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The Pattern of Social Fluidity within the British Class Structure: a Topological Model

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Summary. It has previously been shown that across three British birth cohorts, relative rates of intergenerational social class mobility have remained at an essentially constant level among men and also among women who have worked only full-time. We aim now to establish the pattern of this prevailing level of social fluidity and its sources and to determine whether it too persists over time, and to bring out its implications for inequalities in relative mobility chances. We develop a parsimonious model for the log odds ratios which express the associations between individuals' class origins and destinations. This model is derived from a topological model that comprises three kinds of readily interpretable binary characteristics and eight effects in all, each of which does, or does not, apply to particular cells of the mobility table: i.e. effects of class hierarchy, class inheritance and status affinity. Results show that the pattern as well as the level of social fluidity is essentially unchanged across the cohorts; that gender differences in this prevailing pattern are limited; and that marked differences in the degree of inequality in relative mobility chances arise with long-range transitions where inheritance effects are reinforced by hierarchy effects that are not offset by status affinity effects.

Keywords: Social class, social mobility, loglinear models, topological models, indicator models

1. Introduction

In previously reported research (Bukodi *et al.*, 2015) it has been found that in Britain among men in three birth cohorts whose lives span the later twentieth and early twenty-first centuries relative rates of intergenerational social class mobility have remained more or less unchanged. Further, the same situation has been found (Bukodi *et al.*, 2016a) in the case of those women in the three cohorts who have always, when in employment, worked full-time, even if with one or more periods of absence from the labour market. One could therefore say that for a substantial part of the active British population social fluidity within the class structure – that is, individuals' chances of mobility or immobility considered *net* of class structural change – has been at an essentially constant level. It is with the pattern and sources of this constancy that the present paper is concerned. Among women who at some point have worked part-time, social fluidity does show a change – in fact an increase; but, as discussed at length in Bukodi *et al.*, (2016a), this would appear to result from social processes involving a significant degree of self-selection, and the further analysis of this change would call for a quite separate modelling exercise from that here attempted.

More formally, the results that have been earlier obtained are the following. For a sample of individuals, their social class origin (the individual's father's class position), class destination (the individual's own class position) and birth cohort are recorded. These can be summarized as a three-way contingency table with observed frequencies Y_{ijk} for origin i=1,…,I, destination j=1,…,J and cohort k=1,…,K where I and J are equal (in our analyses I=J=7 and K=3). The data may be modelled with Poisson log-linear or log-multiplicative models for the expected frequencies F_{ijk} = E(Y_{ijk}) (see e.g. Agresti, 2013, for an overview of such models). With the British data for men and (separately) for women who have only worked full-time, the tables are reproduced with a satisfactory fit by the loglinear model

$$\log F_{ijk} = \mu + \lambda_i^{O} + \lambda_j^{D} + \lambda_k^{C} + \lambda_{ik}^{OC} + \lambda_{jk}^{DC} + \lambda_{ij}^{OD} \quad (1)$$

for *i=1,…,I; j=1,…,J; k=1,…,K*. Here the parameters of main interest are the λ_{ij}^{OD}, which quantify the associations – as measured by log odds ratios – between origin (O) and destination (D), separately from their marginal distributions. These associations describe levels and patterns of social fluidity, with stronger associations corresponding to lower levels of fluidity. In model (1) – known as the 'constant social fluidity' model – these parameters take the same values for all cohorts (C). Moreover, no significant improvement on this model is made by the log-multiplicative UNIDIFF model (Erikson and Goldthorpe, 1992; Xie, 1992) which allows the log odds ratios to vary between cohorts by a multiplicative factor.

In the present paper, we consider a series of further questions that arise from these earlier findings. Given that the level of social fluidity within the British class structure displays an essential stability, what is the pattern of this fluidity and how is this pattern created? Does the patterning of social fluidity, as well as its level, remain stable over time? How far does the same pattern prevail for men and women? And, in a wider context, what are the implications of the patterning of fluidity for the propensities for different intergenerational mobility transitions to be made and for consequent inequalities in relative mobility rates?

In terms of the loglinear models, these lines of inquiry correspond to looking for parsimonious and interpretable patterns in the origin-destination odds ratios defined by the parameters λ_{ij}^{OD}. Model (1) has (I-1)(J-1) free parameters for them. We seek well-fitting models where these odds ratios are determined by a smaller number of theoretically informed and substantively interpretable parameters.

Specifically, we begin by developing a model of social fluidity of the general kind that Hout (1983: ch. 4) has labelled as 'topological'. In such models, the cells of the origin-by-destination table (`mobility table') within each cohort are assigned, exclusively and exhaustively, to a number of subsets in each of which a common value of the association parameter λ_{ij}^{OD} is taken to hold. In our model these subsets are determined by a still smaller number of parameters with distinct interpretations, each referring to some characteristic of the cell to which a parameter applies. We then show that this specification also implies a linear model for the log odds ratios defined by the parameters, which thus also depend only on the cell characteristics that define the topological model.

Based on sociological theory and empirical analysis of data from the British birth cohort studies, we propose a topological model with three types of explanatory characteristics: *hierarchy* effects which correspond to the partial ordering of the social classes, *inheritance* effects which capture the tendency of individuals to remain in the same class as their parents, and *status affinity* effects which reflect relatively lower barriers to mobility among certain subsets of social classes.

In Section 2 of the paper we describe the data used for the analyses. Topological models and the resulting models for log odds ratios are described in general terms in Section 3, and our specific model for social fluidity is defined in Section 4. Results for fitting the model to the British mobility data are given in Section 5, and more general conclusions are drawn in Section 6.

2. Data and variables

A full description of the data that we use and of the relevant variables that we derive from these data is provided in Bukodi et al. (2015). Here therefore we give only a rather brief account.

We draw on the data-sets of the three earliest British birth cohort studies: the MRC National Survey of Health and Development (NSHD) (doi: 10.5522/NSHD/Q101), the National Child Development Study (NCDS) and the British Cohort Study 1970 (BCS), which have followed through their life-courses children born in Britain in one week in 1946, 1958 and 1970, respectively. The data-sets have some missing values for the social class variables, resulting primarily from cohort attrition. These missing values have been multiply imputed to allow for the inclusion of the incomplete observations in the analysis. The imputation process is described in an Appendix. The multiply imputed data-sets have been used for all of our analyses.

In forming intergenerational social mobility tables, we cross the two variables of individuals' social class origins and their social class destinations. The former refers to fathers' class positions when cohort members were aged 10 or 11 (or 15 or 16 if this earlier information is not available), and the latter to the class positions in which cohort members were themselves found at age 38 (or, if not then in employment, when last in employment). Age 38 is the latest for which we have relevant information available for members of the 1970 cohort in the data-set we analyse but is usually regarded as an age by which 'occupational maturity' has been achieved: i.e. an age by which the probability of further occupational changes of a kind that would imply changes in class position falls away (see further Bukodi and Goldthorpe, 2009, 2011).

Class positions of both origin and destination are determined according to the 7-class version of the National Statistics Socio-Economic Classification (NS-SEC). This classification derives from employment status and occupation which are together taken as indicators of individuals' positions in the social relations of labour markets and production units or, in short, of their employment relations (see further ONS, 2005; Rose, Pevalin and O'Reilly, 2005: ch.4; and for the theoretical basis of this approach to the determination of class positions, Goldthorpe, 2007: vol. 2, ch. 5). Extensive tests of the validity of basing NS-SEC on these indicators have been carried out with generally positive results (Rose and Pevalin, 2003; Rose, Pevalin and O'Reilly, 2005: ch. 6). We work with the SOC90 occupational classification which can be applied in all three of our cohorts (for further details of the coding scheme involved, see ONS, 2005: Table 17). In Table 1 we show the resulting distributions of the class origins and destinations of men in the three cohorts, and in Table 2 the corresponding distributions for those women in the three cohorts who have worked only full-time.

[Tables 1 and 2 here]

As noted, previous analyses by Bukodi et al. (2015, 2016a) have shown that the constant social fluidity model (1) provides a satisfactory fit for the 7 x 7 class mobility tables that have been constructed for these men and women (the fit of the models is judged by likelihood ratio tests for overall goodness of fit, and against a model where patterns of fluidity are allowed to vary across cohorts, as discussed in Section 1).

3. Topological models and their implications for models for log odds ratios

3.1. Definition and interpretation

The ideas discussed in this section apply generally to associations in loglinear models. For simplicity of notation, however, we describe them in the context of the specific model in our analysis of social fluidity, that is model (1) as defined in Section 1. Here the intercepts and main effects μ, λ_i^O, λ_j^D, and λ_k^C together with the association parameters λ_{ik}^{OC} and λ_{jk}^{DC} refer to the two-way marginal distributions of origin (O) by cohort (C) and destination (D) by cohort, and their estimated values will be such that the observed values of those distributions (and thus also the one-way margins of all three variables) will always be reproduced exactly by the fitted model. These parameters are not of central concern here. Instead, we focus on the parameters λ_{ij}^{OD} which describe the associations in the two-way `mobility tables' between origin and destination. Each such table is an *IxJ* table where *I*=*J*. We assume that the origins *i* and destinations *j* are coded similarly and in the same order, so that, for example, *i*=*j* means that the origin class and the destination class are the same.

The origin-destination associations in a mobility table are quantified by the log odds ratios (log ORs)

$$\log \theta_{il,jm} = \log \frac{F_{ij}F_{lm}}{F_{im}F_{lj}} = \log \frac{P(D=m \mid O=l)/P(D=j \mid O=l)}{P(D=m \mid O=i)/P(D=j \mid O=i)} \quad (2)$$

for all $i=1,\ldots,I-1;$ $l=i+1,\ldots,I;$ $j=1,\ldots,J-1;$ $m=j+1,\ldots,J$. In model (1), the association parameters λ_{ij}^{OD} and consequently the log ORs do not depend on the cohort. Because of this, we omit here and in the following the cohort subscript k from the notation for simplicity, and take $\log\theta_{il,jm}$ to denote the log ORs in the mobility table for any cohort. Expression (2) defines $I^2(I-1)^2/4$ of these quantities (441 of them in our analysis, where $I=J=7$), any ones of which may be used to describe associations in specific parts of the table. A single $\theta_{il,jm}$ is the OR for the 2x2 subtable which includes the four cells corresponding to the four combinations of the ith and lth rows and jth and mth columns of the full IxJ table. It describes the odds that an individual from origin class l is found in destination class m rather than destination class j, relative to the same odds for someone from origin class i. The ORs are variation-independent of and orthogonal to the sufficient statistics for the lower-order margins in the Poisson loglinear model (see, e.g., Barndorf-Nielsen and Cox, 1994, S. 2.9), which in our case include the marginal distributions of origin and destination classes within each cohort. This means that the odds ratio is distinct from and need not be affected by changes in the distributions of the classes over time and across generations, making it a uniquely convenient parameter for describing social fluidity (relative mobility) between origin and destination classes, separately from such marginal changes.

The log ORs are in turn determined by the parameters λ_{ij}^{OD} in (1) as

$$\log\theta_{il,jm} = \lambda_{\mathrm{ij}}^{\mathrm{OD}} + \lambda_{\mathrm{lm}}^{\mathrm{OD}} - \lambda_{\mathrm{im}}^{\mathrm{OD}} - \lambda_{\mathrm{lj}}^{\mathrm{OD}}. \qquad (3)$$

There are *(I-1)(J-1)* degrees of freedom available for setting the IJ values of $\lambda_{\mathrm{ij}}^{\mathrm{OD}}$, so some constraints are required to identify their values uniquely. For example, commonly used baseline constraints set $\lambda_{\mathrm{ia}}^{\mathrm{OD}}$ = 0 for all i and $\lambda_{\mathrm{bj}}^{\mathrm{OD}}$ = 0 for all j for some choice of a and b, typically a = b = *1*. In this case also $\log\theta_{al,bm} = \lambda_{\mathrm{lm}}^{\mathrm{OD}}$. In general, however, the parameters $\lambda_{\mathrm{ij}}^{\mathrm{OD}}$ are not log ORs themselves, so they do not have a direct interpretation individually but only in relation to each other as in (3).

Our aim here is to seek a well-fitting model which defines all of the log odds ratios from a smaller number of distinct parameters than *(I-1)(J-1)*. This is achieved in three steps. First, we define a parsimonious model for the association parameters $\lambda_{\mathrm{ij}}^{\mathrm{OD}}$, employing the idea of a topological model or `levels model' (Hauser, 1978, 1979; see also Hout, 1983; Clogg and Shockey, 1984; Klimova and Rudas, 2012). This divides the $IJ$ cells of the origin-by-destination table into a smaller number $S$ of exhaustive and mutually exclusive subsets (`levels' or `regions'), associates a parameter α_s with each level, and specifies that $\lambda_{\mathrm{ij}}^{\mathrm{OD}} = \alpha_s$ for every cell (i,j) which belongs to level *s=1,…S*.

Second, we derive the levels of a topological model for $\lambda_{\mathrm{ij}}^{\mathrm{OD}}$ as configurations of a set of binary characteristics, each of which either applies or does not apply to each cell of the table (such models are instances of the `indicator models' of Zelterman and Youn, 1992, and `relational models' of Klimova et al., 2012). Let $z_{ij(r)}$ be an indicator variable which is 1 if characteristic *r (=1,…,R)* applies to cell *(i,j)* and 0 otherwise. For example, one such characteristic is that a cell is on the diagonal of the table, in which case $z_{ij(r)} = 1$ if $i = j$ and $z_{ij(r)} = 0$ if $i \neq j$.

We thus specify that $\lambda_{\mathrm{ij}}^{\mathrm{OD}} = \boldsymbol{z}_{ij}'\boldsymbol{\gamma}$, where $\boldsymbol{z}_{ij} = (z_{ij(1)}, \dots, z_{ij(R)})'$ and $\boldsymbol{\gamma} = (\gamma^{(1)}, \dots, \gamma^{(R)})'$ is a vector of parameters. For convenience, we may also write $\gamma_{(ij)}^{(r)} = z_{ij(r)}\gamma^{(r)}$, i.e. $\gamma_{(ij)}^{(r)} = \gamma^{(r)}$ if characteristic *r* applies to cell *(i,j)* and $\gamma_{(ij)}^{(r)} = 0$ if it does not. The model for the origin-destination association parameters in the loglinear model (2) can then be expressed as

$$\lambda_{\mathrm{ij}}^{\mathrm{OD}} = \boldsymbol{z}_{ij}'\boldsymbol{\gamma} = \gamma_{(ij)}^{(1)} + \dots + \gamma_{(ij)}^{(R)}. \qquad (4)$$

This is a topological model where the levels are defined by those distinct combinations of the *R* binary characteristics which actually occur in the table, the number of levels *S* is the number of these combinations, and the levels parameters α_s are given by the distinct possible values of the sum on the right-hand side of (4).

The third and most important step of the model development is to observe that (4) also implies a model for the log odds ratios, as can be seen by substituting it into (3), to give

$$\log \theta_{il,jm} = \left(\boldsymbol{z}_{ij} + \boldsymbol{z}_{lm} - \boldsymbol{z}_{im} - \boldsymbol{z}_{lj}\right)'\boldsymbol{\gamma} = \boldsymbol{x}_{il,jm}'\boldsymbol{\gamma}. \qquad (5)$$

This is linear in the parameters $\boldsymbol{\gamma}$, and its explanatory variables $\boldsymbol{x}_{il,jm}$ are of the form $z_{ij(r)} + z_{lm(r)} - z_{im(r)} - z_{lj(r)}$ for *r=1,…,R*. Each such variable is a ‘net count’ of how many of the cells in the 2x2 subtable which define an odds ratio are such that a characteristic r applies to them, with the off-diagonal cells in the subtable counted with a negative sign. The possible values of this count are -2, -1, 0, 1, and 2.

As the first example, consider the very simple case of a constrained *quasi-independence model*. This uses for each cell only the one characteristic of whether or not the cell is on the diagonal of the full table, so that *R=1* and $z_{ij(1)} = 1$ if $i = j$ and 0 otherwise. The possible log ORs are then

$$\log \theta_{il,jm} = \begin{cases} 2\gamma^{(1)} & \text{if } i = j \text{ and } l = m \text{ (log-OR involving two diagonal cells)} \\ \gamma^{(1)} & \text{if either } i = j \text{ or } l = m \text{ (log-OR involving one diagonal cell)} \\ -\gamma^{(1)} & \text{if either } i = m \text{ or } l = j \text{ (log-OR involving one diagonal cell)} \\ 0 & \text{if } i \neq j, m \text{ and } l \neq j, m \text{ (log-OR involving no diagonal cells)} \end{cases}$$

where the difference between the cases with $\gamma^{(1)}$ and with $-\gamma^{(1)}$ is whether or not the one diagonal cell (in the full table) is on the diagonal of the 2x2 table which defines the odds ratio. In a mobility table the cells on the diagonal correspond to individuals who are in the same class as their fathers. The observed number of such cases is normally higher than would be expected under no association (perfect fluidity), so $\gamma^{(1)}$ will be positive. The model thus specifies no association whenever a log OR does not involve a case of a person staying in their father's class, non-zero association of size $\gamma^{(1)}$ or $-\gamma^{(1)}$ if it involves one such case, and the positive association of $2\gamma^{(1)}$ if two. These associations could then be interpreted as being due to the persistence of class membership across generations. This is a simple case of an *inheritance* effect, instances of which will be included in our model.

Topological models are still loglinear models, so maximum likelihood estimates of their parameters can be obtained using estimation algorithms for loglinear models, as long as these allow the user to specify the design matrix of the model. We have used the *gnm* package in R (Turner and Firth 2015) to fit the models (examples of the R code for doing this are included in on-line supplementary materials to this article). This gives estimates $\hat{\boldsymbol{\gamma}}$ of the association parameters $\boldsymbol{\gamma}$. Estimates of log odds ratios are then obtained by substituting $\hat{\boldsymbol{\gamma}}$ into (5), and standard errors of estimated log ORs by applying the delta method to (5) with the estimated variance matrix of $\hat{\boldsymbol{\gamma}}$.

3.2. Specification and identification of the models

We thus propose to derive a parsimonious model for the log odds ratios by specifying first topological models for the origin-destination association parameters λ_{ij}^{OD}. This indirect approach raises two preliminary questions, which we address in this section: why is the focus not on the λ_{ij}^{OD} which are modelled first, and why is the model not defined directly for the log ORs.

The ultimate focus of interest is on the log ORs because the association parameters λ_{ij}^{OD} themselves are not individually interpretable. They are also not uniquely identified, in the sense that many different but equivalent sets of λ_{ij}^{OD} with different parameter constraints will (together with the rest of the model parameters) define the same joint distribution of the expected frequencies and cell probabilities for a table. In the context of topological models this means that there will be many equivalent models with different configurations of topological regions which have constant values of the association parameters. This also implies that even if two cells have the same value of λ_{ij}^{OD} in a given parametrization, this does not imply that those cells are similar in the sense of having equal joint or conditional probabilities. The topological regions are also not necessarily uniquely defined even for a given number of levels (Macdonald, 1981), i.e. there can exist an equivalent model with the same number of levels in a non-trivially different configuration (although this is not always the case; for example, the model for social fluidity which we define later appears to be unique in this sense).

All such equivalent parametrizations will, however, imply the same values for the log odds ratios. A simple illustration of this idea is given in Table 3 (an extended version of this example is included in the supplementary materials). It shows three versions of the same 2x2 sub-table of a larger two-way table, under three ostensibly different but equivalent topological models. Within each of the 2x2 tables, the cells with the same value of the association parameter (denoted here by $\gamma^{(1)}$ or $\gamma^{(2)}$) are on the same topological level. In all three instances the log OR is 0, i.e. there is no association in the 2x2 table. However, the explanations for *why* this is the case are not the same, because the levels are different. In sub-table (1), all four cells are on the same level, so the value of $\lambda_{ij}^{OD}=\gamma^{(1)}$ is the same for all of them and the log OR from (6) is obviously $\log\theta = \gamma^{(1)} + \gamma^{(1)} - \gamma^{(1)} - \gamma^{(1)} = 0$. In sub-table (2), there are not one but two distinct levels, but within each row the two columns are on the same level (1 for the first row, 2 for the second). So the two rows are still similar in this sense, and $\log\theta = \gamma^{(1)} + \gamma^{(2)} - \gamma^{(1)} - \gamma^{(2)} = 0$. Finally, in sub-table (3) the two columns within each row are different in level, but in the same way for both rows (both having level 2 for the second column and 1 for the first), so the level parameters $\gamma^{(1)}$ and $\gamma^{(2)}$ again cancel out and $\log\theta = 0$ for the 2x2 table.

[Table 3 here]

Because the levels of a topological model are not uniquely defined, developing such a model purely empirically is very difficult if not impossible (see also Macdonald, 1983, for a discussion of this point). Instead, the numbers and configurations of levels for candidate models have to be motivated primarily by substantive theory and interpretability. For our models, this means selecting the interpretable characteristics of the cells whose configurations determine the levels of the topological model and thus the explanatory variables in the model for the log odds ratios. These models, focusing on the log ORs, can typically be considered well-defined for substantive interpretation, despite the formal unidentifiability of the levels of the initial topological model.

Since the log odds ratios are the quantities of ultimate interest, an alternative modelling approach would be to specify models for them directly. This can be done, under the family of `generalized loglinear models' (Lang and Agresti, 1994; see also Lang, 2005 and Bergsma *et al.*, 2009, for further developments and references). The models that we propose are members of this family, in the special case where the explanatory variables for each odds ratio are defined by counts of characteristics of the individual cells, as in equation (5). This clearly does not encompass all possible model specifications for the log odds ratios. Ones that go beyond it include, for example, models where explanatory variables refer to the four cells as a group or which impose equality constraints within specific sets of log ORs or for a given log OR across different groups. Breen (2008) gives examples of models for social fluidity with such constraints across countries. Models like this may be fitted using specialised algorithms for generalized loglinear models.

For our purposes, explanatory variables or constraints for a log OR in general provide little added value. This is in large part because substantive theory provides few suggestions for such models. In contrast, the approach of starting with the individual cells has the virtue that the cells are more basic entities to which it is easier to assign interpretable characteristics. In a mobility table each cell corresponds to a pair of one origin class i and one destination class j, and the characteristics of the cells are characteristics of these pairs – for example, that a person is in the same class as his or her father ($i=j$), or in a hierarchically higher class ($j>i$). Starting from such cell characteristics alone a rich class of models for the log odds ratios can be derived. In the rest of the article, we propose and apply one such a model for social fluidity in Britain.

4. Topological models for social fluidity

4.1. Previously proposed models

In the versions of topological models that were first developed for modelling social fluidity in the US by Hauser (1978) and Featherman and Hauser (1978), and that were then adapted to the British case by Goldthorpe (1987), the cells of the mobility table were partitioned directly into subsets (levels) with constant association parameters. The assignment of cells to different subsets was guided by theoretical expectations in only a rather general way and also by rather ad hoc considerations of balancing parsimony, as regards the number of subsets created, and fit. To try to improve on this situation in producing a model of the 'core' pattern of social fluidity within the class structures of modern industrial societies, Erikson and Goldthorpe (1992: ch. 4) took the then novel approach of moving to the kind of specification discussed as the second step in our model development in Section 3, that is by deriving the levels of the topological model based on combinations of different binary characteristics of the cells, each with its own theoretical motivation.

In the context of their cross-national comparative research, Erikson and Goldthorpe in fact proposed four different classes of characteristics (`effects') bearing on social fluidity:

Hierarchy effects. effects limiting social mobility that derive from differences in the general desirability of class positions and further from the relative advantages that are offered by different classes when considered as classes of origin – e.g. in terms of the availability of family economic, cultural and social resources; and from the relative barriers that exist to their attainment when considered as classes of destination – e.g. in terms of required skills, qualifications or capital.

Inheritance effects. effects enhancing social *im*mobility, and thus limiting mobility, that derive from the special desirability for individuals of positions falling within their own class of origin and, further, from their distinctive opportunities for entry into such positions – e.g. via the intergenerational transmission of capital or 'going concerns' or family connections; or from distinctive constraints existing on mobility away from their class of origin – e.g. as resulting from restricted possibilities in local labour markets.

Sector effects. effects limiting social mobility that derive from economic divisions creating vertical rather than, or in addition to, hierarchical barriers to mobility in that mobility between them is likely to require geographical and/or sociocultural relocation – as, most notably, in the case of mobility between the agricultural and non-agricultural sectors.

Affinity or disaffinity effects. effects enhancing or limiting social mobility that derive from specific linkages or discontinuities between classes that offset or increase the more generalised effects of hierarchy, inheritance or sector – as e.g. in the case of the effects of social status as distinct from those of class.

4.2. Our topological model for social fluidity

We follow here the same approach as Erikson and Goldthorpe (1992) but since we are concerned only with a model of the pattern of social fluidity within the British class structure, rather than with one of wider, cross-national applicability, it is possible for us to proceed on simpler lines. We first disregard sector effects, which, as was noted, mainly relate to barriers to mobility existing between the agricultural and non-agricultural sectors. Given the very small number of farmers and farm workers within the active labour force in Britain since the middle of the last century, this can be done with little loss, and in any event the numbers in our cohorts employed in the agricultural sector would be too small to allow for any separate analysis. We are then also able to disregard certain inheritance and affinity and disaffinity effects that Erikson and Goldthorpe introduced into their model in order to deal with further distinctive features of propensities for mobility either into or out of the agricultural sector.

Our model comprises eight effects in all, as follows:

Hierarchy effects. We propose four hierarchy effects that are determined by the five hierarchical levels which it has become standard practice to distinguish within the 7-class version of NS-SEC, and which are indicated by the dotted lines in Tables 1 and 2. It can be seen that these levels result from treating Classes 3, 4 and 5 as being at the same hierarchical level. While members of these classes do hold qualitatively different class positions – that is, are involved in different kinds of employment relations – the classes cannot be seen as unequivocally ordered as regards the relative advantages they offer if considered as classes of origin or as regards the relative barriers to their entry if considered as classes of destination. Our first hierarchy effect, labelled HI1, operates in cells of the 7 x 7 mobility table (within each cohort) that imply the crossing of any one of the five hierarchical levels, the second effect, HI2, in cells implying the crossing of two levels, the third effect, HI3, in cells implying the crossing of three levels, and the fourth, HI4, in cells implying the crossing of four levels. These hierarchy effects are thus cumulative, so that, for example, cells in which HI4 applies will be ones in which HI1, HI2 and HI3 also apply.

Inheritance effects. We propose two inheritance effects. The first, IN1, is intended to capture a general propensity for intergenerational class *im*mobility. It operates in all cells of the mobility table defined by the same class of origin and destination or, that is, in all seven cells on the main diagonal of the mobility table. The second inheritance effect, IN2, is then limited to just two cells on this diagonal: those relating to immobility in Class 1, that of higher-level managers and professionals, and in Class 4, that of small employers and own account workers. This further effect, additional to IN1, is introduced in order to reflect the fact that in these two classes the propensity for immobility is likely to be increased in that inheritance may occur more directly than in other classes through the intergenerational transmission of capital or of actual businesses or practices. (We note that although Class 1 is predominantly made up of employee – i.e. salaried (managers and professionals), it does also include a small number of 'large' employers (i.e. those with more than 25 employees) – and some number of managers who, while formally salaried, will also have ownership interests in the businesses they manage, and of professionals who are, at least in some degree, self-employed.)

Affinity effects. We propose two effects that are intended to capture affinities of social status – specifically, of 'white-collar' and 'blue-collar' status – that are taken as in some degree offsetting the constraints on mobility imposed by hierarchical class effects. Status is here treated (see further Chan and Goldthorpe, 2007; Goldthorpe, 2012) as a form of social stratification qualitatively different from, and only imperfectly correlated with, class that is expressed in distinctive lifestyles and differential association, especially in more intimate aspects of social life such as close friendship or marriage. A major line of status division still prevails in British society between white-collar and blue-collar work (Chan and Goldthorpe, 2004) and this does map more or less closely onto the version of NS-SEC that we use. An affinity effect is thus taken to operate, on the one hand, in the case of all cells of the mobility table implying mobility within the largely white-collar world – that is, as between Classes 1, 2 and 3; and, on the other hand, in all cells implying mobility within the largely blue-collar world – that is, as between Classes 5, 6 and 7. We allow for these white-collar and blue-collar status affinity effects to be of differing strength, with the former being labelled AF1 and the latter AF2.

Each of the eight effects specified either applies or does not apply to any given cell of the mobility table, and indicator variables for each of them are defined as described in Section 3. Online Supplementary Material shows the IxJ = 7x7 design matrices of these indicators for all the cells, separately for each of the eight effects. Our model for the pattern of social fluidity within the British class structure is thus a loglinear model (1) with the origin-destination association parameters λ_{ij}^{OD} given by the topological model (4) with R=8 distinct effects. Different combinations of presences and absences of the effects in the 49 cells of the mobility table define 11 distinct values of λ_{ij}^{OD}, including 0 in six cells where none of the effects apply. These levels and the effects which contribute to them are shown in Table 4. Our model is then equivalent to an eleven-level topological model of the older kind, but has a more explicit theoretical basis and derives the eleven levels from eight basic parameters. It may further be observed that the model is symmetrical in its specification for cells above and below the main diagonal (i.e. for upward and downward mobility, for pairs of hierarchically ordered classes).

[Table 4 here]

This topological model for the association parameters then also implies a model of the form (5) for the log odds ratios between origin class and destination class. We will describe and interpret this latter model in the next section, in the context of its use in the analysis of social fluidity in Britain.

5. Results

Table 5 shows results for our topological model fitted to the 7 x 7 class mobility tables for men in our three cohorts, together with two other models for comparison. The overall model fit and comparisons of fit between certain nested models are assessed using modified versions of likelihood ratio tests designed for use with multiply imputed data (Meng and Rubin, 1992; Li *et al.*, 1991; see Appendix for more information). The table also shows for each model the estimated index of dissimilarity (DI), which is used as an overall summary measure of the fit of a model. It can be interpreted as the smallest percentage of observations in the observed contingency table which would need to be moved to other cells to make the model fit perfectly. We use a bias-adjusted version of the index and confidence interval for it calculated as described in Kuha and Firth (2011).

[Table 5 here]

The top panel of the table shows first, as a baseline, the fit of the independence model where $\lambda_{ij}^{OD} = 0$ for all *i,j*: that is, a model which postulates conditional independence between men's class origins and destinations within each cohort. Its fit, as would be expected, is quite poor with around 14 per cent of all cases being misclassified. In the second row we then show the results of fitting our topological model with its parameters constrained to be the same for each cohort. The fit is in this case acceptable, with p = 0.116 for the overall goodness of fit test and now only around 4 per cent of all cases are misclassified. In the third row of the table we show the fit of the model with parameters being allowed to vary by cohort. In this way, some further improvement in fit appears to be obtained but, as can be seen, this improvement falls just short of significance at the 5% level.

The lower panel of Table 5 gives estimates of the parameters $\gamma^{(r)}$ for the eight effects of our topological model when these are constrained to be equal across the cohorts. All of them are statistically significant and take their expected sign. (We will return to the interpretation of the parameters later.)

On the basis of these results, we are then inclined to accept our model in its common parameters version and to believe that, for men at least, it gives a reasonably good representation of the pattern of the essentially stable level of social fluidity within the class structure that our earlier work revealed.

Table 6, which has the same format as Table 5, shows the results for the models fitted for women who have worked only full-time (while this qualification should always be kept in mind, we will henceforth usually refer simply to women). The model with common parameters for each cohort fits well, with again only around 4 per cent of all cases misclassified, and the improvement achieved by allowing parameters to vary by cohort is clearly non-significant. The pattern of the parameter values is similar to that for men, although three of the parameters (HI1, HI4, and AF1) fall short of statistical significance.

[Table 6 here]

For the women we cover as well as for men, we have, therefore, reasonable grounds for supposing that our model, with common effect parameters across cohorts, can adequately capture the pattern of the more or less unchanging level of social fluidity. However, a question that directly follows is that of how far the pattern that the model expresses is, in more detailed terms, the same in the case of men and women alike. To examine this question, we pool the data for men and women and fit the model with common origin-destination association parameters for men and women as well as for cohorts (and with all other parameters of the model varying freely between the genders and cohorts). As is shown in Table 7, this version of the model fits the data satisfactorily but the model with its parameters being allowed to vary by gender does make a statistically significant improvement (with $p=0.017$ for the likelihood ratio test between the two models).

[Table 7 here]

To throw further light on the matter, we revert to the estimated parameters in Tables 5 and 6 where the model is fitted to men and women separately, and consider the differences between these parameters. From the results reported in Table 8, it is, overall, the degree of cross-gender similarity that is most notable. However, gender differences are indicated in two respects. The white-collar affinity effect AF1 is stronger for men than for women and the general inheritance effect IN1 is also stronger for men, although to a smaller extent (with p=0.060). As regards the first of these differences, what should be noted is that women, even if from white-collar backgrounds, tend to be concentrated in their own employment in the *lowest white-collar status groups*, mainly those of routine office and sales workers (Chan and Goldthorpe, 2004: 388-9), and are more likely than men to remain at this level within the white-collar world during their working lives rather than achieving upward mobility – as, say, from Class 3 to Class 1 or 2 positions (Bukodi *et al.*, 2016b). As regards the second difference, a general tendency exists – and is found in our own data (results available on request) – for greater class immobility to occur among men than among women because of a stronger propensity for men to follow their fathers *in specific occupations* than for women to follow either their fathers or their mothers; or, one could say, men tend to be more favoured by, or responsive to, family occupational traditions (Jonsson *et al.*, 2009; Erikson, Goldthorpe and Hällsten, 2012).

[Table 8 here]

Any set of odds ratios may be used to further interpret the fitted models. Here we focus on the set of symmetric log ORs, that is $\log\theta_{il,il}$ for *i=1,…,I-1; l=i+1,…I*. These are the *I(I-1)/2* associations which are calculated from the 2x2 sub-tables which involve the same pair of classes for both the two origin classes and the two destination classes and which thus have the most straightforward sociological meaning.

To illustrate the calculations, consider $\log \theta_{12,12}$. This is the log of the odds of an individual from origin Class 2 to be in destination Class 2 (lower managers and professionals) rather than in destination Class 1 (higher managers and professionals), relative to the same odds for someone from origin Class 1. Our topological model implies that it is obtained as

$\log \theta_{12,12}$ = (2·IN1 + IN2) – (2·HI1 + 2·AF1) = (2·0.371 + 0.305) – (2·[-0.154] + 2·0.483) = (1.047) – (0.658) = 0.389

where for simplicity of notation we use letters only to refer to the effects parameters (i.e. IN1 means the estimate of $\gamma^{(r)}$ for the IN1 effect, and so on), and the numbers are the corresponding estimates for men, from Table 5.

Note first that the inheritance effects, on the one hand, and the hierarchy and affinity effects, on the other, always refer to different cells of the table, appearing only in the diagonal and off-diagonal cells of the full table respectively. This provides an interpretation for the signs of the estimated effects in Tables 5 and 6. Since the inheritance and hierarchy parameters have opposite signs, they in fact contribute in the same direction to increase a log odds ratio, while the affinity effects work in the opposite direction, attenuating the associations back toward zero.

Inheritance effects contribute to $\log\theta_{12,12}$ in several ways. The first row of the 2x2 table in it includes the cell (1,1), that is individuals who stay in Class 1, which contributes both the general and the additional inheritance parameters IN1 and IN2. Similarly, the second row includes cell (2,2) of individuals who stay in Class 2, contributing IN1 again. The total inheritance contribution is then 2·IN1+IN2 = 1.047, indicating a fairly strong association which shows that staying in classes 1 and 2 rather than moving away from them is substantially more likely than would be expected under independence.

The hierarchy effect is in this case -2·HI1 = 0.308 because classes 1 and 2 are only one hierarchical level apart (and counted twice with a negative sign, from the two off-diagonal cells (1,2) and (2,1)). This is more than offset by the white-collar affinity effect -2·AF1 = -0.966 which quantifies the lower barriers to mobility between the otherwise hierarchical classes 1 and 2. The affinity effect then also reduces the overall association to 0.389, substantially less than would be implied by the inheritance and hierarchy effects alone.

In general, the symmetric log ORs from the model are of the form

$\log\theta_{il,il}$ = (2IN1 + aIN2) – 2(HI1 + … + HIb) – 2(c_1AF1 + c_2AF2)

where a is the number (0, 1, or 2) of times cells (1,1) and/or (4,4) contribute to the association, HIb is the hierarchy effect for the number of hierarchical levels between classes i and l (or HI1 + … + HIb=0, if they are both among classes 3,4,5), and c_1 and

c_2 are indicator variables respectively for whether classes *i* and *l* are both white-collar classes (1, 2 or 3) or both blue-collar classes (5, 6 or 7).

[Table 9 here]

Table 9 shows, separately for men and women, the estimates of the symmetric log ORs under the fitted models and also the contributions made by the hierarchy, inheritance and affinity effects.

The log ORs themselves are nearly all significantly different from zero, the value which would indicate the independence of class origins and destinations or the existence of 'perfect mobility'. The only exceptions, and in general the smallest ratios, are found in the top-left and bottom-right corners of the table where either only classes on the white-collar side of the status division (Classes 1, 2 and 3) or only on the blue-collar side (Classes 5, 6 and 7) are involved, and where status affinity effects thus substantially modify the hierarchy effects that apply. The log ORs involving Class 4, that of small employers and own account workers, where the additional inheritance effect IN2 operates, then show a notable increase. However, the most marked increase in the log ORs is to be seen in moving towards the top-right corner of the table: that is, where what is involved are the relative chances of mobility between positions, on the one hand, within the professional and managerial salariat and, on the other, within the body of routine wage-workers. The hierarchical distance between the classes involved thus widens and strong hierarchical effects (see Tables 5 and 6) cumulate, status affinity effects no longer apply, and, where Class 1 is concerned, the IN2 effect is again present. Thus, at the extreme, the Class 1/ 7 log OR is, for men and women alike, in the region of 3, which can be exponentiated ($e^{3.0}$ = 20.08) to say that the chance of someone originating in Class 1 being found in Class 1 rather than in Class 7 is around 20 times greater than the same relative chance of someone originating in Class 7.

The estimated symmetric log ORs are in fact generally quite similar for men and for women although the direction of any differences does show some consistency: i.e. the ratios tend to be higher for men. This difference becomes statistically significant in two cases: that is, with the Class 2/5 and Class 3/6 log ORs, and chiefly on account of the stronger IN1 effect for men. However, exceptions to this tendency arise in cases involving classes within the white-collar world. This is so because of the stronger status affinity effect that here operates with men, and that thus offsets hierarchy effects to a greater degree than with women. The Class 1/3 log OR is significantly higher for women than for men.

As regards the contributions of different effects to the symmetric log ORs, it can be said that inheritance effects are dominant insofar as short-range mobility is concerned. Their contribution is exceeded by that of hierarchy effects only in the cases of the Class 1/6, Class 2/7 and Class 1/7 log ORs involving quite long-range mobility and where (see Table 4) the HI3 and then the HI4 effect come into play. Again, gender differences are not for the most part significant. Nonetheless, because inheritance effects tend to be somewhat stronger for men than for women, the contribution made to the symmetric log ORs of hierarchy effects *relative to* that of inheritance effects is regularly greater with women than with men. And this difference is then accentuated in those cases where affinity effects apply in that these effects, serving to counter hierarchy effects, do so to a greater extent for men than for women and, as earlier noted, especially – and significantly – so where the white-collar status affinity effect is in operation (see Note to Table 9).

6. Conclusions

In this paper we have started out from previous findings that across three British birth cohorts, whose members' lives span the later twentieth and early twenty-first centuries, relative rates of intergenerational class mobility have remained at a more or less constant level among men and also among women who have worked only full-time. Our concerns have then been to establish the pattern of this prevailing level of fluidity and its sources, to determine whether it too persists over time and is on the same lines for the men and women we consider, and to bring out its implications for inequalities in relative mobility chances. To this end, we have sought to develop a parsimonious model for the log ORs expressing the associations between class origins and destinations in our mobility tables for men and women. This model is derived from a topological model which uses a limited and readily interpretable number of binary characteristics, each of which does, or does not, apply to particular cells of the tables. We have shown that an acceptable model can be obtained that accounts for the log ORs in terms of three kinds of such characteristics and eight effects in all: that is, class hierarchy (four cumulative effects), class inheritance (two cumulative effects), and status affinity (two separate effects). The main findings we obtain under this model may be summarised as follows.

First, the pattern of social fluidity as well as its level is essentially unchanging across the three cohorts. If we fit our model with its effect parameters being allowed to vary by cohort, no significant improvement in fit is obtained over the model with its parameters being constrained to be the same for each cohort. The long-term stability – or powerful resistance to change – of the class mobility regime is in this way further confirmed.

Second, the pattern of social fluidity does not vary greatly by gender, at least if we limit our attention to women who have worked only full-time. If we fit our model to the pooled data for men and for these women an acceptable result is obtained, although further analysis reveals two differences of some sociological interest. The white-collar status affinity effect is stronger in the case of men and so also – though at a marginally significant level – is the general inheritance effect. While, then, it is apparent from the symmetric log ORs that we present that no strong claims can be made concerning greater fluidity among women than among men, what could be said on the basis of the decomposition of these ratios is that this broad similarity in level comes about in somewhat different ways. Specifically, women's class mobility appears, in comparison with men's, to be more impeded by hierarchical barriers than by the propensity for inheritance - i.e. for the same class positions to be passed on from generation to generation.

Third, within the degree of cross-cohort and cross-gender similarity that prevails in the pattern of social fluidity, our model brings out marked differences in the levels of fluidity that exist in regard to different mobility transitions, and the sources of these differences. Our analysis of symmetrical log ORs indicates that where class mobility is short-range - that is, involves crossing only one or at most two of the hierarchical levels that we distinguish – and especially where it occurs between classes on the same side of the white-collar/blue-collar status divide, so that status affinity effects modify hierarchy effects, inequalities in relative chances are often not that great and reflect chiefly inheritance effects. In other words, regions of the mobility table can be identified where fluidity is generally high and, in the case of some transitions, does not in fact diverge significantly from 'perfect mobility' expectations. A qualification to this finding is that with even short-range transitions involving Class 4, greater inequality in relative chances is found because of the high propensity for intergenerational immobility within this class. However, the main contrast with the high fluidity regions of the mobility table arises in those regions where long-range mobility transitions are entailed, as between positions involving the crossing of three or four hierarchical divisions, and thus also moving between the white-collar and blue-collar worlds so that hierarchy effects are no longer offset by status affinity effects. Hierarchy effects then dominate and inequalities in relative mobility chances increase dramatically and to an extreme that could be thought disturbing.

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References

Agresti, A. (2013) *Categorical Data Analysis*, 3rd ed., Hoboken, NJ: Wiley.

Barndorf-Nielsen, O.E. and Cox, D.R. (1994) *Inference and Asymptotics*, London: Chapman & Hall.

Bergsma, W., Croon, M. and Hagenaars, J. A. (2009) *Marginal Models: For Dependent, Clustered, and Longitudinal Categorical Data*, Dordrecht: Springer.

Breen, R. (2008) Statistical Models of Association for Comparing Cross-Classifications. *Sociological Methods & Research*, **36**, 442-61.

Bukodi. E. and Goldthorpe, J. H. (2009) Class Origins, Education and Occupational Attainment: Cross-Cohort Changes among Men in Britain. Centre for Longitudinal Studies, *Working Paper 2009/3*. London: Institute of Education.

Bukodi, E. and Goldthorpe, J. H. (2011) Class Origins, Education and Occupational Attainment in Britain: Secular Trends or Cohort-Specific Effects? *European Societies*, **13**, 347-75.

Bukodi, E., Goldthorpe, J. H., Waller, L. and Kuha, J. (2015) The Mobility Problem in Britain: New Findings from the Analysis of Birth Cohort Data. *British Journal of Sociology*, **66**, 93-117.

Bukodi, E., Goldthorpe, J. H., Joshi, H. and Waller, L. (2016a) Why have Relative Rates of Class Mobility become More Equal among Women in Britain? Manuscript submitted for publication.

Bukodi, E., Goldthorpe, J. H. and Halpin, B. (2016b) Is Education Now Class Destiny? Class Histories Across Three British Birth Cohorts. Manuscript submitted for publication.

van Buuren, S. (2012) *Flexible Imputation of Missing Data*, Boca Raton: CRC Press.

Carpenter, J. R. and Kenward, M. G. (2013) *Multiple Imputation and its Application*, Chichester: Wiley.

Chan, T.-W and Goldthorpe, J. H. (2004) Is There a Status Order in Contemporary British Society? Evidence from the Occupational Structure of Friendship. *European Sociological Review*, **20**, 383-401.

Chan, T.-W and Goldthorpe, J. H. (2007) Class and Status: the Conceptual Distinction and its Empirical Relevance. *American Sociological Review*, **72**, 512-32.

Clogg, C. C. and Shockey, J. W. (1984) A Note on Two Models for Mobility Tables. *Comparative Social Research*, **7**, 443-62.

Erikson, R. and Goldthorpe, J. H. (1992) *The Constant Flux: A Study of Class Mobility in Industrial Societies*. Oxford: Clarendon Press.

Erikson, R., Goldthorpe, J. H. and Hällsten M. (2012) No Way Back Up from Ratcheting Down? A Critique of the 'Microclass' Approach to the Analysis of Social Mobility. *Acta Sociologica*, **55**, 211-29.

Featherman, D. L. and Hauser, R. M. (1978) *Opportunity and Change*. New York: Academic Press.

Gelman, A. and Rubin, D. B. (1992) Inference from iterative simulation using multiple sequences. *Statistical Science*, **7**, 457-511.

Goldthorpe, J. H. (with Llewellyn, C. and Payne, C.) (1987) *Social Mobility and Class Structure in Modern Britain*, 2nd ed., Oxford: Clarendon Press.

Goldthorpe, J. H. (2007) *On Sociology*, 2nd ed., 2 vols., Stanford: Stanford University Press.

Goldthorpe, J. H. (2012) Back to Class and Status: Or Why a Sociological View of Social Inequality should be Re-asserted. *Revista Española de Investigaciones Sociológicas*, **137**, 1-16.

Hauser, R. M. (1978) A Structural Model of the Mobility Table. *Social Forces*, **56**, 919-52.

Hauser, R. M. (1979) Some Exploratory Methods for Modeling Mobility Tables and Other Cross-Classified Data. In Schuessler, K. F. (ed.), *Sociological Methodology 1980*, 413-58. San Francisco: Jossey-Bass.

Hout, M. (1983) *Mobility Tables*. Beverly Hills: Sage.

Jonsson, J. O., Grusky, D. B. Pollak, R. Di Carlo, M. and Brinton, M. C. (2009) Microclass Mobility: Social Reproduction in Four Countries. *American Journal of Sociology*, **114**, 977-1036.

Klimova, A. and Rudas, T. (2012) Coordinate-Free Analysis of Trends in British Social Mobility. *Journal of Applied Statistics*, **39**, 1681-91.

Klimova, A., Rudas, T. and Dobra, A. (2012) Relational Models for Contingency Tables. *Journal of Multivariate Analysis*, **104**, 159-73.

Kuha, J. and Firth, D. (2011) On the Index of Dissimilarity for Lack of Fit in Loglinear and Log-multiplicative Models. *Computational Statistics and Data Analysis*, **55**, 375-88.

Lang, J. B. and Agresti, A. (1994) Simultaneously Modelling Joint and Marginal Distributions of Multivariate Categorical Responses. *Journal of the American Statistical Association,* **89**, 625-632.

Lang, J. B. (2005) Homogenous Linear Predictor Models for Contingency Tables. *Journal of the American Statistical Association*, **100**, 121-134.

Li, K.-H., Raghunathan, T. E. and Rubin, D. B. (1991) Large-sample significance levels from multiply imputed data using moment-based statistics and an F reference distribution. *Journal of the American Statistical Association*, **86**, 1065-1073.

Macdonald, K. I. (1981) On the Formulation of a Structural Model of the Mobility Table. *Social Forces*, **60**, 557-81.

Macdonald K.I. (1983) On the Interpretation of a Structural Model of the Mobility Table. *Quality and Quantity*, **17**, 203-24.

Meng, X.-L. and Rubin, D.B. (1992) Performing Likelihood Ratio Tests with Multiply-Imputed Data Sets. *Biometrika*, **79**, 103-11.

Office of National Statistics (2005) *The National Statistics Socio-Economic Classification: User Manual*, London: Palgrave-Macmillan.

Rose, D. and Pevalin, D. (eds.) (2003) *A Researcher's Guide to the National Statistics Socio-economic Classification*, London: Sage.

Rose, D., Pevalin. D and O'Reilly, K. (2005) *The National Statistics Socio-economic Classification: Origins, Development and Use*, London: National Statistics and Palgrave Macmillan.

Rubin, D. B. (1987) *Multiple Imputation for Nonresponse in Surveys*, New York: Wiley.

Schafer, J. L. (1997) *Analysis of Incomplete Multivariate Data*, London: Chapman & Hall.

Turner, H. and Firth, D. (2015). Generalized Nonlinear Models in R: An Overview of the gnm Package. (R package version 1.0-8). (http://CRAN.R-project.org/package=gnm).

Xie, Y. (1992) The Log-Multiplicative Layer Effect Model for Comparing Mobility Tables. *American Sociological Review*, **57**, 380-395.

Zelterman, D. and Youn, T.I.K. (1992) Indicator Models in Social Mobility Tables. *Computational Statistics & Data Analysis*, **14**, 39-53.

Table 1. Estimated distribution of cohort members by class of origin at age 10/11 and class of destination at age 38, *men*

	1946 cohort		1958 cohort		1970 cohort	
	Class of origin	Class of destination	Class of origin	Class of destination	Class of origin	Class of destination
Class 1: Higher managers and professionals	4.6	8.9	6.7	15.3	11.3	20.8
Class 2: Lower managers and professionals	9.7	26.6	15.2	19.1	17.2	20.5
Class 3: Intermediate occupations	9.8	9.8	14.7	8.5	7.4	9.5
Class 4: Small employers and own account workers	10.1	10.7	5.7	13.8	14.1	14.4
Class 5: Lower supervisory and technical occupations	12.6	12.6	19.3	10.5	14.0	8.7
Class 6: Semi-routine occupations	16.5	13.0	10.9	12.5	14.1	12.8
Class 7: Routine occupations	36.7	18.5	27.4	14.5	22.0	11.9
Total	100.0	100.0	100.0	100.0	100.0	100.0
N †	2394		7219		5979	

†: N denotes the total number of respondents, including ones for whom the variable was not observed. The proportions shown in the table were estimated using multiple imputed data to allow for the nonresponse.

Table 2. Estimated distribution of cohort members by class of origin at age 10/11 and class of destination at age 38, *women who have worked only full-time*

	1946 cohort		1958 cohort		1970 cohort	
	Class of origin	Class of destination	Class of origin	Class of destination	Class of origin	Class of destination
Class 1: Higher managers and professionals	3.9	2.3	6.4	7.4	11.6	12.9
Class 2: Lower managers and professionals	7.8	19.8	17.4	23.5	19.2	27.6
Class 3: Intermediate occupations	9.0	34.5	14.4	28.0	6.9	28.6
Class 4: Small employers and own account workers	8.5	6.7	5.0	6.7	13.0	5.8
Class 5: Lower supervisory and technical occupations	15.3	2.5	18.1	1.5	13.9	1.4
Class 6: Semi-routine occupations	19.7	17.0	9.9	19.0	13.9	16.2
Class 7: Routine occupations	35.8	17.2	28.8	14.0	21.6	7.6
Total	100.0	100.0	100.0	100.0	100.0	100.0
N †	1020		3535		2432	

†: N denotes the total number of respondents, including ones for whom the variable was not observed. The proportions shown in the table were estimated using multiple imputed data to allow for the nonresponse.

Table 3. An example of equivalent formulations of the same model for a log odds ratio as discussed in the text†

(1)

$\gamma^{(1)}$	$\gamma^{(1)}$
$\gamma^{(1)}$	$\gamma^{(1)}$

(2)

$\gamma^{(1)}$	$\gamma^{(1)}$
$\gamma^{(2)}$	$\gamma^{(2)}$

(3)

$\gamma^{(1)}$	$\gamma^{(2)}$
$\gamma^{(1)}$	$\gamma^{(2)}$

†: The figure shows three equivalent topological models for the same 2x2 table. Within each table, cells with the same value of the association parameter ($\gamma^{(1)}$ or $\gamma^{(2)}$) are on the same level of the model. The log odds ratio is 0 for each table.

Table 4. Distribution of effects under the topological model and the eleven levels of overall association parameter entailed

Class of origin	Class of destination						
	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
Class 1	IN1 IN2	HI1 AF1	HI1 HI2 AF1	HI1 HI2	HI1 HI2	HI1 HI2 HI3	HI1 HI2 HI3 HI4
	Level 1	*Level 3*	*Level 4*	*Level 7*	*Level 7*	*Level 8*	*Level 9*
Class 2	HI1 AF1	IN1	HI1 AF1	HI1	HI1	HI1 HI2	HI1 HI2 HI3
	Level 3	*Level 2*	*Level 3*	*Level 6*	*Level 6*	*Level 7*	*Level 8*
Class 3	HI1 HI2 AF1	HI1 AF1	IN1			HI1	HI1 HI2
	Level 4	*Level 3*	*Level 2*	*Level 5*	*Level 5*	*Level 6*	*Level 7*
Class 4	HI1 HI2	HI1		IN1 IN2		HI1	HI1 HI2
	Level 7	*Level 6*	*Level 5*	*Level 1*	*Level 5*	*Level 6*	*Level 7*
Class 5	HI1 HI2	HI1			IN1	HI1 AF2	HI1 HI2 AF2
	Level 7	*Level 6*	*Level 5*	*Level 5*	*Level 2*	*Level 10*	*Level 11*
Class 6	HI1 HI2 HI3	HI1 HI2	HI1	HI1	HI1 AF2	IN1	HI1 AF2
	Level 8	*Level 7*	*Level 6*	*Level 6*	*Level 10*	*Level 2*	*Level 10*
Class 7	HI1 HI2 HI3 HI4	HI1 HI2 HI3	HI1 HI2	HI1 HI2	HI1 HI2 AF2	HI1 AF2	IN1
	Level 9	*Level 8*	*Level 7*	*Level 7*	*Level 11*	*Level 10*	*Level 2*

Table 5. Estimated effect parameters and model fit statistics for topological models for social fluidity for data from three birth cohorts, *men*

Model	Modified LR[a]	df[b]	p	DI[c] Estimate	DI[c] 95% CI
(1) Independence	10.20	108	<0.001	14.37	(13.31; 15.42)
(2) Topological model with common effect parameters across cohorts	1.175	100	0.116	4.21	(3.18; 5.25)
(3) Topological model with varying effect parameters across cohorts	1.068	84	0.316	3.46	(2.61; 4.31)
(3)-(2)	1.638	16	0.056		

Effect parameters under Model (2)

		P	95% CI
HI1	-0.154	<0.001	(-0.252; -0.056)
HI2	-0.132	<0.001	(-0.190; -0.073)
HI3	-0.349	<0.001	(-0.459; -0.239)
HI4	-0.352	<0.001	(-0.509; -0.195)
IN1	0.371	<0.001	(+0.253;+0.490)
IN2	0.305	<0.001	(+0.151;+0.459)
AF1	0.483	<0.001	(+0.398;+0.567)
AF2	0.304	<0.001	(+0.192;+0.416)

a: Likelihood ratio test calculated using the method for multiply imputed data proposed by Meng and Rubin (1992).

b: The p-value of the test statistic is obtained from an F distribution. Only its first degrees of freedom are reported. These are identical to the degrees of freedom for the likelihood ratio test if the data were complete.

c: Index of Dissimilarity, with standard errors and bias-corrected estimate as proposed by Kuha and Firth (2011).

Table 6. Estimated effect parameters and model fit statistics for topological models for social fluidity for data from three birth cohorts, *women who have worked only full-time*

Model	Modified LR[a]	df[b]	p	DI[c] Estimate	DI[c] 95% CI
(1) Independence	3.916	108	<0.001	11.17	(9.89; 12.50)
(2) Topological model with common effect parameters across cohorts	0.739	100	0.976	3.92	(2.67; 5.17)
(3) Topological model with varying effect parameters across cohorts	0.736	84	0.966	3.68	(2.41; 4.95)
(3)-(2)	0.757	16	0.736		

Effect parameters under Model (2)

		p	95% CI
HI1	-0.129	0.101	(-0.283;+0.026)
HI2	-0.231	<0.001	(-0.326; -0.136)
HI3	-0.462	<0.001	(-0.609; -0.314)
HI4	-0.242	0.064	(-0.498;+0.015)
IN1	0.176	0.048	(+0.001;+0.351)
IN2	0.394	0.001	(+0.158;+0.629)
AF1	0.158	0.084	(-0.023;+0.338)
AF2	0.250	<0.001	(+0.119;+0.380)

See the notes to Table 5.

Table 7. Model fit statistics for models fitted to data on both genders together

Model	Modified LR[a]	df[b]	p	DI[c] Estimate	DI[c] 95% CI
(1) Independence	7.230	216	0.000	13.37	(12.57; 14.16)
(2) Topological model with common effect parameters across cohorts and gender	1.019	208	0.412	4.42	(3.69; 5.15)
(3) Topological model with effect parameters common across cohorts but varying by gender	0.968	200	0.612	4.12	(3.38; 4.89)
(3)-(2)	2.366	8	0.017		

See the notes to Table 5.

Table 8. Significance tests for gender difference in effect parameters

Parameter	Difference between men and women	p	95% CI
HI1	-0.025	0.780	(-0.205; +0.154)
HI2	0.099	0.080	(-0.011; +0.209)
HI3	0.113	0.220	(-0.067; +0.293)
HI4	-0.110	0.470	(-0.407; +0.187)
IN1	0.195	0.060	(-0.012;+0.402)
IN2	-0.088	0.530	(-0.366; +0.190)
AF1	0.325	0.001	(+0.134; +0.516)
AF2	0.054	0.530	(-0.113; +0.221)

Table 9. Symmetric log odds ratios and decomposition of symmetric log odds ratios into hierarchy (HI), inheritance (IN) and affinity (AF) effects as implied by our topo

Class of origin		Class 2			Class 3			Class 4			Class 5			Class 6			
		LogOR	HI	IN	**LogOR**	HI	IN	**LogOR**	HI	IN	**LogOR**	HI	IN	**LogOR**	HI	IN	**LogOR**
Class 1	Men	**0.39*** **	0.31**	1.05***	**0.65*** **	0.57***	1.05***	**1.92*** **	0.57***	1.35***	**1.62*** **	0.57***	1.05***	**2.32*** **	1.27***	1.05***	**3.02*** **
	Women	**0.69*** **	0.26	0.75***	**1.15*** **	0.72***	0.75***	**1.86*** **	0.72***	1.14***	**1.47*** **	0.72***	0.75***	**2.39*** **	1.64***	0.75***	**2.87*** **
	Diff.	***-0.30***	*0.05*	*0.30*	– ***0.50*** ***	*-0.15*	*0.30*	***0.07***	*-0.15*	*0.21*	***0.15***	*-0.15*	*0.30*	***-0.07***	*-0.37*	*0.30*	***0.18***
Class 2	Men				**0.08**	0.31**	0.74**	**1.36*** **	0.31**	1.05***	**1.05*** **	0.31**	0.74**	**1.31*** **	0.57***	0.74**	**2.01*** **
	Women				**0.29***	0.26	0.35*	**1.00*** **	0.26	0.75***	**0.61*** **	0.26	0.35*	**1.07*** **	0.72***	0.35*	**2.00*** **
	Diff.				***-0.21***	*0.05*	*0.39*	***0.35***	*0.05*	*0.30*	***0.44*** ***	*0.05*	*0.39*	***0.24***	*-0.15*	*0.39*	***0.02***
Class 3	Men							**1.05*** **	0	1.05***	**0.74*** **	0	0.74**	**1.05*** **	0.31**	0.74**	**1.31*** **
	Women							**0.75*** **	0	0.75***	**0.35***	0	0.35*	**0.61*** **	0.26	0.35*	**1.07*** **
	Diff.							***0.30***	*0*	*0.30*	***0.39***	*0*	*0.39*	***0.44*** ***	*0.05*	*0.39*	***0.24***
Class 4	Men										**1.05*** **	0	1.05***	**1.36*** **	0.31**	1.05***	**1.62*** **
	Women										**0.75*** **	0	0.75***	**1.00** **	0.26	0.75***	**1.47*** **
	Diff.										***0.30***	*0*	*0.30*	***0.35***	*0.05*	*0.30*	***0.15***
Class 5	Men													**0.44*** **	0.31**	0.74**	**0.71*** **
	Women													**0.11**	0.26	0.35*	**0.57*** **
	Diff.													***0.33***	*0.05*	*0.39*	***0.13***
Class 6	Men																**0.44*** **
	Women																**0.11**
	Diff																***0.33***

†: Affinity effects (AF) apply to the associations highlighted in grey. For the log ORs among classes (1,2,3) the affinity effects is -0.97*** for men and -0.32 for women (difference is -0.65**
among classes (5,6,7) the Affinity effect is -0.61*** for men and -0.50*** for women (difference is 0.11).

Appendix: Multiple imputation of missing data

Table A.1 shows the proportions of observed and missing values in the respondents' classes of origin and destination, separately by gender and cohort. The proportion of missing observations was higher for destination (23-49% missing) than for origin (10-16%). The largest proportions of missing data occur in the 1946 cohort.

We used the method of multiple imputation to accommodate the incomplete observations. This generates several sets of possible values for the missing observations in a set of data, drawn from some distribution conditional on the observed data. Several ostensibly complete data sets are thus created. The statistical analysis of interest is then applied to each of these data in turn, and the results are combined into final estimates of the target parameters. The idea of multiple imputation is due to Rubin (1987), and overviews of more recent developments are given by Schafer (1997), van Buuren (2012), and Carpenter and Kenward (2013).

[Table A.1 here]

The imputation was carried out separately for each cohort and gender. Here imputing values for one missing class variable given the other would not in fact be helpful for the estimation of the odds ratio parameters that are the focus of our analysis, because observations where only one of these variables is observed carry no information about the odds ratios (this is analogous to the fact that in any standard regression model, observations with only explanatory variables observed carry no information about the conditional distribution of the response variable).

The situation is different, however, if the imputation model includes also additional variables which provide additional information for predicting the origin and destination classes. We included in this role the respondent's level of education, recorded in eight categories at age 37. The proportion of missing values was much smaller for education than for either of the social class variables, and education was expected to be predictive especially of the class of destination (at age 38) which was most frequently missing. (The same multiply imputed data were also used for other analyses – not considered here – which included education directly.)

We used a Markov Chain Monte Carlo (data augmentation) estimation approach for imputing categorical data from a saturated model, as proposed by Schafer (1997). The joint distribution of origin, education and destination was specified as a multinomial distribution without constraints on its probabilities, and with a Dirichlet prior distribution for the probabilities with all its parameters equal to 0.5 (this gives a noninformative Jeffreys prior). The data augmentation algorithm then iterates between (i) imputing for each respondent values for any missing variables from a conditional multinomial distribution given observed variables and the current values of the probability parameters, and (ii) generating new values for the parameters from a Dirichlet posterior distribution given the observed and most recently imputed data. Final imputed values for the missing data are saved from some number of the iterations after the algorithm has converged to a stationary posterior distribution. We used the statistic proposed by Gelman and Rubin (1992) to monitor convergence, comparing results from five parallel runs of the algorithm. Convergence was clearly achieved after 5000 iterations, after which one of the chains was continued for a further 1000 iterations and the imputed values from every 100th iteration were retained (with this gap, autocorrelations between the retained values were negligible). We thus created 10 sets of imputed data.

The estimated percentages in Tables 1 and 2, and the point estimates, standard errors, p-values and confidence intervals of individual parameters in Tables 5-7 were obtained by applying standard methods for combining results for multiply imputed data sets (see the references cited above). Estimates and inference for quantities derived from the model parameters in Tables 5 and 6, that is the differences between men's and women's parameters in Table 8, and the estimated log odds ratios in Table 9, were then calculated using the point estimates and covariance matrices of the model parameters obtained from the multiple imputation analysis, and using the standard normal distribution as their approximate sampling distribution. For the likelihood ratio tests in Tables 5-7, the method proposed by Meng and Rubin (1992) was used. This refers a combined test statistic to an F distribution for which the first degrees of freedom are what they would be for the likelihood ratio test if the data were complete, and the second degrees of freedom are obtained from a formula due to Li et al. (1991). We note that this test appears to have relatively low power in the cases considered here, where it is used to test hypotheses of large numbers of parameters together.

Table A.1. Percentages of different patterns of observed values in the two social class variables

	Class (origin and/or destination) observed:				
	Both observed	Origin only observed	Destination only observed	Both missing	Total
1946, Men	43.1%	43.7%	6.0%	7.2%	2394
1946, Women	54.6%	34.9%	5.6%	4.9%	1020
1958, Men	71.0%	19.9%	6.4%	2.8%	7219
1958, Women	60.1%	29.3%	7.0%	3.6%	3535
1970, Men	58.5%	25.5%	9.7%	6.4%	5979
1970, Women	58.2%	25.5%	8.1%	8.2%	2432