladeshi	-0.033	0.000	-0.095	0.009	-0.150	0.000	0.034	0.406	0.165	0.028	0.053	0.142	0.025	0.396
	(0.005)		(0.036)		(0.014)		(0.041)		(0.075)		(0.036)		(0.030)	
Other race	-0.018	0.000	-0.099	0.000	-0.091	0.000	0.063	0.002	0.113	0.000	0.040	0.020	-0.007	0.566
	(0.005)		(0.016)		(0.012)		(0.021)		(0.031)		(0.017)		(0.013)	
Social housing	0.033	0.000	0.030	0.001	0.028	0.000	-0.020	0.010	-0.047	0.000	-0.008	0.185	-0.016	0.001
	(0.004)		(0.009)		(0.007)		(0.008)		(0.011)		(0.006)		(0.005)	
Father's occupation:														
Managerial/professional	-0.022	0.000	-0.098	0.000	-0.073	0.000	0.066	0.000	0.115	0.000	0.008	0.325	0.004	0.519
	(0.004)		(0.010)		(0.009)		(0.012)		(0.015)		(0.008)		(0.006)	
Skilled non-manual	-0.018	0.000	-0.083	0.000	-0.078	0.000	0.065	0.000	0.095	0.000	0.013	0.205	0.005	0.500
	(0.004)		(0.011)		(0.009)		(0.015)		(0.018)		(0.010)		(0.008)	
Skilled manual	-0.005	0.194	-0.009	0.379	-0.011	0.165	0.026	0.011	0.002	0.870	0.001	0.847	-0.004	0.423
	(0.004)		(0.010)		(0.008)		(0.010)		(0.012)		(0.007)		(0.005)	
Unskilled non-manual	-0.012	0.005	-0.047	0.000	-0.052	0.000	0.037	0.008	0.069	0.000	0.006	0.530	-0.001	0.927
	(0.004)		(0.012)		(0.010)		(0.014)		(0.018)		(0.010)		(0.007)	

Father unknown occupation	-0.003	0.435	-0.029	0.009	-0.022	0.015	0.038	0.001	0.003	0.817	0.014	0.106	-0.002	0.789
	(0.004)		(0.011)		(0.009)		(0.012)		(0.014)		(0.009)		(0.007)	
Mother's occupation:														
Managerial/professional	-0.012	0.042	-0.110	0.000	-0.075	0.000	0.064	0.001	0.123	0.000	0.008	0.529	0.002	0.865
	(0.006)		(0.013)		(0.012)		(0.019)		(0.024)		(0.013)		(0.009)	
Skilled non-manual	-0.013	0.016	-0.092	0.000	-0.061	0.000	0.058	0.004	0.107	0.000	-0.002	0.862	0.003	0.738
	(0.006)		(0.014)		(0.012)		(0.020)		(0.025)		(0.012)		(0.010)	
Skilled manual	-0.008	0.123	-0.031	0.032	-0.009	0.467	0.019	0.247	0.018	0.389	0.007	0.572	0.004	0.679
	(0.005)		(0.015)		(0.013)		(0.017)		(0.021)		(0.012)		(0.010)	
Unskilled non-manual	-0.011	0.008	-0.036	0.005	-0.027	0.013	0.017	0.225	0.041	0.024	0.006	0.520	0.010	0.240
	(0.004)		(0.013)		(0.011)		(0.014)		(0.018)		(0.010)		(0.008)	
Unknown occupation	-0.002	0.706	-0.049	0.000	-0.029	0.007	0.029	0.031	0.029	0.106	0.014	0.155	0.009	0.278
	(0.005)		(0.013)		(0.011)		(0.013)		(0.018)		(0.010)		(0.008)	
Log(unemployment rate)	0.009	0.039	-0.074	0.000	0.062	0.000	0.009	0.347	-0.017	0.158	0.012	0.118	-0.001	0.884
	(0.004)		(0.011)		(0.010)		(0.009)		(0.012)		(0.007)		(0.007)	
Log(vacancy rate)	-0.014	0.002	0.017	0.176	-0.002	0.871	-0.012	0.255	-0.009	0.501	0.001	0.901	0.019	0.008
	(0.005)		(0.012)		(0.010)		(0.010)		(0.013)		(0.008)		(0.007)	
Outcome sample size	1579		5414		5895		2830		11228		2437		1713	
	Diagnostics													
Total sample size	31096													
Log likelihood	-9734.84													
LR Chi2(300)	27260.12													
Prob > chi2	0.000													
Pseudo R2	0.26													

See notes to Table 4.

Table 6 The determinants of dropping out of post-compulsory education - single risk and competing risk duration models, Females

	Single risk model (r = 1, 2)		Competing risks model			
			Employment (r = 1)		Unemployment (r = 2)	
	Coef Odds ratio	Prob-value	$\partial P_{rj}/\partial x$	Prob-value	$\partial P_{rj}/\partial x$	Prob-value
Comprehensive school (11-18)	0.157 1.170	0.010	-0.014	0.474	0.104	0.007
Secondary modern school	0.015 1.015	0.929	-0.013	0.755	0.013	0.305
Grammar/independent school	-0.298 0.742	0.018	-0.006	0.069	0.006	0.191
Other school	0.150 1.162	0.699	0.189	0.356	-0.189	0.080
5+ GCSE A-C	-0.429 0.651	0.024	0.071	0.048	-0.071	0.000
1-4 GCSE A-C	-0.314 0.731	0.073	0.075	0.819	-0.075	0.000
5+ GCSE D-G	-0.314 0.731	0.095	0.091	0.441	-0.091	0.000
1-4 GCSE D-G	-0.061 0.941	0.752	0.076	0.221	-0.076	0.006
Low academic course	3.267 26.233	0.000	0.352	0.000	-0.352	0.000
Low vocational course	3.919 50.350	0.000	0.313	0.000	-0.313	0.000
High vocational course	1.070 2.930	0.000	0.003	0.000	-0.003	0.000
Afro-Caribbean	-0.835 0.434	0.001	0.001	0.008	-0.001	0.003
Indian	-1.297 0.273	0.000	-0.364	0.001	0.364	0.071
Bangladeshi/Pakistani	-1.310 0.270	0.000	-0.422	0.000	0.422	0.343
Other race	-0.668 0.513	0.001	0.028	0.295	-0.028	0.056
One sibling at home	-0.327 0.721	0.000	0.020	0.151	-0.020	0.000
Two siblings	-0.173 0.841	0.056	0.014	0.833	-0.014	0.097
Three siblings	0.151 1.163	0.210	0.012	0.569	-0.012	0.621
Four siblings	-0.260 0.771	0.072	-0.027	0.009	0.027	0.514
Lives in social housing	0.286 1.331	0.000	-0.036	0.772	0.036	0.000
Both parents work	0.056 1.058	0.370	-0.006	0.782	0.006	0.526
Neither parents work	-0.013 0.987	0.900	0.021	0.115	-0.021	0.580
Single parent - mother only	0.272 1.313	0.008	-0.052	0.305	0.052	0.000
Single parent - father only	0.417 1.517	0.047	-0.025	0.252	0.025	0.023

Table 6 (continued)

	Single risk model (r = 1,2)			Competing risks model			
				Employment (r = 1)		Unemployment (r = 2)	
	Coef	Prob-value	Odds ratio	$\partial P_{rj}/\partial x$	Prob-value	$\partial P_{rj}/\partial x$	Prob-value
Other household	0.393	0.051	1.480	-0.067	0.662	0.067	0.006
Father managerial/professional	-0.438	0.000	0.645	0.022	0.096	-0.022	0.000
Father skilled non-manual	-0.347	0.002	0.707	0.014	0.291	-0.014	0.034
Father skilled manual	-0.016	0.865	0.984	0.009	0.667	-0.009	0.622
Father unskilled non-manual	-0.006	0.961	0.994	-0.000	0.997	0.000	0.993
Father unknown occupation	-0.033	0.771	0.968	-0.020	0.572	0.020	0.241
Mother managerial/professional	-0.328	0.032	0.720	0.028	0.282	-0.028	0.004
Mother skilled non-manual	-0.336	0.004	0.715	0.019	0.454	-0.019	0.017
Mother skilled manual	-0.033	0.809	0.968	0.036	0.618	-0.036	0.053
Mother unskilled non-manual	-0.131	0.245	0.877	0.025	0.862	-0.025	0.050
Mother unknown occupation	-0.283	0.022	0.754	0.034	0.582	-0.034	0.001
Present in cohort 3	0.029	0.750	0.971	0.017	0.856	-0.017	0.149
Present in cohort 4	-0.192	0.089	0.825	-0.032	0.017	0.032	0.514
Present in cohort 5	-0.353	0.000	0.703	-0.062	0.000	0.062	0.226
Present in cohort 6	0.031	0.737	1.031	-0.053	0.008	0.053	0.002
Log(unemployment rate)	-0.050	0.510	0.951	-0.038	0.002	0.038	0.069
Log(vacancy rate)	0.008	0.916	1.008	0.015	0.357	-0.015	0.367
Individuals[b]	2875			1386		1489	
Variance (σ^2_μ)	0			5.365		1.756	
Mass point 1 (probability)	-			-0.728 (0.910)		0.508 (0.872)	
Mass point 2 (probability)	-			7.366 (0.090)		3.457 (0.128)	
Log likelihood	-14260.03			-7808.05		-8249.207	

[a] $\partial P_{rj}/\partial x$ is a marginal effect.
[b] Number of females exiting to the state described. Another 20439 females were censored. There are 332794 individual-month observations.

Table 7 The determinants of dropping out of post-compulsory education – single risk and competing risk duration models, Males

	Single risk model (r = 1,2)			Competing risks model			
				Employment (r = 1)		Unemployment (r = 2)	
	Coef	Prob-value	Odds ratio	$\partial P_{rj}/\partial x$	Prob-value	$\partial P_{rj}/\partial x$	Prob-value
Comprehensive to age18	0.083	0.233	1.087	0.010	0.238	-0.010	0.466
Secondary modern	0.531	0.777	1.701	-0.015	0.978	0.015	0.801
Grammar/independent	-0.378	0.005	0.685	-0.072	0.006	0.072	0.155
Other school	0.699	0.022	2.012	-0.074	0.189	0.074	0.025
5+ GCSE A-C	-0.471	0.016	0.624	0.229	0.705	-0.229	0.000
1-4 GCSE A-C	-0.381	0.035	0.683	0.134	0.370	-0.134	0.008
5+ GCSE D-G	-0.343	0.066	0.710	0.209	0.788	-0.209	0.009
1-4 GCSE D-G	0.092	0.644	1.096	0.083	0.391	-0.083	0.685
Low academic course	2.477	0.000	11.905	0.116	0.000	-0.116	0.000
Low vocational course	3.978	0.000	53.410	0.287	0.000	-0.287	0.000
High vocational course	1.067	0.000	2.907	0.047	0.000	-0.047	0.000
Afro-Caribbean	-0.409	0.117	0.664	-0.028	0.318	0.028	0.473
Indian	-1.557	0.000	0.211	-0.513	0.000	0.513	0.010
Bangladeshi/Pakistani	-0.821	0.001	0.440	-0.485	0.000	0.485	0.105
Other race	-0.698	0.002	0.498	-0.199	0.001	0.199	0.471
One sibling at home	-0.056	0.534	0.946	-0.021	0.416	0.021	0.912
Two siblings	0.041	0.676	1.042	0.008	0.726	-0.008	0.923
Three siblings	-0.007	0.956	0.993	-0.003	0.828	0.003	0.786
Four siblings	0.155	0.325	1.168	-0.109	0.802	0.109	0.054
Social housing	0.297	0.003	1.346	-0.115	0.422	0.115	0.000
Both parents work	0.146	0.039	1.157	-0.022	0.237	0.022	0.030
Neither parents work	-0.062	0.617	0.940	0.027	0.859	-0.027	0.353
Household-mother only	0.192	0.098	1.212	-0.119	0.952	0.119	0.001
Household-father only	0.424	0.139	1.528	0.130	0.061	-0.130	0.894

Table 7 (continued)

	Single risk (r = 1,2)			Competing risks			
				Employment (r = 1)		Unemployment (r = 2)	
	Coef	Prob-value	Odds ratio	$\partial P_{rj}/\partial x$	Prob-value	$\partial P_{rj}/\partial x$	Prob-value
Household-other	0.654	0.008	1.923	-0.113	0.480	0.113	0.023
Father managerial/professional	-0.576	0.000	0.562	-0.077	0.000	0.077	0.010
Father skilled non-manual	-0.413	0.001	0.662	-0.078	0.001	0.078	0.168
Father skilled manual	0.043	0.685	1.044	-0.023	0.999	0.023	0.500
Father unskilled non-manual	0.020	0.879	1.020	0.039	0.634	-0.039	0.668
Father unknown occupation	-0.047	0.707	0.954	-0.045	0.387	0.045	0.804
Mother managerial/professional	-0.181	0.280	0.834	-0.019	0.376	0.019	0.528
Mother skilled non-manual	-0.316	0.026	0.729	-0.102	0.006	0.102	0.594
Mother skilled manual	-0.224	0.187	0.799	0.030	0.242	-0.030	0.102
Mother unskilled non-manual	-0.064	0.643	0.938	-0.064	0.258	0.064	0.777
Mother unknown occupation	-0.257	0.068	0.773	-0.096	0.013	0.096	0.716
Present in cohort 3	-0.190	0.075	0.827	0.049	0.372	-0.049	0.054
Present in cohort 4	-0.139	0.307	0.870	-0.097	0.067	0.097	0.609
Present in cohort 5	-0.334	0.004	0.716	-0.238	0.000	0.238	0.225
Present in cohort 6	-0.130	0.220	0.878	-0.205	0.000	0.205	0.021
Log(unemployment rate)	-0.016	0.851	0.984	-0.104	0.060	0.104	0.082
Log(vacancy rate)	0.028	0.757	1.028	0.019	0.595	-0.019	0.900
Individuals[b]	2166			1046		1120	
Variance (σ^2_μ)	0			2.818		2.123	
Mass point 1 (probability)	-			-0.702 (0.851)		-0.610 (0.851)	
Mass point 2 (probability)	-			4.015 (0.149)		3.482 (0.149)	
Log likelihood	-10650.657			-5850.356		-6180.66	

[a] See note to table 6.

[b] Number of males exiting to the state described. Another 16701 males were censored. The number of individual-month observations is 262859.