European Sociological Review VOLUME 30 | NUMBER 1 | 2014 107–118
DOI:10.1093/esr/jct025, available online at www.esr.oxfordjournals.org
Online publication 11 October 2013

Education and Social Mobility: New Analytical Approaches

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Abstract: This article develops tools for measuring the role of education in intergenerational social class mobility. Sociologists have long sought a method of decomposing the log odds-ratios involving class origins and destinations into a direct part and an indirect part mediated by education. Drawing on recent work we, first, present such a method and, second, suggest ways in which researchers might summarize the mediating role played by education. We apply these methods to examine whether education has come to play an increasing role in intergenerational social class mobility in Britain during the 20th century. Our results suggest that the mediating role of education did not change across the 20th century: roughly half of the association between class origins and destinations is mediated via educational attainment.

Introduction

Education is widely regarded as the key to individual economic and social mobility. However, studies of intergenerational income mobility and intergenerational social mobility have shown that although education mediates some of the relationship between origins and destinations, it does not mediate it entirely: even controlling for educational attainment, an association between origins and destinations persists. Nevertheless, some schools of thought claim that an increasing share of the relationship between origins and destinations should be mediated through education. This is argued by those who believe in the growing importance of merit as the basis on which rewards in society are allocated (Treiman, 1970) and by those who view the monopolizing of educational credentials as one of the most important means by which privileged families secure privileged positions for their children (Halsey, Heath and Ridge, 1980).

In this article, we examine whether education has come to play an increasing role in intergenerational social class mobility in Britain during the 20th century. But to answer this question, we need to address a number of problems. It is widely believed that path decompositions for linear multi-equation models, such as the Blau and Duncan (1967) model of status attainment, do not extend to systems of categorical or ordinal variables. We show that this belief is erroneous: a method recently developed by Karlson, Holm, and Breen (2012; see also Breen, Karlson and Holm, 2013) allows one to decompose the relationship between categorical measures of class origins and class destinations into direct effects and effects mediated by categorical, ordinal, or continuous indicators of educational attainment.

But this leads to a second problem. Decomposing log odds-ratios between origins and destinations into direct and indirect (through education) components generates a plethora of parameters. Accordingly, we suggest ways of imposing constraints on the direct and indirect log-odds ratios of these models to yield summary measures of direct and indirect effects. Such summaries are likely to be most useful when making comparisons among groups, such as countries, or, as in our case, birth cohorts. Yet, this approach is itself problematic, for reasons explained by Allison (1999). He pointed out that when comparing coefficients from non-linear probability models across groups, we cannot distinguish differences in effects from differences in residual variation. This means that we cannot compare total effects, direct effects, or indirect effects over birth cohorts. However, as we point out, we can compare the *ratio* of any two sorts of effect, and in this article, we focus on the ratio of the indirect to the total effect because it measures the extent to which education mediates the effects of class origins

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on destinations. We demonstrate how imposing testable constraints on the parameters of our models leads to parsimonious summary measures of this ratio.

Education and Social Fluidity in Britain

Scholars who study comparative social stratification debate how trends in educational inequality and social fluidity developed during the 20th century in Western democracies. Much of the literature from the 1990s found little change in educational inequalities related to social origins (notably Shavit and Blossfeld, 1993) and little change in social fluidity (especially Erikson and Goldthorpe, 1992). Social fluidity refers not to the observed relationship between class origins and class destinations but to the association between them, usually captured in the form of odds ratios, and often interpreted as measuring the outcome of competition between people from different class origins to attain more desirable class positions (destinations) and to avoid less desirable ones. But subsequent research, such as Breen *et al.* (2009, 2010), in relation to educational inequality, and Breen (2004), dealing with social mobility, has challenged this depiction of stability, claiming that class inequalities in educational attainment did indeed diminish in several European countries during the 20th century and that social fluidity likewise increased (and shows a good deal of variation between different countries). Breen and Jonsson (2005) review these debates and discuss many empirical studies that bear on them.

One striking result from almost all comparative studies, whether they claim to find stability or change, is that in Great Britain (or England and Wales, depending on the particular analysis), class inequalities in education and mobility appear to have changed less than in other European countries—indeed, some authors (Halsey, Heath and Ridge, 1980: p. 205; Heath and Clifford, 1990: p. 15) claim that they have remained substantially unchanged for most of the 20th century. In their comparative study, Breen *et al.* (2009) find weaker declines in class origin inequalities in educational attainment in Britain than in most of the other European countries in their analysis, and, as for social fluidity, Breen (2010: p. 377) reports a strengthening of the origin–destination association in Britain among cohorts born in the earlier part of the 20th century, followed by constancy among those born in the second half of the century. This echoes the results of, among others, Goldthorpe and Mills (2004), who report 'a high degree of temporal stability' (Goldthorpe and Mills, 2004: p. 222) in social fluidity among British men when comparing surveys conducted in the last decades of the 20th century.

Assessing the Role of Education in Social Mobility

In the social mobility literature, researchers have employed various methods to try to ascertain the impact of education on social fluidity. These include, *inter alia,* comparing the parameters of a model of social fluidity with and without controlling for educational attainment (Goldthorpe and Mills, 2004), simulating the evolution of counterfactual origin–destination tables under different assumptions about educational change (Breen, 2010; Torche and Costa-Ribeiro, 2010), *ad hoc* path decompositions of the three-way origin–education–destination table (Breen and Luijkx, 2004), and the approximate decomposition of the origin–destination odds ratios into direct and indirect (via education) parts (Kuha and Goldthorpe, 2010). In contrast to these earlier attempts, we draw on Karlson, Holm and Breen (2012) to derive an exact decomposition of the total effect of social origins on destinations into an indirect effect, mediated via educational attainment, and an unmediated direct effect. We motivate our exposition with the simple case in which the outcome, Y, is a binary variable, the main predictor variable, X, is also binary, and the mediating variable, Z, is also categorical. We then show how the results obtained can be generalized to the multinomial case and thus to the log-linear analysis of contingency tables. But we begin by recapping the logic of path analysis for continuous variables.

Given a continuous outcome, say, W, and continuous predictors, V and U, in the linear path model framework first used by Blau and Duncan (1967), the total effect of V on W, β_{WV}, estimated from the regression of W on V alone, decomposes exactly into $\beta_{WV.U}$ (the direct effect, estimated as the partial regression coefficient of V when U is also included as a predictor) plus $\beta_{WU.V}\gamma_{UV}$ (the indirect effect).[1] The latter is equal to the partial regression coefficient of U, controlling for V, multiplied by the regression coefficient of V when U is regressed on V.

When Y is binary, taking the values 0 or 1, and using logistic regression, a seemingly straightforward analogy to the linear case would be to take the log odds of Y as the dependent variable and write an equation that specified a linear relationship between the log odds and X and Z:

$$\text{log odds}\left[\frac{Y=1}{Y=0}\right] = b_0 + b_1 X + b_2 Z \qquad (1)$$

Parallel to the linear case we could define b_1 as the direct effect of X on Y, and $b_2[E(Z|X=1) - E(Z|X=0)]$ as the indirect effect.[2] If we denote $\gamma_1 = E(Z|X=1) - E(Z|X=0)$, then $b_2\gamma_1$ is the indirect effect.

However, given the reduced model

$$\log \text{odds}\left[\frac{Y=1}{Y=0}\right] = a_0 + a_1 X \tag{2}$$

that returns the unconditional or total effect of X on Y, we have

$$a_1 = (b_1 + b_2\gamma_1)\sqrt{\frac{\pi^2/3}{\pi^2/3 + b_2^2 \text{var}(Z|X)}} \tag{3}$$

Here var(Z|X) is the variance of the residual from the linear regression of Z on X. When Z and X are independent, var(Z|X) is just var(Z) and so, even when Z and X are independent, the hypothesized total effect, a_1, will not equal the sum of the direct and indirect effects (Breen, Karlson and Holm, 2013; Mood, 2010).[3]

Equation (3) can be obtained from a general latent variable derivation of the logit model. We begin with a regression model for a continuous latent response variable, Y*:

$$Y^* = \beta_0 + \beta_1 X + \beta_2 Z + e \tag{4}$$

We call this the full model, which we take to be the true model, i.e., the model on which we base our inferences. We can also write a reduced model:

$$Y^* = \alpha_0 + \alpha_1 X + \nu \tag{5}$$

e and v are error terms. However, we do not observe Y* but, rather, Y, a dichotomized version of the latent variable such that:

$$Y = 1 \text{ if } Y^* > \tau$$
$$Y = 0 \text{ otherwise}$$

where τ is a threshold, normally set to zero for identification. Assuming that the error term in (4) follows a logistic distribution we can write $e = s_F u$ where s_F is a scale parameter and u is a standard logistic random variable with mean 0 and variance $\pi^2/3$. The scale parameter rescales the variance of the error term relative to the variance of the standard logistic distribution and so $sd(e) = s_F\pi/\sqrt{3}$. The coefficients of the logit model (1) will be equal to their latent variable model counterparts, (4), divided by s_F.

The error variance of the reduced model, (5), is

$$\begin{aligned}\text{var}(\nu) &= s_F^2 \text{var}(u) + \beta_z^2 \text{var}(Z|X) \\ &= s_F^2\left[\text{var}(u) + b_z^2 \text{var}(Z|X)\right]\end{aligned}$$

and so the scale parameter for this model, s_R, will be

$$s_R = \frac{s_F\sqrt{\text{var}(u) + b_z^2 \text{var}(Z|X)}}{sd(u)} \tag{6}$$

The logit coefficients of (2) will equal their latent linear counterparts in (5) divided by s_R, and so we have

$$\alpha_1 = a_1 \frac{s_F\sqrt{\text{var}(u) + b_z^2 \text{var}(Z|X)}}{sd(u)} \tag{7a}$$

and

$$\beta_1 + \beta_2\gamma_1 = s_F(b_1 + b_2\gamma_1) \tag{7b}$$

Substituting the right hand side of (7b) for the left hand side of (7a), canceling the scale parameter, s_F, and recalling that u has a standard logistic distribution, yields (3).

One approach to dealing with the fact that the full and reduced logit models have different scalings would be to compute the relative scaling of the reduced and full models directly from (3), but Karlson, Holm, and Breen (2012) show that, given the model:

$$\log \text{odds}\left[\frac{Y=1}{Y=0}\right] = a_0^* + a_1^* X + a_2^* \tilde{Z} \tag{8}$$

where $\tilde{Z}$ is the residual from a regression of Z on X, it holds that $a_1^* = b_1 + b_2\gamma_1$. While the formal proofs can be found in Karlson, Holm, and Breen (2012), the intuition is that we replace Z with its residualized counterpart in the logit model and this variable is, by design, mean independent of X, so allowing us to estimate the parameter a_1^* on the same scale as the b parameters. The intuition is based on the fact that the underlying latent variable model in (4) and

$$Y^* = \alpha_0^* + \alpha_1^* X + \alpha_2^* \tilde{Z} + e^* \tag{9}$$

have the same residual variance and thus the same scale parameter.[4]

Extension to the Multinomial Case

Suppose now that X, Z, and Y are all categorical variables with more than two categories. The categories of X are indexed by i = 1, . . . ,I, of Y by j = 1, . . . ,J and of Z by k = 1, . . . ,K. The additive log-linear model of all two-way interactions can be written in the more general multinomial form as:

$$\log \text{odds}\left[\frac{Y=j}{Y=1}\right] = \mu_j + \sum_{i=1}^{I} b_{ij} x_i + \sum_{k=1}^{K} c_{kj} z_k \quad \text{for } j = 2, \ldots J \tag{10}$$

We set Y = 1 as the reference category. There are I dummy variables, x_i representing the categories of X, and

K representing the categories of Z, z_k. For identification we set $b_{1j} = 0$ and $c_{1j} = 0$ for all j. This means that the b parameters are estimates of partial log odds-ratios: b_{ij} is an estimate of the ratio of the partial log odds of Y = j rather than Y = 1 among observations with $x_i = 1$ and $x_{i'} = 0$ for all $i' \neq i$. These are partial log odds-ratios because they are conditional on the inclusion of the Z dummies and the dummies for the other categories of X.

While the method proposed by Karlson, Holm, and Breen (2012) applies to the single equation binary case, the method does not generalize to the multinomial in a straightforward fashion. This is because the coefficients of the multinomial logit model are contrast-specific (that is, specific to the contrast between a given alternative and the baseline alternative). This means that we must residualize the control variables on the subsample to which the contrast pertains. If we ignore this sample selection and residualize the control variables for the entire sample, the control variables will not be mean independent of the predictor variables of interest within contrasts. But mean independence is exactly what the Karlson, Holm, and Breen (2012) method requires for it to yield an exact decomposition.[5]

One way of solving this problem is to re-specify the multinomial model as an alternative-specific multinomial model. This model is identical to the multinomial in terms of fit to the data, but it allows a more flexible specification of the linear predictor. Being based on the conditional or mixed logit model, it permits each contrast to depend on its own set of predictor variables.[6] In this situation, we residualize the control variables for each of the contrast-specific samples in the model, and we include these contrast-specific residualized control variables in each of the corresponding logits of the model. That is, we specify the following model

$$\log \text{odds}\left[\frac{Y=j}{Y=1}\right] = \mu_j^* + \sum_{i=1}^{I} b_{ij}^* x_i^{Y=1,Y=j} + \sum_{k=1}^{K} c_{kj}^* \tilde{z}_k^{Y=1,Y=j}, \quad \text{for } Y = 2, \ldots, J \tag{11}$$

where $x_i^{Y=1,Y=j}$ is the set of *I-1* predictor variables for the fraction of the sample that is defined by being in categories Y = 1 or Y = j, and $\tilde{z}_k^{Y=1,Y=j}$ is the set of *K-1* residualized control variables for the fraction of the sample that is defined by being in categories Y = 1 or Y = j, where the residualized control variables are estimated with *K-1* linear regressions

$$E\left(z_k^{Y=1,Y=j}\right) = \gamma_{0k} + \sum_{i=1}^{I} \gamma_{ik} x_i^{Y=1,Y=j} \tag{12}$$

Using the notation of Equation (11), we may rewrite (10) as

$$\log \text{odds}\left[\frac{Y=j}{Y=1}\right] = \mu_j + \sum_{i=1}^{I} b_{ij} x_i^{Y=1,Y=j} + \sum_{k=1}^{K} c_{kj} z_k^{Y=1,Y=j} \tag{13}$$

stressing that this model is identical to that in (10), the only difference being the notation that makes clear that only a fraction of the sample (i.e., defined by Y = 1 or Y = j) is used for the estimation of each contrast.

Similar to the binary case, the coefficients of Equations (11) through (13) can be used to calculate the total, direct, and indirect effects of each X dummy on each log odds-ratio: in other words, we can calculate the direct and indirect (through Z) log odds-ratios. The total effects are the gross effects of the *I-1* dummy variables in (11), b_{ij}^*, measured on the scale of the full model (i.e. the model in (13)). The direct effects are the partial log odds-ratios, b_{ij}, in (13). The indirect effect for the log odds-ratio involving the ith (for i > 1) and omitted (i = 1) categories of X and the jth and omitted categories of Y is consequently equal to the difference between the total and direct effect, $b_{ij}^* - b_{ij}$. An equivalent way of estimating this indirect effect uses the coefficients, γ_{ik}, in (12), writing the indirect effects as $b_{ij}^* - b_{ij} = \sum_{k=1}^{K} c_{kj}\gamma_{ik}$, where c_{kj} are the coefficients of the mediating variables in (13). Thus, the complete decomposition of the total effect into direct and indirect effects is

$$b_{ij}^* = b_{ij} + \sum_{k}^{K} c_{kj}\gamma_{ik} \text{ for all } i \geq 2 \tag{14}$$

Too Much Information?

Given I categories of X and J categories of Y, there are (I-1)(J-1) linearly independent log odds-ratios, yielding a minimum total of 3(I-1)(J-1) parameter estimates (total, direct, and indirect effects) from the application of our method. Applied to our data, in which I = J = 6, this implies 75 odds ratios to interpret. Furthermore, because the mediating variable, educational attainment, is also categorical (with, say, K categories), there would be even more parameters (in fact, (1 + K)(I-1)(J-1) of them) if we wanted to focus on the K-1 separate indirect effects, rather than summing them as we do here. If we want to look in detail at particular odds-ratios in the mobility table, then the possibility of retrieving such rich information will obviously be valuable; we might, for example, focus on access to the highest destination class and the extent to which this is mediated in different

ways by educational attainment, depending on a person's class origins. On the other hand, if we want to know how much of the influence of origins on destinations is mediated through education, such approach yields too much information. In a comparative study, we may care less about specific comparisons of classes and more about the degree to which education has grown more or less important in mediating the origin–destination relationship. Even in a cross-sectional analysis, we might want to know whether the class origin differentials in class destinations were more strongly mediated through education for some class origins than others. In these cases, it would be helpful to have a more parsimonious approach.

Reducing Information by Imposing Constraints

The number of odds ratios to be decomposed can be reduced by imposing constraints on the parameters of the underlying model, shown in Equations (12) and (13). There is a long tradition in social mobility research of imposing such constraints in the analysis of the table of origins by destinations (see Breen, 2004, chapter 2). Ideally such constraints would be chosen on the basis of theory, and several mobility models have been developed in this way, notably Erikson and Goldthorpe's (1992) 'core model of social fluidity'. This approach models the origin–destination association in a seven-by-seven mobility table using only 8 of the 36 available parameters. In the present case, this approach would require us to assume that the same pattern of odds characterized *both* the gross origin–destination table *and* the table controlling for the effects of the intervening variable, educational attainment. Because we lack a strong theoretical basis for building such a model, we do not pursue that approach here.

A related way of imposing constraints is to assume a proportionality relationship between the corresponding parameters in each logit of the dependent variable. The one-dimensional stereotyped logit model, SOR (Anderson, 1984), imposes the constraint that $b_{ij} = \varphi_j b_{i1}$, for j = 2,...,J. That is, the coefficients for each X dummy in each logit of a multinomial logit model are equal to their baseline coefficient (in this case, the coefficient in the logit comparing $Y=2$ with $Y=1$) scaled up or down by a logit-specific multiplier, φ_j. Each logit retains an unrestricted intercept, but otherwise there are *I-1* coefficients for the origin classes and *J-2* multipliers. Applied to our origin by destination table, this would give 14 coefficients, compared with 36 in the unrestricted multinomial logit.

One could also impose a similar constraint on the parameters of the equations for the Z variables, shown in Equation (12). So we could set $\gamma_{ik} = \psi_k \gamma_{i1}$. As in the SOR model, a baseline set of coefficients from an ordinary least squares regression linking the X dummies to one particular Z dummy is raised or lowered by a Z-category multiplier, ψ_k, to capture the relationship between the X dummies and the other categories of Z.

Most ambitiously, one could further constrain the γ parameters by setting their baseline values equal to the baseline coefficients of the SOR model: $\gamma_{ik} = b_{i1}\psi_k$. This specification would constrain the coefficients for class origins in the models predicting education to be equal to the corresponding coefficients for the class origins in the models for class destinations.

Applying constraints like these would certainly reduce the number of direct and indirect effects, but if our goal is to compare total, direct, and indirect effects across groups, such as birth cohorts, there remains a significant obstacle. Allison (1999) brought to the attention of sociologists a problem in the interpretation of the coefficients of non-linear probability models similar to that addressed by Karlson, Holm, and Breen (2012). Just as scaling differences make it impossible to compare the parameter estimates from differently specified models estimated on the same sample, so they make it impossible to compare parameters from identically specified models estimated on different samples or groups. We cannot know the extent to which the differences we find reflect real differences between groups in the processes of interest or differences in the underlying residual variation in the outcomes that lead to variation in scaling across groups. Because comparisons of log odds-ratios from log-linear or multinomial logit models form the backbone of much comparative social mobility research, this is indeed a serious problem that awaits a widely accepted solution. Applied to the present case, no matter how much we may constrain the parameters of our models to reduce the number of log odds-ratios that we decompose into direct and indirect parts, if we cannot find a way to make them comparable between different birth cohorts, then we cannot say anything about trends in social fluidity or in the role of education in social mobility.

However, although log odds-ratios and their direct and indirect decompositions are not comparable across cohorts, the ratios of log odds-ratios are. This property means that although we cannot compare, say, the direct effect of class origins on destinations across countries or birth cohorts, we can compare the ratio of direct to indirect effects or the ratio of the indirect to the total effect. The reason is simple: because the direct, indirect, and total effects are identified up to scale, when we form their ratio, the scale parameters cancel.

In light of this result, and given that we want to know how the mediating role of education might have

changed, we can ask 'what patterns would be imposed on the ratio of indirect to total effects by the proportionality constraints we have outlined?' To answer this we consider a simple case in which *Y*, *X*, and *Z* each have three categories. Then we can write:

$$\text{logit}\left[\frac{Y=j}{Y=1}\right] = \mu_j + b_{1j}x_2 + b_{2j}x_3 + c_{1j}z_2 + c_{2j}z_3 \text{ for j} = 2,3$$

$$E(z_k) = \gamma_{0k} + \gamma_{1k}x_2 + \gamma_{2k}x_3 \text{ for k} = 2,3$$

So we treat $Y=1$ as the reference category in the multinomial logit, $Z=1$ as the reference category for the Z dummies, and $X=1$ as the reference for the X dummies. This setup defines four ratios of indirect to total effects, as follows: in the logit for $\text{Y}=2$ compared with $\text{Y}=1$, comparing $X=2$ with $\text{X}=1$, $r_{2,2} = \frac{\gamma_{12}c_{12}+\gamma_{13}c_{22}}{b_{12}+\gamma_{12}c_{12}+\gamma_{13}c_{22}}$. In the same logit, for $\text{X}=3$ compared with $\text{X}=1$, we have $r_{2,3} = \frac{\gamma_{22}c_{12}+\gamma_{23}c_{22}}{b_{22}+\gamma_{22}c_{12}+\gamma_{23}c_{22}}$. For $\text{Y}=3$ compared with $\text{Y}=1$, we have $r_{3,2} = \frac{\gamma_{12}c_{13}+\gamma_{13}c_{23}}{b_{13}+\gamma_{12}c_{13}+\gamma_{13}c_{23}}$ and $r_{3,3} = \frac{\gamma_{22}c_{13}+\gamma_{23}c_{23}}{b_{23}+\gamma_{22}c_{13}+\gamma_{23}c_{23}}$. Imposing the SOR constraint $b_{i3} = b_{i2}\varphi$ and $c_{i3} = c_{i2}\varphi$ yields

$$r_{3,2} = r_{2,2} = \frac{(\gamma_{12}c_{12}+\gamma_{13}c_{22})\varphi}{b_{12}\varphi+(\gamma_{12}c_{12}+\gamma_{13}c_{22})\varphi} = \frac{\gamma_{12}c_{12}+\gamma_{13}c_{22}}{b_{12}+\gamma_{12}c_{12}+\gamma_{13}c_{22}}$$

and

$$r_{3,3} = r_{3,2} = \frac{(\gamma_{12}c_{13}+\gamma_{13}c_{23})\varphi}{b_{13}\varphi+(\gamma_{12}c_{13}+\gamma_{13}c_{23})\varphi} = \frac{\gamma_{12}c_{13}+\gamma_{13}c_{23}}{b_{13}+\gamma_{12}c_{13}+\gamma_{13}c_{23}}$$

So, this specification implies that the ratio of indirect to total effects (that is, the mediation proportion or percentage) is constant across destination class logits for each X dummy variable. In this case, there are only I-1 such ratios.

An even more parsimonious result can be obtained if we also apply the constraint

$$\gamma_{i2} = b_{i2}\psi_2$$
$$\gamma_{i3} = b_{i2}\psi_3$$

This constraint sets the effects of each X dummy on each Z dummy equal to the effect of that X dummy on the logit for $Y=2$, scaled by a factor, ψ_k specific to each Z dummy. This yields:

$$r_{2,2} = \frac{b_{12}(\psi_2c_{12}+\psi_3c_{22})}{b_{12}+b_{12}(\psi_2c_{12}+\psi_3c_{22})}$$
$$r_{2,3} = \frac{b_{22}(\psi_2c_{12}+\psi_3c_{22})}{b_{22}+b_{22}(\psi_2c_{12}+\psi_3c_{22})}$$
$$r_{3,2} = \frac{b_{12}(\psi_2\varphi c_{12}+\psi_3\varphi c_{22})}{\varphi b_{12}+b_{12}(\psi_2\varphi c_{12}+\psi_3\varphi c_{22})}$$
$$r_{3,3} = \frac{b_{22}(\psi_2\varphi c_{12}+\psi_3\varphi c_{22})}{\varphi b_{22}+b_{22}(\psi_2\varphi c_{12}+\psi_3\varphi c_{22})}$$

From which it is evident that all the ratios of indirect to total effects are the same across both Y logits and X dummies and equal to $\frac{\psi_2c_{12}+\psi_3c_{22}}{1+(\psi_2c_{12}+\psi_3c_{22})}$. While the plausibility of these constraints may be debated, they can be tested against the data using likelihood ratio tests.

Data

The data we use come from the General Household Survey (GHS) for the years 1973, 1975–1976, 1979–1984, and 1987–1992, and were kindly made available to us by John Goldthorpe and Colin Mills.[7] Social class of origin and destination is categorized using the following version of the Erikson and Goldthorpe (1992) class schema:

I + II + IVa:	Salariat (managers, professionals, higher administrative workers, small employers)
IIIa:	Higher-grade routine non-manual workers
IVb:	Self-employed workers
IVc:	Farmers
V + VI:	Foremen and technicians and skilled manual workers
VII + IIIb:	Unskilled manual workers, farm workers, and lower-grade routine non-manual workers

Respondents' education is measured by their highest level of educational attainment categorized using the CASMIN (Müller *et al.*, 1989) educational schema. The mapping from British qualifications to the five CASMIN categories used here is as follows (Goldthorpe and Mills, 2004: p. 214):

- 1abc (compulsory education only = no qualifications, CSE or lower-grade GCE O-level, clerical or commercial qualification or apprenticeship),
- 2ab (secondary intermediate education, vocational and general = some higher-grade GCE O-levels),
- 2c (full secondary education = some GCE A-levels, ONC or OND),
- 3a (lower tertiary education = HNC, HND, on-graduate teaching or nursing qualification), and
- 3b (higher tertiary education = University degree or diploma, higher degree).

We restrict our sample to men aged between 35 and 49. The upper bound is 49 because, in some years, respondents to the GHS aged 50 or more were not asked the occupation of their father. Because our outcome variable, class destination, is likely to vary with age, we confine our analysis to men whose class position can reasonably be considered fixed. Certainly, men aged 35 or more may still change jobs, but it is widely accepted

that relatively few of them change class position after this age (Breen, 1984). Restricting the sample in this way means that we can focus on change over cohorts without having to deal with the possible confounding effects of age. We define three birth cohorts: those born 1925–1934, 1935–1944, and 1945–1954. Omitting cases with missing information on one or more variables gives a sample size of 53,229. In all analyses, we apply a weight that takes into account the oversampling of Scots.[8]

Social Mobility and Education in Britain

We examine whether education has come to play a greater role in mediating the relationship between origin and destination class in Britain. We first apply the method developed here for decompositions of log odds-ratios in a multinomial logit model, and then we apply the SOR model to provide a summary of how the role of education in social mobility has changed.[9]

Following from our discussion of the non-identification of differences over cohorts in total, direct, or indirect effects, we focus on change in the ratio of the indirect to the total effect. But the indirect effect itself (the numerator of our measure) is the product of the association between origins and education and the association between education and destinations. Comparisons among cohorts of these two effects, however, are not separately identified. For example, constancy in the ratio of indirect to total effects may involve constancy in the origin–education association and in the education–destination association or changes in one or the other or in both, but we cannot know which. This limitation is not a consequence of our method: rather, it is inherent in the use of log-linear models for mobility analysis. Log-linear analyses that report changes or country differences in total, direct, or indirect effects, or in the components of the indirect effect, ignore the fact that such comparisons are not identified. Nevertheless, the measure that we use—the ratio of the indirect to the total effect—answers the questions we care about in this analysis: namely, the extent to which education mediates the effect of origins on destinations, and the degree to which this changed. It seems likely that if we were to find change in the British data, we should see it in a comparison between the oldest and the two youngest cohorts, with education coming to play a greater role. This is because members of our oldest cohort would not have been able to take advantage of the major educational reforms instituted in the 1944 Education Act, which, among other things, made secondary education free of charge, whereas members of the 1935–1944 and, even more, of the 1945–1954 cohorts would potentially have benefitted from this change.

Origins, Education, and Destination Classes

Table 1, panel A, reports the estimated ratio of the indirect effect, via education, to the total log odds-ratio, for the six-class classification of origins and destinations

Table 1 Ratio (in per cent) of indirect to total effect log odds-ratios among men in Britain, GHS cumulated data, 1973 through 1992

Panel A:	**Salariat (I + II + IVa) versus the remaining five classes**				
	D: IIIa	**D: IVb**	**D: IVc**	**D: V + VI**	**D: VII + IIIb**
O: IIIa	27	54	−47	50	42
O: IVb	68	38	144	61	58
O: IVc	107	56	19	64	57
O: V + VI	54	59	−91	50	53
O: VII + IIIb	55	56	94	52	52

Panel B:	**Unskilled manual workers, farm workers and lower-grade routine non-manual workers (VII + IIIb) versus the remaining five classes**				
	D: I + II + IVa	**D: IIIa**	**D: IVb**	**D: IVc**	**D: V + VI**
O: I + II + IVa	26	26	25	44	57
O: IIIa	26	10	14	19	45
O: IVb	2	−3	3	16	30
O: IVc	25	20	−25	13	52
O: V + VI	33	23	17	30	52

Row is origin class, column is destination class.

in the full GHS data, spanning the period 1973–1992. The percentages are all defined relative to the same omitted class, I + II + IVa, in both origins and destinations. So, for example, the first percentage in the table is a measure of the extent to which education mediates the relationship, measured in log odds-ratios, between being found in destination class IIIa rather than class I + II + IVa among those brought up in class IIIa rather than class I + II + IVa. In this case, we find that roughly one-quarter of the association is mediated by education. In most of the cells in this panel, the mediation percentage is ~50, suggesting a robust and fairly marked role played by education in mediating entrance to the salariat among those brought up in one of the five classes other than class I + II + IVa. It is, however, difficult to discern any sort of trend (such as the percentages being a function of the social distance to the reference class), except for the group of individuals entering the class of farmers (IVc) relative to the salariat (I + II + IVa). For example, among those brought up in class V + VI rather than I + II + IVa, education markedly suppresses the association (−91 percent), and among those brought up in class VII + IIIb rather than I + II + IVa, education mediates almost the entire association (94 percent). These high percentages may be a result of strong farm inheritance or of the relatively small number of observations in the farmer category or both.

In panel B of Table 1, we report results similar to those of panel A with the reference class now being unskilled manual workers, farm workers, and lower-grade routine non-manual workers (VII + IIIb). We see that the decomposition percentages are, on average, lower than those reported in Table 1, with most of them lying between one-quarter and one-third, suggesting that education plays less of a role of in mediating the entrance into class VII + IIIb (relative to the other classes). One exception to this pattern is for those entering class V + VI relative to VII + IIIb, because here the destination classes are differentiated depending on whether they comprise skilled or unskilled workers. We find that most of the mediation percentages are ~50 percent and never <30 percent, indicating that education matters more for entry into the skilled rather than unskilled manual classes among those brought up in one of the five classes other than class VII + IIIb.

Did the Mediating Role of Education Change?

If we want to look in detail at particular decomposition percentages in the mobility tables, then the possibility of retrieving such rich information will obviously be valuable; we might, for example, want to focus on access to the highest destination class and the extent to which this type of mobility is mediated in different ways by educational attainment, depending on a person's class origins. But in this analysis, our concern is the degree to which education has grown more or less important in mediating the origin–destination relationship across cohorts born in 20th-century Britain. In Table 2, we therefore replicate the analysis reported in panel A of Table 1, but now broken down by the three birth cohorts. Except for the extreme values related to origins or destinations in class IVc (farmers), Table 2 does not reveal any strong evidence of education becoming more important over time. Certainly for some cells, we see an increasing mediating influence of education, but for many others, we find either declining or constant influence. While the results reported here do not support the expectation that education has come to play a more prominent mediating role, any trends would be difficult to discern because of the large amount of information contained in Table 2. What is more, if we were to replicate Table 2 for all possible class contrasts, we would have just too much information, making it extremely difficult to draw meaningful conclusions. In any case, in a comparative study such as ours, we may care less about specific comparisons of classes and more about the degree to which education has grown more or less

Table 2 Ratio (in per cent) of indirect to total effect log odds-ratios among men in Britain for three birth cohorts

	D: IIIa	D: IVb	D: IVc	D: V + VI	D: VII + IIIb
Panel A: 1925–1934					
O: IIIa	19	7	−13	36	28
O: IVb	92	33	98	58	59
O: IVc	90	44	20	55	56
O: V + VI	50	68	−40	48	55
O: VII + IIIb	54	54	72	49	53
Panel B: 1935–1944					
O: IIIa	23	62	−21	42	41
O: IVb	67	41	195	59	62
O: IVc	83	58	21	66	61
O: V + VI	52	56	−132	49	55
O: VII + IIIb	51	56	127	52	55
Panel C: 1945–1954					
O: IIIa	31	47	−22	49	39
O: IVb	53	36	−177	63	50
O: IVc	−54	57	12	67	52
O: V + VI	61	58	−117	49	47
O: VII + IIIb	57	55	196	52	48

Salariat (I + II + IVa) versus the remaining five classes.
Row is origin class, column is destination class.

important, overall, in mediating the origin–destination relationship.

Summarizing Trends in the Mediating Role of Education

To obtain a more parsimonious set of decomposition percentages, we apply the method of Karlson, Holm, and Breen (2012) to the coefficients of the SOR model, as outlined earlier. In Figure 1, using the SOR model for a decomposition of the total effect, we show the cohort trends in the ratio of the indirect effect to the total effect—in other words, the extent to which education mediates the relationship between class origins and destination class. Recall that imposing the SOR constraint gives us one value per origin class dummy per cohort—15 in all. The reference category is the highest origin class (I + II + IVa).[10] There is no evidence of systematic change over birth cohorts. All decomposition percentages—except for the farmers (class IVc) born 1935–1944—are ~50, suggesting that education mediates half of the relationship between origins and destinations in all of the three cohorts studied. However, this model performs poorly when set against the unconstrained multinomial logit. As Table 3 shows, for all three cohorts, the chi-squared test for the goodness-of-fit of the SOR model compared with the multinomial logit is always statistically significant at $P = .001$ or less. The Akaike information criterion and Bayesian information criterion corroborate this result. More stringently constrained models would fit even less well, and this is one reason why we did not employ them.

On the other hand, the model does provide a convenient summary picture, showing that the widely reported constancy in both social fluidity and educational inequality in Britain has been underpinned by a similar, general constancy in the degree to which education mediates the effects of class origins on destinations. Contrary to our expectations, changes in the British educational system after 1944 did not lead to an increase in the extent to which class origin effects were mediated *via* educational attainment. The various schools of thought (such as Treiman, 1970; Halsey Heath

Table 3 Goodness of fit of SOR compared with multinomial logit in each birth cohort

Cohort	Likelihood ratio test −2LogL	df	*P*-value	AIC	BIC
1925–1934					
Multinomial	25,331.0	50	–	25,431.0	25,794.5
SOR	26,054.1	18	–	26,090.1	26,221.0
Difference	723.1	32	0.000	659.1	426.5
1935–1944					
Multinomial	50,165.3	50	–	50,265.3	50,663.1
SOR	51,502.6	18	–	51,538.6	51,681.8
Difference	1337.3	32	0.000	1,273.3	1,018.7
1945–1954					
Multinomial	31,054.7	50	–	31,154.8	31,529.2
SOR	32,040.9	18	–	32,076.9	32,211.7
Difference	986.2	32	0.000	922.2	682.5

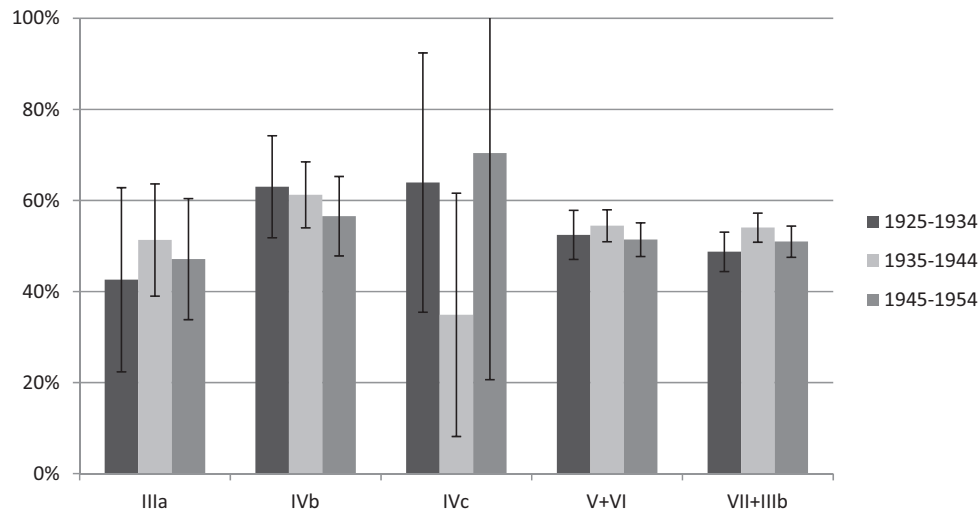


Figure 1 The extent to which education mediates social mobility. Decomposition percentages using the SOR model. Service class origin (I + II + IVa) is reference category. Black bars are 95 per cent bootstrapped confidence intervals

and Ridge, 1980) that argue, albeit for different reasons, for such a trend find no support in our results.

Conclusion

We have applied two new methods to examine the role played by educational attainment in intergenerational social class mobility and how this might have changed between successive cohorts of British men born during the middle part of the 20th century. The first method was a path decomposition for categorical data, drawing on recent work by Karlson, Holm, and Breen (2012). The second method developed a path decomposition of the coefficients from the stereotype ordered regression of Anderson (1984) to provide a convenient summary of the role of education in class reproduction. While the first method solves the long-standing problem of developing path decompositions for systems of categorical variables, the second may have equal or even greater utility in the analysis of social mobility. In particular, the micro-class approach (Weeden and Grusky, 2005) leads to log-linear models of mobility that generate even more parameters than the traditional 'big classes' approach. In this case, the application of the SOR model may be a valuable way of avoiding the hazard of failing to see the wood for the trees.

Although our summary measure can be useful for purposes of comparison, we nevertheless meet the problem of the non-identification of group differences in the parameters of non-linear probability models, as described by Allison (1999). Our solution was to compare not total, direct, or indirect effects, but the ratio of indirect to total effects because then the scaling parameters, which differ between the groups being compared, cancel. This approach appears to limit what we can say. We cannot, for example, measure changes in the indirect effect itself or changes in the components of that effect (that is, we cannot say by how much class inequality in education changed or how the role of education in determining class destination varied). But, in fact, changes in ratios of effects are all we can reliably assess when we use non-linear probability models to make comparisons. And, if we want to know the degree to which education mediates the origin–destination association, the ratio of the indirect to the total effect supplies the answer.

Notes

1. We use the term 'effect' in its conventional use as a regression coefficient. However, as our purpose here is to describe the role of education in social mobility, effects can perhaps better be understood as *differences*. That is, the total effect refers to the total gap between two groups (e.g., classes), whereas the indirect effect refers to the fraction of the gap that can be explained by the mediating variable (e.g., education) and the direct effect is the residual gap, unexplained by the mediating variable. We thank an anonymous reviewer for pointing out this important clarification.
2. Writing the effect of X on Z non-parametrically as the difference in group means, as we do here, presupposes that X is a dummy variable. More generally, however, for a continuous X, we can use the linear regression coefficient regressing Z on X (see Breen, Karlson and Holm, 2013).
3. Equation (3) holds only approximately. The reason for this, as we explain later, is that Models (1) and (2) not only differ by a scale factor but also in the fit of their latent distribution to the assumed logistic distribution.
4. Another consequence of this property is, as Karlson, Holm, and Breen (2012) notice, that the fit of the distribution of the latent errors in Models (4) and (9) to the assumed logistic functional form is identical (because the error terms are identical).
5. In passing we notice that this issue is related to the assumption of Independence of Irrelevant Alternatives in the multinomial logit model (Olsen, 1982). If Independence of Irrelevant Alternatives holds, then we would only need a single set of auxiliary regressions using the entire sample to residualize the mediating variables.
6. Another solution is to apply the method of Karlson, Holm, and Breen (2012) on a series of independent, binary logistic regressions on each contrast. As Begg and Grey (1984) show, this approach is consistent, but inefficient in comparison with the multinomial approach, and so we use the alternative-specific formulation of the multinomial model we suggest here.
7. Although the GHS has been fielded annually since 1971, information on the employment of the respondent's father (or head of the family) was not collected in 1977 or 1978, nor after 1992. Information on the last job held by those not currently working was not gathered in 1985 and 1986.

8. Analyses involving class position usually restrict attention to people who are currently participating in the labour force: failure to do this would mean, for example, the inclusion of some people whose class position is one that they occupied in the distant past. But this means that temporal comparisons will be compromised if rates of labour force participation change within birth cohorts as they age. In general terms, this will not be a problem where men are concerned, but in Britain, not only is there a historical trend towards greater female labour force participation but there are also pronounced life-cycle patterns of participation and non-participation, and these may vary according to class position. To avoid the resulting difficulties, we restrict attention to men.
9. All analyses were carried out in Stata ® 12.0. Code is available from the authors on request.
10. The confidence intervals shown in Figure 1 were estimated using a bootstrap.

Acknowledgements

Helpful comments on earlier drafts of this article were received from Seongsoo Choi, Anders Holm, Matthew Lawrence, Timothy Malacarne, and Elizabeth Roberto, and participants at the RC28 meeting in Hong Kong, May 2012.

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