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Education and Social Fluidity: A Reweighting Approach

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Abstract: Although sociologists have devoted considerable attention to studying the role of education in intergenerational social class mobility using log-linear models for contingency tables, findings in this literature are not free from rescaling or non-collapsibility bias caused by adjusting for education in these models. Drawing on the methodological literature on inverse probability reweighting, I present a straightforward standardization approach free from this bias. The approach reweighs in an initial step the mobility table cell frequencies to create a pseudo-population in which social class origins and education are independent of each other, after which one can apply any loglinear model to the reweighted mobility table. In contrast to the Karlson-Holm-Breen method, the approach yields coefficients that are comparable across different studies because they are unaffected by education's predictive power of class destinations. Moreover, the approach is easily applied to models for various types of mobility patterns such as those in the core model of fluidity; it yields a single summary measure of overall mediation; and it can incorporate several mediating variables, allowing researchers to control for additional merit proxies such as cognitive skills or potential confounders such as age. I illustrate the utility of the approach in four empirical examples.

Keywords: social mobility; social class; education; direct effects; stratification; inequality

ALTHOUGH many consider education a key promoter of social mobility across generations, sociological research shows that family background affects social class destinations even among individuals with similar levels of schooling (Breen and Jonsson 2005). Lower-class kids experience a penalty for their disadvantaged family background and have to attain more schooling on average than middle- or upper-class kids if they are to attain similar social class positions (Erikson and Goldthorpe 1992; Ishidi, Müller, and Ridge 1995; Breen 2004; Bernardi and Ballarino 2016; Breen and Müller 2020). This direct effect of social origins indicates that the promises of an education-based meritocracy remain unfulfilled (Goldthorpe 2003).

In analyzing the role of education in intergenerational class mobility, scholars have relied heavily on loglinear models for contingency tables (Hout 1983). As these models are mathematically equivalent to the multinomial logit model (Logan 1983; Breen 1994), results based on these models are not free from the rescaling or non-collapsibility bias pertaining to these models (Yamaguchi 2012; Breen and Karlson 2013; Breen, Karlson, and Holm 2018). Breen and Karlson (2014) attempted to resolve this issue by employing the Karlson-Holm-Breen (KHB) decomposition method (Karlson, Holm, and Breen 2012; Breen, Karlson, and Holm 2013). Recent comparative work on education and social mobility has adopted this method (Breen and Müller 2020).[1] However, although the KHB method effectively controls for rescaling bias, it is not straightforward to apply to theoretically relevant mobility parameters such as those in Eriksen and Goldthorpe's (1992) "core model" of fluidity.

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Moreover, the KHB approach does not yield population-averaged effects (Karlson, Popham, and Holm 2021), making it difficult to compare the method's direct effects of social origins on destinations across countries, cohorts, or different studies (as the direct effects depend on the predictive power of schooling on destinations).

In this article, I present an alternative approach based on inverse probability weighting (IPW) to evaluate the mediating role of education in social class mobility. Although using IPW to gauge mediation is not new (see, e.g., Hong 2015), it has not been applied to the study of social class mobility, including how key mobility parameters are mediated by education such as unidiff model parameters or parameters from the core model of fluidity. Drawing on Yamaguchi (2012) and Karlson, Popham, and Holm (2021), I demonstrate the advantages of using this approach in the loglinear setting. I also present a way of obtaining an overall summary measure of the mediating role of education in social mobility, something that has been lacking in the class mobility literature (Breen and Karlson 2014).

The approach consists of two steps. The researcher first reweighs the cell frequencies (or conditional probabilities) of the mobility table and, second, applies conventional loglinear models to the reweighted mobility table. Because origins and education are independent of each other in the reweighted table, one can compare parameters based on this table with those from the gross or unadjusted mobility table to assess mediation. Apart from being free from rescaling bias, the IPW-based approach can be applied to any parameters of a mobility table, it yields population-averaged effects, and it can incorporate multiple mediators or confounders. It thus presents itself as a viable alternative to the KHB approach.

A Reweighting Approach

The Loglinear Model

Following the notation in Breen (2004), the mobility table has I rows and J columns, where $i = 1, \ldots, I$ and $j = 1, \ldots, J$. The expected number of observations in cell ij, f_{ij}, is then modeled using four additive terms on the log scale:

$$\ln\left(f_{ij}\right) = \lambda + \lambda_i^O + \lambda_j^D + \lambda_{ij}^{OD}, \tag{1}$$

where λ is an intercept, λ_i^O is the effect of originating in class i, λ_j^D is the effect of ending in class j, and λ_{ij}^{OD} is the effect of being in cell ij; that is, λ_{ij}^{OD} captures the association between class origins and destinations. To study different types of mobility, mobility scholars place different restrictions on the association parameters λ_{ij}^{OD} (Hout 1983). One restriction is the pattern of quasi-perfect mobility in which all diagonal cells have unique parameters while the off-diagonal cells are set to have the same parameter. Another example is the core model of social fluidity by Erikson and Goldthorpe (1992), which tests different theoretically derived patterns of mobility.

In cross-national or temporal comparisons, multiplicative extensions of the loglinear model are widely used to gauge overall differences in social fluidity, most prominently the unidiff or log-multiplicative layer effect model (Erikson and Goldthorpe 1992; Xie 1992). Under some parametric restrictions, this model compares in multiplicative terms a weighted average of log odds ratios in different countries' or cohorts' mobility tables. A useful overall effect metric derived from the unidiff model is the kappa-index (Hout, Brooks, and Manza 1995; Barone 2011; Bouchet-Valat 2019), which is the standard deviation of the mobility table's log odds ratios implied by the unidiff model. I present an example in which I use this kappa-index for gauging in a single number the overall impact of education on social fluidity.[2] Such a summary measure has been lacking in the literature (Breen and Karlson 2014).

Adjusting for Education Using Inverse Probability Weights

The approach I suggest is based on adjusting the cell frequencies in the mobility table for education using inverse probability reweighting. I also demonstrate that these adjusted cell frequencies are equal to the directly standardized cell frequencies (standardizing the origins–destinations table with respect to education). Before I present the approach, however, I briefly describe the logic of inverse probability reweighting (Cole and Hernán 2008). The reweighting creates a pseudo-population in which the predictor and covariate are independent of (or orthogonal to) each other. One can then compare estimates based on this pseudo-population with those obtained from the real population to gauge the extent to which adjusting for the covariate explains or mediates the effect of the predictor on an outcome. The reweighting occurs in an initial step before estimating the model for the outcome, meaning that the approach can be applied to any type of outcome model (Yamaguchi 2012). In my application of the reweighting approach, I use it for reweighting the cell frequencies (or conditional probabilities) of the mobility table as an initial step after which I can apply it to any loglinear or log-multiplicative model.

The approach draws on results in Karlson, Popham, and Holm (2021) and is very similar to the approach presented in Yamaguchi (2012). Karlson, Popham, and Holm (2021) show how a simple standardization approach yields odds ratios that have a marginal or population-average interpretation. Because these odds ratios are not affected by rescaling effects, they can be directly compared across versions that adjust for different covariates. Karlson, Popham, and Holm (2021) also show how the standardization approach can be obtained by inverse probability weighting. In a similar vein, Yamaguchi (2012) suggests using inverse probability weighting to recover causal effects in loglinear analyses and also shows how this approach is directly related to the method of direct standardization.[3]

Whereas Yamaguchi (2012) focuses on causal effects, I focus here on mediation, in particular how education mediates specific class mobility parameters of interest. Using inverse probability weighting for gauging direct and indirect effects is, however, not new. Huber (2014) shows how inverse probability weighting can recover average direct and indirect effects (also see Hong 2015:254ff). Huber (2014) focuses on conditional mean effects (via average counterfactual outcomes), not loglinear modeling and odds ratios, although the reweighting principle is the same.

Let O_l and E_l denote class origin and education for individual l. Then the inverse probability weight for individual l is given by

$$\mathrm{IPW}_l = \frac{1}{\Pr\left(O_l|E_l\right)}, \tag{2}$$

where $\Pr(O_l|E_l)$ is the propensity score, that is, the conditional distribution of class origins given education.[4] The propensity score can be obtained via a multinomial logit model regressing class origins on education. Letting D_l denote the class destinations of individual l, the adjusted mobility table cell frequencies (in cell i, j) are given by

$$\tilde{f}_{ij} = \frac{\sum_{O_l=i,D_l=j} \mathrm{IPW}_l}{I}, \tag{3}$$

showing that the adjusted cell frequencies equal the cell-specific sum of individual inverse probability weights up to a factor I, which ensures that the adjusted frequencies add up to the sample total (the factor being the number of class origins categories). Using some algebra, including Bayes' theorem, it is possible to show that Equation (3) equals

$$\tilde{f}_{ij} = \frac{N}{I} \sum_{E=k} \Pr\left(D = j|E = k, O = i\right) \cdot \Pr\left(E = k\right), \tag{4}$$

where $\Pr(D = j|E = k, O = i)$ is the conditional probability of being in destination class j given education level k and origin class i, $\Pr(E = k)$ is the marginal probability of attaining education level k, and N is the sample total. In other words, $\sum_{E_l=k} \Pr(D = j|E = k, O = i) \cdot \Pr(E = k)$ is the directly standardized conditional probability in mobility cell i, j (Yamaguchi 2012), and this can be obtained directly from a three-way table of origins, education, and destinations, and the marginal distribution of education. Odds ratios based on these directly standardized conditional probabilities equal the marginal adjusted odds ratio presented in Karlson, Holm, and Popham (2021). As Karlson, Holm, and Popham (2021) demonstrate, this odds ratio can be compared with the gross or unadjusted odds ratio to measure confounding or mediation that is free from rescaling or non-collapsibility bias. The odds ratio is a population-averaged or "average marginal" effect on the logit scale. As these effects do not depend on the predictive power of education, they can be compared across different countries or cohorts.[5] As Karlson, Holm, and Popham (2021) show, this is not the case for the KHB method that recovers conditional (subject-specific) effects. Comparing conditional effects across populations would conflate cross-population differences in effects with variation in the predictive power of schooling for class destinations.

One attractive property of the IPW-based approach is that it can easily accommodate multiple discrete and/or continuous mediators or confounders. For example, mobility scholars might be interested in whether fluidity is mediated by merit proxies other than education (Breen and Goldthorpe 2001). This is done by adding further covariates to the conditioning set in the propensity score in Equation (2). However, in cases with multiple covariates, the IPW-based method requires that covariates are balanced among the origin classes (cf. Austin 2009; Austin and Stuart

2015). Such balancing tests are widely available in statistical software today and can easily be implemented.

Empirical Examples

To illustrate the usefulness of the IPW-based approach, I present four empirical examples. First, I examine the extent to which inheritance parameters of the core model of fluidity are affected by adjusting for education. Second, using the unidiff model and kappa-indices derived from this model, I present summary estimates of the overall mediating role of education in four countries. Third, I examine how cognitive skills in addition to education mediate quasi-perfect mobility parameters. Fourth, I investigate whether trends in social fluidity are confounded by age in a data set consisting of multiple cross-sections.[6]

Inheritance Effects

I draw on data for England & Wales and Sweden in Ishida, Müller, and Ridge (1995) to examine the mediating effect of education on inheritance parameters from the core model of fluidity (Erikson and Goldthorpe 1992).[7] Inheritance effects refer to the effect of being on the diagonal of the mobility table, that is, any increased likelihood of a person being found in the same class as they originated in (Erikson and Goldthorpe 1992:125). Ishida, Müller, and Ridge (1995) use a six-class Erikson-Goldthorpe-Portocarero (EGP) scheme (I+II, III, IVab, IVc+VIIb, V+VI, and VIIa) and a three-level education indicator (high, medium, or low). I investigate the mediating impact of schooling on two inheritance effects. First, I follow Ishida, Müller, and Ridge (1995) and assign a reproduction parameter to each diagonal cell (DIG), effectively making this parametrization equivalent to a pattern of quasi-perfect mobility. Second, I follow Erikson and Goldthorpe (1992) and assign a single parameter to the diagonal, the so-called IN1 parametrization.

According to Table 1, England & Wales and Sweden have similar reproduction parameters for the service class (I+II), and education explains a substantial portion of this parameter in both countries (67 and 80 percent, respectively). The parameter for the petty bourgeoisie (IVab) is similar between the two countries, but education does not play a role in this type of reproduction in either country. Although the parameter for farmers and farm workers (IVc+VIIb) is larger in England & Wales than in Sweden, education plays a negligible role for this parameter in both countries. Reproduction parameters of the skilled working class (V+VI) are slightly larger in Sweden than in England & Wales, but whereas none of the effect is explained by education in England & Wales, it is fully explained in Sweden, suggesting that education plays very different roles in terms of skilled worker reproduction in the two countries. Whereas the gross reproduction parameter for unskilled workers (VIIa) is positive in England & Wales, it is zero in Sweden, and in both countries, adjusting for education has little effect on this parameter.

The final column in Table 1 shows the IN1 parameter unadjusted and adjusted for education using the reweighting approach. This parameter can be considered a weighted average of the six DIG parameters. Although the parameter is virtually

Table 1: Inheritance parameters in two countries. Unadjusted and IPW-adjusted for education.

	Parameters						
	DIG (I+II)	DIG (III)	DIG (IVab)	DIG (IVc+VIIb)	DIG (V+VI)	DIG (VIIa)	IN1
England & Wales							
Unadjusted	1.68	0.06	1.06	3.36	0.26	0.46	0.77
Adjusted	0.56	0.06	1.00	3.22	0.30	0.37	0.67
Percentage mediated	67%	5%	5%	4%	−18%	20%	14%
Sweden							
Unadjusted	1.61	0.33	0.91	2.11	0.39	−0.03	0.78
Adjusted	0.33	−0.06	0.95	1.87	0.39	0.19	0.51
Percentage mediated	80%	120%	−5%	11%	−1%	675%	35%

Notes: Based on data analyzed in Ishida, Müller, and Ridge (1995). Roman numerals refer to EGP classes (see description in the main text).

identical in the two countries, education explains a larger portion of it in Sweden (35 percent) than in England & Wales (14 percent). Thus, class inheritance effects are to a larger degree mediated by education in Sweden than in England & Wales, also implying larger direct effects other than through education in England & Wales.

The Unidiff Model and the Kappa-Index

In cross-national comparisons, researchers are often interested in summarizing in a single number the overall level of social fluidity. In class mobility research (Erikson and Goldthorpe 1992; Breen 2004; Breen and Müller 2020), this is achieved by comparing phi-parameters of the unidiff model. This model is a multiplicative model in which one country's overall fluidity is chosen as a reference and subsequently compared with the overall fluidity of other countries under the constraint that the pattern of log odds ratios in each country's mobility table is the same. Given that the IPW approach ensures that education is orthogonal to class origins, the unidiff model can easily be applied to the reweighted data. In this case, the unidiff phi-parameters would represent country differences (expressed multiplicatively) in the direct effect of social origins on destinations. Because these direct effect estimates are population-averaged coefficients, they can be directly compared across countries, something that would not have been possible had the KHB method been used.

In Figure 1 below, I present unadjusted and adjusted (for education) unidiff phi-parameters based on data on Sweden, England & Wales, France, and West Germany in Ishida, Müller, and Ridge (1995). The figure shows that, compared with Sweden, England & Wales are about 10 percent less fluid, France is about one-third less fluid, and West Germany is around 15 percent less fluid. These differences reflect differences in gross levels of relative social mobility. Adjusting for education using my IPW-based approach means that these differences now

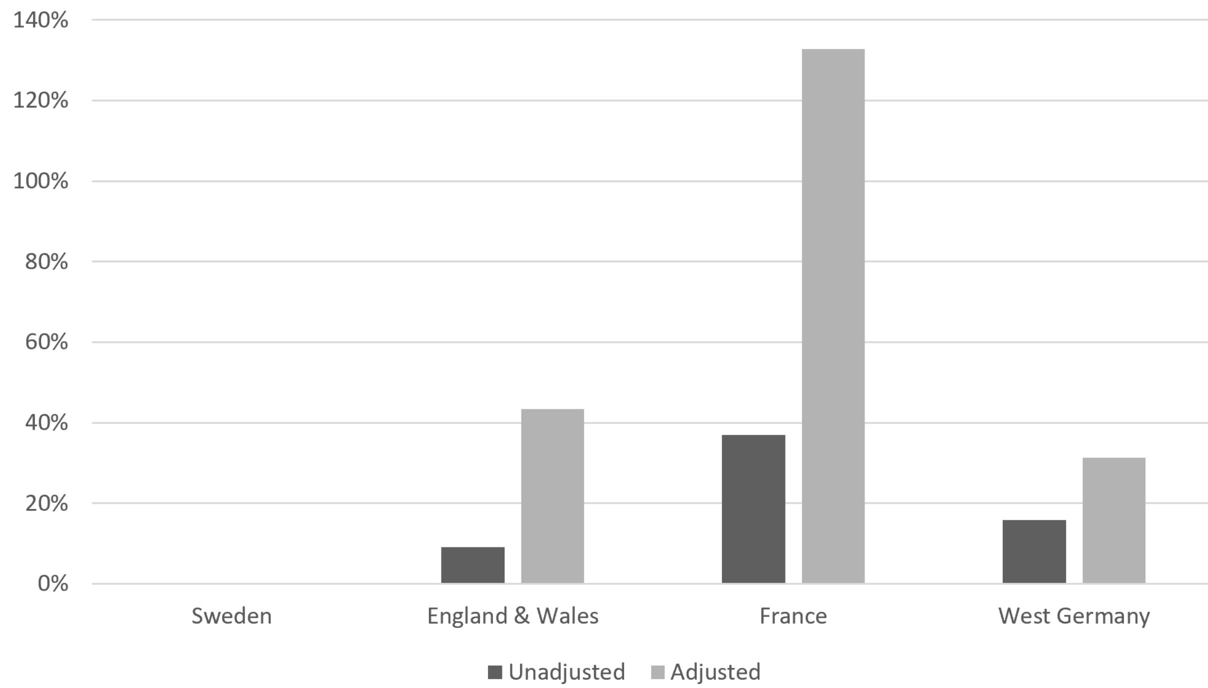

Figure 1: Unidiff phi-parameters for Sweden (reference), England & Wales, France, and West Germany. Unadjusted (gross) and adjusted for education. *Note:* Based on data analyzed in Ishida, Müller, and Ridge (1995).

represent differences in the direct effect of social origins that do not operate via formal educational qualifications. I find that compared with Sweden, the direct effects in the other countries are larger than the unadjusted estimates. The direct effect is about 40 percent larger in England & Wales, 30 percent larger in West Germany, and more than 100 percent larger in France. Thus, evaluated in terms of the direct effect, country differences are much more pronounced, and West Germany and England & Wales also swap placement in the country ranking. This result speaks to a differential role of education in class reproduction in the four countries.

Although the unidiff phi-parameters show trends in the direct effects, they cannot be used for evaluating the overall level of mediation. For this purpose, I use the kappa-index implied by the coefficients of the unidiff model (Bouchet-Valat 2019). Table 2 presents unadjusted and adjusted (for education) kappa-indices for the four countries as well as the percentage mediated (calculated as the percentage change from the unadjusted to the adjusted kappa-index). I find Sweden's mediation percentage of 61 percent to be the largest, closely followed by 55 percent for West Germany. England & Wales have a mediation percentage close to 50, and France has by far the lowest with only one-third of overall fluidity being mediated by education. These cross-national differences in mediation percentages are consistent with country differences in the direct effects of social origins being more pronounced than the gross associations (cf. Figure 1). Thus, on average, the leveling

Table 2: Kappa-indices implied by the unidiff model. Unadjusted and adjusted for education.

	Unadjusted	Adjusted	Percentage mediated
Sweden	0.33	0.13	61%
England & Wales	0.36	0.19	47%
France	0.45	0.30	33%
West Germany	0.38	0.17	55%

Notes: Based on data analyzed in Ishida, Müller, and Ridge (1995). Percentage mediated is calculated as the proportional difference between the unadjusted and adjusted estimates.

impact of education is very different in the countries, particularly when it comes to a comparison between Sweden and France.

Controlling for Additional Merit Proxies

To illustrate how the approach can incorporate merit proxies in addition to formal schooling, I draw on data analyzed in Breen and Goldthorpe (2001).[8] These data include the National Child Development Study (1958 cohort) and the British Cohort Study (1970 cohort). I have available a seven-class EGP schema (I, II, III, IV, V, VI, and VII), a six-level educational classification (no qualifications, Certificate of Secondary Education grade 2 to 5, O-levels, A-levels, first degree, and higher degree), and a measure of cognitive skills (standardized to zero mean and unit variance). I pool the two cohorts and examine whether cognitive skills in addition to educational attainment mediate the inheritance parameter IN1. Section A of the online supplement shows the Stata code generating the results of this example.

I estimate the unadjusted IN1 parameter to 0.48. Adjusting for education reduces this estimate by about 40 percent to 0.28. Further adjusting for cognitive ability has virtually no effect on the estimate, reducing it to 0.26. This result suggests that for intergenerational class reproduction, education is a significant mediator, but cognitive ability does not mediate any additional portion of the reproduction. Given that the analysis involves entering cognitive ability into the equation generating the inverse probability weight, I conduct a balancing analysis reported in section B of the online supplement. It shows that education and ability are appropriately balanced among class origins, suggesting that the results are not driven by a misspecified propensity score.

Controlling Fluidity Trends for Age

Comparative mobility research often relies on pooled cross-sections for which respondents' information is recorded at different ages. Ignoring that occupational destinations are measured at different points in the life cycle could, in principle, affect the results in such comparative work. To control for potentially confounding effects of age, I apply the IPW-based approach.[9] I draw on data for British men analyzed in Breen and Karlson (2014).[10] I have available a six-class EGP schema

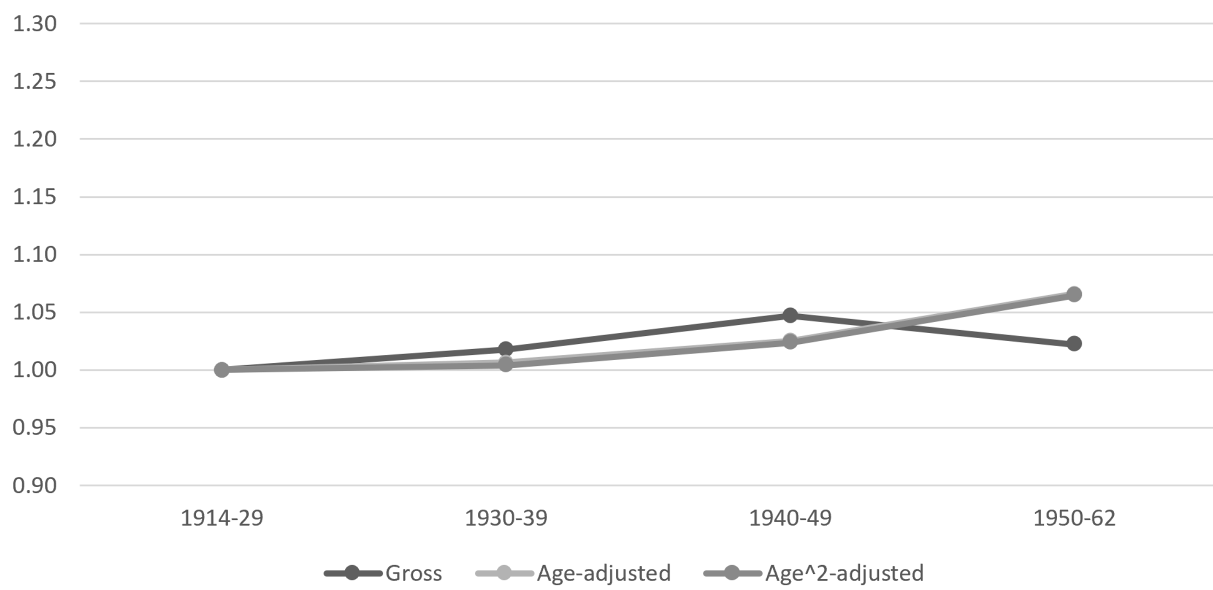

Figure 2: Unidiff phi-parameters (1914-to-1929 cohort as reference). Gross, age-adjusted, and age plus age-squared adjusted. *Note:* Estimation based on data analyzed by Goldthorpe and Mills (2004).

(I+II+IVa, IIIa, IVb, IVc, V+VI, and VII+VIIb) and a five-level CASMIN-coded education variable (1abc, 2ab, 2c, 3a, and 3b). I group respondents into four major synthetic birth cohort groups (1914 to 1929, 1930 to 1939, 1940 to 1949, and 1950 to 1962). Moreover, I have available a continuous age variable, restricted to ages 30 through 59. As I report in section C of the online supplement, age distributions overlap substantially across cohort groups, particularly for the two middle cohorts.

To investigate whether age is a confounder, I report in Figure 2 unidiff phi-parameters for the gross or unadjusted model and two models adjusting for age and age plus age-squared, respectively. The gross estimates point to constant social fluidity, a result that is confirmed by a likelihood-ratio test comparing the unidiff with the constant fluidity model. This result stands after I control for age or age plus age-squared via my IPW-based approach. Although Figure 2 points to a slight upward trend in the phi-parameters, none of the parameters are significant. A likelihood ratio test comparing the model to the constant fluidity model confirms this result. In sum, age does not appear to confound the constant flux pattern in Britain reported in previous studies (Erikson and Goldthorpe 1992; Breen 2004).

Discussion

This article shows how inverse probability reweighting can be used for examining the mediating role of education in social class fluidity. The approach can be applied to any fluidity parameters of interest. It also yields a single overall summary measure of the mediating effect of education, something that has been lacking in the comparative mobility literature. The approach, which involves a simple standardization procedure, is inherently descriptive and is not targeted causal inference or causal mediation analysis (for such approaches, see Hong 2015).

Future research could follow at least three avenues. First, it should consider examining the relationship of the approach to the counterfactual approach developed in Breen (2010). Breen's approach examines what-if temporal changes in the overall level of fluidity by imposing restrictions on the conditional probabilities implied by loglinear models. Second, although I suggest using inverse probability reweighting (yielding the attractive result in Eq. [4]), other and more efficient reweighting approaches exist (e.g., Cole and Hernán 2008; Tchetgen Tchetgen 2013; Zhou and Wodtke 2020). Such approaches could be pursued in situations with multiple mediators or confounders. Third, although I suggest using the IPW approach to examining the role of education in social class mobility, it can readily be applied to other areas in which loglinear or multinomial modeling is used such as in studies of assortative mating.

Notes

1 See Kuha and Goldthorpe (2010) for another approach.

2 I thus follow the suggestion by Hout, Brooks, and Manza (1995) to compare kappa-indices across models to gauge mediation.

3 Yamaguchi (2012) also highlights how this approach overcomes the problems associated with scaling effects or noncollapsibility.

4 Another possibility would be to use stabilized IPWs, where the numerator is replaced by the marginal probability of being in a given origin class, that is, $\Pr(O_I) / \Pr(O_I|E_I)$ (Robins, Hernán, and Brumback 2000). I do not pursue this idea here.

5 Such comparisons of effects would also be affected by compositional differences in education across layers such as countries if there is an interaction between origins and education on destinations. In this situation, the estimate would present a weighted average (Kuha and Mills 2018).

6 For readers interested in code implementing the approach, in section A of the online supplement I provide Stata code for one of the examples. Throughout I use the user-written Stata command *unidiff* by Pisati (2001) for estimating fluidity parameters.

7 I thank Hiroshi Ishida and Walter Müller for kindly sharing the data. My purpose here is not to reproduce the results in Ishida, Müller, and Ridge (1995) but to give an example of my approach. See Erikson and Goldthorpe (1992:123ff) or Breen (2004:27ff) for a description of the core model of fluidity.

8 I thank Richard Breen for sharing these data.

9 Breen (1994) examines the consequences of controlling for age in a multinomial logistic regression context.

10 I thank John Goldthorpe and Colin Mills for sharing these data. The data come from the General Household Survey for the years 1973, 1975 to 1976, 1979 to 1984, and 1987 to 1992 and were originally analyzed in Goldthorpe and Mills (2004).

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