This is an Accepted Manuscript of a book chapter published by Routledge/CRC Press in *The Routledge Handbook of Contemporary Inequalities and the Life Course* on 31 December 2021, available online: http://www.routledge.com/9781138601505

Contribution to the Routledge "Handbook on Inequalities and the Life Course"

Optimising the use of measures of social stratification in research with intersectional and longitudinal analytical priorities

Paul Lambert, Camilla Barnett

(both University of Stirling, UK)

Last updated: 12 Sep 2019

Word count: 5477

(Main text: 4233; bibliographic references: 532; Abstract: 103; Tables: 609)

--

Abstract

Many different approaches are available to measure the social stratification position of individuals. It is well known that different approaches can be associated with different theoretical and empirical properties. Nevertheless there is little consistent advice when confronting two important and interconnected considerations that affect many analyses of inequalities: how can we best exploit stratification measures when an intersectional and/or longitudinal understanding is prioritised? This paper will review the features of a number of important candidate measures of social stratification and discuss the challenges and opportunities for adapting conventional practices in ways that can take better account of intersectional and longitudinal analytical considerations.

1) Introduction

This chapter will review how we measure the concept of social stratification. Social stratification is understood here as a social structure of enduring and consequential inequalities in access to valued resources (e.g. Tumin 1967; Bottero 2005). A system of social stratification can reasonably be thought of as *the core* structure of social inequality - a system that is more important than any other in its pervasiveness and consequences. Nevertheless, it is difficult to know how best to measure positions within a society's structure of social stratification. Social scientists use many alternative measurement instruments to tap into stratification positions, and many alternative labels for the concept (e.g. 'social class', 'socio-economic status'), without clear consensus. Some approaches can seem quite old fashioned – terminologies and measures are sometimes little changed over many decades – and any measure is likely to include some level of measurement error. Yet over and above these alternatives, contemporary social scientists are often concerned with two further complications, themselves often interconnected: the value of understanding how social inequalities can be 'intersectional', defined across multiple axes of inequality; and the value of analysing complex longitudinal data and studying inequalities in their longitudinal context. Hitherto there hasn't been much attention directed to how we might refine our use of measures of social stratification in these extension scenarios, but in this chapter we highlight plausible strategies that seem to us to be amongst the more compelling responses.

2) Measuring social stratification

A very common data requirement, and the focus of this chapter, is the effort to assign to individuals a measure that indicates their position within the structure of social stratification. Academics, civil servants, and researchers in the commercial sector have exploited many different measures through the years (e.g. Lambert and Bihagen 2014; Hoffmeyer-Zlotnik and Warner 2014; Shaw et al. 2007). Many measures are 'occupation-based': starting from the premise that occupations are key influences upon the circumstances of inequality experienced by individuals and their families, these measures use some agreed rules to classify individuals or families on the basis of data about their current or former jobs. Consider for instance a heterosexual couple where the male works full-time as a lorry driver, and the wife works part-time as a secretary. This couple might be classified as belonging to the 'skilled manual' social class (if this were the class category, in the chosen measure of stratification, that an employed lorry driver were assigned to, and if the male job was judged as the more consequential to the circumstances of the household). Occupation-based measures of social stratification are particularly widely used in sociology, but in other domains it has been common to use alternative indicators, which are typically either asset-based (for instance, in economics); based upon locality characteristics (for instance, in social geography and education); or based upon combining multiple items from different sources (for instance, in public health and commercial sector research, where it is common to construct a summary scale based on a combination of information about occupations, assets, areas, and lifestyles).

Table 1 summarises features of six popular stratification measures as they can be operationalised in UK data (from the 'Understanding Society' or 'UKHLS' survey, University of Essex 2018). These measures are often used, but they represent just a few examples from a vast number of plausible alternatives. In many data scenarios, as is illustrated in Table 1, measures can either be based only upon information about a specific individual, or they may also take account of information about other individuals in the household; likewise, they may use data only on the individual's current circumstances, or occupation-based measures conventionally may also use data on the last (or principal career) job held by a person, if they are not currently working. The measurement options illustrated in Table 1 also encompass important variations in the functional form of the measure. Occupation-based measures often comprise a social class categorisation with a small number of different classes (e.g. the UK's National Statistics Socio-Economic Classification ('NS-SeC') and Registrar General's Social Classification ('RGSC') schemes in Table 1; see Rose et al. 2005). However one-dimensional metric scales based on occupations are also often calculated (e.g. the International Socio-Economic Index ('ISEI'), see Ganzeboom et al. 1992, and the Cambridge Social Interaction and Stratification Scales ('CAMSIS'), see Lambert and Griffiths 2018, from Table 1). In a few examples a much higher number of different occupation-based social class categories are studied (e.g. Weeden and Grusky 2012), and researchers sometimes try to disentangle different dimensions of stratification inequality by using multiple occupation-based schemes in the same analysis (e.g. Chan and Goldthorpe 2007). Non-occupation-based measures are perhaps more frequently expressed in a metric functional form (e.g. the scale of equivalised household income shown in Table 1; see e.g. Jenkins 2011), but they too can be represented in categories, such as illustrated in Table 1 with the measure of housing tenure (a categorisation of housing circumstances between owner-occupation, private renting and social renting; housing data can be measured much more fully, such as by taking account of housing status and condition –e.g. Shaw et al. 2007).

TABLE 1 ABOUT HERE

As illustrated in Table 1, different measures of stratification invariably have differences in their empirical properties. As in Table 1 (right panel), the differences are often fairly modest, but they are usually enough to modify results, and they can sometimes lead to more substantial differences in emphases or conclusions. There are many ways of responding to the different measurement options. It is not yet common practice to do so, but in other reviews we have argued that social scientists ought to undertake extensive sensitivity analysis, in which they derive many plausible measures, then compare and contrast their empirical properties, in order to make a well informed decision (e.g. Lambert and Bihagen 2014; Connelly et al. 2015). At present however, most studies proceed by selecting only one measure to focus upon, according to some other reasoning. Firstly, many researchers hold a strongly positioned opinion about their preferred measure (we are not immune - we have often encouraged people simply to use the measure that we feel is the most compelling, namely the CAMSIS occupation-based stratification scale that features within Table 1 - e.g. Lambert and Griffiths 2018). Secondly, researchers sometimes use a measure that they are told to use by others – they might follow the prescriptions of a relevant national statistics institute, or follow patterns in academic literature, based on volume of citations or canonical endorsements. Third, and less easily defended, many researchers simply choose the most conveniently available indicator – perhaps the measure that happens to be most immediately available in their empirical data, or the measure that they have used most often before. Also seen as problematic, researchers often generate a new (‘ad hoc’) measure, derived according to their own data or theory. Yet whilst there have been some methodological reflections upon alternative measures of social stratification in standard contexts, at the time of writing we are not aware of many materials that extend these considerations to the two important data scenarios that we discuss below: taking account of longitudinal and life-course contexts, and taking account of intersectional inequalities.

(3) Adapting stratification measures to acknowledge the temporal and life-course context

Social stratification is deeply longitudinal in its theorisations. Circumstances of inequality ordinarily evolve across people’s lifespans, whilst the accumulation of life-course circumstances is recognised as itself a key mechanism of socially structured inequality (e.g. DiPrete and Eirich 2006). For many writers the very concept of social stratification concerns the persistence and reproduction through time of social inequalities (e.g. Bottero 2005). More pragmatically, longer term structural economic transformations ordinarily alter the underlying distribution of stratification measures in a society over time – expansion and re-structuring of educational systems, in particular, means that for different birth cohorts the relative distribution of educational qualifications is often very different.

Nevertheless, conventional uses of measures of stratification often ignore time outright. Existing measures are often treated, in practice, as applicable in the same format across a range of dates and across different life-course stages (e.g., a secondary school teacher gets an ISEI score of 69, regardless of the year that the data is recorded, and regardless of their own career or life-course stage). In sociology, some influential comparative evaluations of occupation-based stratification measures have argued that harmonised international measures work reasonably consistently across time as well as across countries (e.g. Rose and Harrison 2010; Ganzeboom et al. 1992; Treiman 1977). Within countries, academics have often issued revised and updated measures in response to changing industrial distributions through time, but these approaches do not generally provide guidance on making comparisons between time points (rather they focus on advocating a revised measure suitable to a new time point). All of these examples can be described as a model of *a priori* ‘measurement equivalence’ in terms of comparisons over time: an assertion that measures can be interpreted consistently across time because they are operationalised in a consistent way. To our knowledge, the only common exception is when an approach to arithmetic standardisation is used for a stratification measure that has a continuous functional form – for instance, if inflation adjustment calculations are applied to data on income or wealth.

High quality repeated cross-sectional longitudinal survey data collections now sometimes provide coverage over an impressively long timespan. Repeated contacts studies such as panel and cohort designs also often feature coverage of the same individuals over an extended life-course, and/or facilitate life-course comparisons between cohorts over several decades. Despite the wealth of temporal coverage in longitudinal data - and the persistent relevance of measures of stratification to most application areas - approaches that critically consider embedding temporal contexts into stratification measures are few and far between. Yet although they are rarely considered, there are analytical strategies that can be deployed to better capture temporal and life-course context. Below we highlight three strategies that we think are worthy of more attention. These are a selective choice, and other possibilities could be considered – a topic that seems to us to be a promising area for further methodological research.

Firstly, when the priority is of consistent interpretation across extended time-periods, there is often a good case for standardisation according to the appropriate temporal distribution. As in the example of inflation-adjusted income calculations, standardisation refers to re-scaling stratification measures, in order that they are expressed in consistent relative terms (such as for each time period or birth cohort that is analysed)[1]. Standardisation is theoretically compelling as social stratification position is often conceived of as relative position within a given inequality structure: what matters for comparison is relative position, not an absolute position which might be contingent upon societal-level change in industrial or economic structures. For continuous measures of stratification, arithmetic mean standardisation is an obvious option (i.e. subtract the mean for the context, and divide by the standard deviation). One important caveat is that the standardisation parameters (e.g. the mean and standard deviation) might preferably be obtained from a large-scale, representative external data source, rather than the same study that is being analysed (as the latter may be subject to sampling bias). For categorical measures of stratification such as social class schemes, a comparable approach to standardisation is not conventional. One plausible option however is to use ‘effect proportional scaling’ to generate scale scores for categories, then mean standardise those scores within the temporal context (the scale scores themselves might be generated from an arithmetic rule, or by applying a more complex data reduction technique). Alternatively, a theoretical temporal standardisation might be obtained on *a proiri* criteria, for instance by defining modal categories, or other key categories that are specific to the context, and making contrasts with them. Lastly, the approaches described above are examples of ‘post-hoc’ standardisation, where the representation of an existing measure is re-scaled in order to adapt to the surrounding distribution of inequality. It is also plausible, however, to deploy a pre-analysis standardisation, in which different stratification measures are derived bespoke to the appropriate temporal context – examples include the derivation of new CAMSIS scales for new time periods in the same country (e.g. Lambert and Griffiths 2018), and the calculation of alternative social class schemes for alternative points in history (e.g. van Leeuwen and Maas 2011).

A second plausible response to longitudinal contexts, that constitutes an extension beyond conventional uses of stratification measures, is to embed an extended control for an individual’s life-course stage within any statistical analysis. Most stratification measures have some correlation with age and life-course circumstances – asset based measures, in particular, tend to increase substantially across the working life, and adapt sharply at key life-course transition points such as employment entry or exit and family formation or dissolution. Although it is a classical statistical

[1] Statistically, standardisation is often a linear reformulation of an existing measure, which means it may not impact statistical results which are robust to linear transformations of variables. However, if a model is fit across data from different time points, or interaction relations between stratification measures and other variables are considered, more substantial changes in key statistical parameters are likely.

concern to control for correlated moderator variables, it is still common to find naïve analyses that ignore or downplay the link between stratification measures and the life-course. A popular strategy is to fit control variables that indicate life-course stage in a statistical model, but even when doing so, controls might be under-developed, if they are captured in only a rudimentary functional form: for instance, age effects are usually non-linear, and life-course effects can be related to multiple social states, and both main effects and interaction terms can justifiably be considered for all relevant measures. In our opinion there is often potential for a richer control for life-course circumstances in many analyses of social inequalities, and we would also recommend consideration of more creative, bespoke strategies related to the application in hand. At its simplest, it may be compelling to restrict an analysis to a narrower range of ages or life-course circumstances; more ambitiously, we might use strategies that focus upon fine-grained conjunctions of age, life-course stage and stratification position, for instance a statistical matching approach or the tools used to model 'intersectionality' as described in section 4.

A third response to longitudinal context requires a more specialist adjustment and might only be feasible when rich, large-scale repeated contacts datasets are available. Statistical techniques have long been available to identify, summarise and operationalise career trajectories in other measures, and some researchers have applied these productively to characterise trajectories in socio-economic circumstances related to social stratification. A commitment to modelling trajectories can involve a data reduction analysis, where latent patterns in trajectories are identified, then subsequently analysed (e.g. Pollock 2007; Wielgoszewska 2018). Profiles might also be defined on *a priori* grounds – for instance, analysing a measure derived arithmetically from circumstances over time (e.g. Bottero 2005). Modelling techniques might also be used to allow for varying patterns in a trajectory, for instance, by fitting person-specific growth curves to repeated contacts data on a stratification outcome (e.g. Jenkins 2011), or in the impact of a stratification measure upon a pattern of growth. In such examples, the analysis of the trajectory may itself become a substantial part of the analytical procedure: an orientation to trajectories might fundamentally change the social processes that are being summarised, but, in the case of social stratification when understood as a longitudinal concept, this may very well lead to an improved portrayal of complex social inequalities.

Table 2 summarises the empirical performance of the six measures mentioned in Table 1, when they are applied to UK datasets on adults aged 20-65 in 1995 and 2013 (University of Essex 2018). Columns (ii) to (iv) summarise relationships between the stratification measures and a health indicator – which ought, theoretically, to be linked to social stratification – under the three strategies for adapting to longitudinal context that are mentioned above, and in contrast to a fourth strategy (i), of ignoring the longitudinal context altogether. The operationalisations of (ii) to (iv) are selective, and could have been approached through other means (for the interested reader, the Stata code that we used to operationalise these longitudinally contextualised measures is available at https://github.com/paul-lambert/). The figures we report are percentages that depict by how much the relevant 2013 statistic (on the left, an association; on the right, a regression parameter) is different to that of the 1995 statistic. We see again that the different stratification measures can give somewhat different results. More interesting, results often change substantially in their magnitude and statistical significance when different plausible strategies for adapting to longitudinal context are deployed: strategy (i) is by far the most common approach, but the other strategies can lead to consequentially different results.

TABLE 2 ABOUT HERE

(4) Embedding an intersectional analytical approach

There is a growing recognition in contemporary social sciences that many accounts of social inequality can benefit from an 'intersectional' approach. Intersectionality broadly refers to an interest in recognising the multiple simultaneous positions in inequality structures that individuals may occupy: classically, an individual's gender, ethnicity and social class should be considered not just in isolation, but in terms of the implications of their unique conjunctions. The term 'intersectionality' was coined by civil rights activist and legal scholar Kimberlé Crenshaw (1989), though the concept has been evident in women's studies for much longer (Walby 2007). However, only recently has intersectionality become a more mainstream field of study for the social sciences in general, and a prominent area of interest for empirical sociological research. The range of social inequalities for which intersectional inequalities are explored has also rapidly escalated – it is common in the UK for instance to explore conjunctions of nine 'protected characteristics' as defined by the Equality Act 2010 (sex, gender identity, sexual orientation, age, ethnicity, religion, disability, marriage status, and pregnancy/maternity). Interestingly, there is a natural longitudinal relationship between intersectional conjunctions of inequality, and social stratification position – for instance, the way in which life-course trajectories of social class or stratification position develop may well be different for different groups defined by characteristics such as gender and ethnicity (e.g. Blossfeld et al. 2011). To the best of our knowledge however, there have not been previous reflections upon the distinctive challenges of bringing an intersectional analytical framework to a longitudinal analysis of measures of social stratification.

Indeed, when we consider how measures of social stratification are deployed in empirical analyses, we can argue that, just as with longitudinal research designs, there has been a lack of attention to plausible analytical modifications that might better adapt to intersectional circumstances (cf. McCall 2005). Weldon (2006) suggests four ways in which intersectionality might be conceptualised empirically: (i) an 'additive' approach, that fits parameters for each different inequality category, suggesting a 'double jeopardy' conceptualisation of accumulating inequalities (typically achieved by modelling dummy variable indicators of each category membership); (ii) a 'multiplicative' approach, that fits both main effects, and interaction effects, for inequality categories, suggesting a 'mutually reinforcing' conceptualisation of intersecting inequality's; (iii) an approach described as 'intersectional only', where intersectionality is conceptualised at something 'qualitatively different' that might only be assessed in a qualitative research design; and (iv) an approach labelled 'intersectionality plus', which allows for any of the above three permutations and allows for their effects to vary over time and place.

In quantitative research that aims to take an intersectional approach, approaches (i) and (ii) are reasonably common, but in theoretical terms (ii) is often preferred (fitting only main effects might suggest that disadvantages combine in an unrealistically stable way). However, some have also advocated an 'intercategorical' approach (McCall 2005), concerned with comparisons between and within multiple groups. Typically the intercategorical approach involves fitting a model and fully saturating it with all possible interaction effects (or with separate dummy variables for every possible combination). The interpretation of the many parameters involved in an intercategorical approach is challenging, but Evans et al. (2018) demonstrate how fitting 'random effects' ('multilevel models') for the distinctive groups can provide a parsimonious device to this end. Indeed, the use of random effects in this way might also fit the 'intersectionality plus' approach, as it allows for multiple group comparisons simultaneously, and could allow for temporal variation in the group differences such as with 'random slopes' for the effect of time.

Arguably, our examples above applied to longitudinal data also suggest methods that could be deployed when exploring intersectionality. Firstly, measures of stratification position might reasonably be standardised within a suitable context, whether by pre-analysis standardisation within a category (such as calculating separate stratification scales for men and women - e.g. Prandy 1986) or by post-hoc standardisation around the empirical distribution. Secondly, richer controls for age and life-course stage might be combined with those for other social identities, for instance with three way interaction effects between stratification measures, inequality category, and temporal effects. Lastly, an analysis that captures longitudinal trajectories in inequality categories might readily link those trajectories to other positions, or might even deploy different tools for defining different trajectories for different inequality categories.

Table 3 shows selected results (for only one stratification measure, the CAMSIS scale based on current or previous occupation) on the empirical consequences of incorporating these strategies for recognising intersectional social inequalities. We see a variety of modest, and occasionally substantial, changes in empirical results in different settings (in treatment (iv), for example, the controls for intersectional circumstances dominate the model, minimising the estimated stratification effect, but perhaps in an unreasonable way). As with Table 2, a command file showing code in Stata that can generate suitable measures and implement the analysis behind Table 3 is available (at https://github.com/paul-lambert/). Also of interest in Table 3 is evidence, in the right panel, that adaptations for intersectional inequalities may well interact with adaptations for longitudinal contexts: both can be implemented in combination, and, when they are, we can see some differences in patterns of results compared to if we adjusted for only one or the other complexity. Table 3 is a selective example, on health-stratification relationships, and only reveals relatively modest variations in results. It immediately provides a proof of concept, however, that how longitudinal context is addressed, and how intersectional inequalities are allowed for, can both simultaneously have empirical consequences.

TABLE 3 ABOUT HERE

(5) Conclusion

The choices over how to measure social stratification are complicated enough if we focus upon a particular society at a specific point in time, and if we focus upon social stratification in isolation from other relationships of inequality. Even more issues emerge, however, if we think – in the themes of this book – about longitudinal context, and the analysis of heterogeneous life course inequalities. It is theoretically compelling to consider both of these extension issues in themselves, but we might also want to respond to both in combination. In applied research, it is by far the more common strategy to ignore both complications, but by using empirical strategies such as those that we have highlighted, there seems an exciting opportunity to acknowledge these contexts more fully in the future.

One important point is that various routes are available to refine stratification measures into a functional form and measurement structure that makes them more amenable to longitudinal comparisons and intersectional analyses. It is often thought that occupation-based measures, specifically, are inflexible - an important occupation-based social class measure such as ESeC, for instance, is purportedly fixed in time and context, and uses categories that are hard to compare between contexts, yet this doesn't mean that all occupation-based measures work in this way. An ESeC operationalisation might itself be adapted to temporal or intersectional contexts, or an alternative but more easily used occupation-based stratification measure might be selected. Indeed, most of the adaptations that are described above are much easier to implement for measures of stratification that approximate a continuous functional form. Some traditions in studying social inequality have historically been more comfortable with categorical representations of social stratification position (e.g. social class groups), but, in nearly all circumstances when complex longitudinal and/or intersectional inequalities are also of interest, it is likely that a continuous measure will capture similar inequalities (e.g. Lambert and Bihagen 2014), but will be much more amenable to appropriate statistical extensions.

As highlighted in several contributions to this book, longitudinal social research data and its analysis can often exploit a more expansive analytical design than is actually deployed. We probably under-exploit longitudinal data if we use only the more popular and simpler strategies in measuring social stratification; perhaps our standard measurement approaches have some work to do to catch up with the richness of data resources and analytical opportunities that are now prevalent. As longer spans of longitudinal data are increasingly available for social research, is it realistic to continue using measures of social stratification from an existing pool of instruments which were largely conceived as atemporal and universal across the life-course? And as the interplay of complex social heterogeneities is increasingly recognised, for instance in theorisations of intersectionality, should we still produce and use stratification measures as if they were largely independent of other social heterogeneities? Current patterns in research practice do suggest that in all likelihood, most studies will continue to use measures that are fixed in time and which only allow for intersectional inequalities to a very limited extent. Nevertheless, in this chapter we have argued that it is not so difficult to access and exploit measures of stratification, and/or use alternative analytical devices, which have features better suited to both complications.

References cited

Blossfeld, H. P., Buchholz, S., Hofacker, D., & Kolb, K. (Eds.). (2011). *Globalized labour markets and social inequality in Europe* Basingstoke: Palgrave MacMillan.

Bottero, W. (2005). *Stratification: Social Division and Inequality*. London: Routledge.

Chan, T. W., & Goldthorpe, J. H. (2007). Class and Status: The Conceptual Distinction and its Empirical Relevance. *American Sociological Review, 72*(4), 512-532.

Connelly, R., Gayle, V., Lambert, P. S., & (2016). A Review of occupation-based social classifications for social survey research *Methodological Innovations Online, 2016*(9:2059799116638003).

Crenshaw, K. (1989). Demarginalizing the Intersection of Race and Sex: A Black Feminist Critique of Antidiscrimination Doctrine, Feminist Theory and Antiracist Politics. *University of Chicago Legal Forum*, 139-167.

DiPrete, T. A., & Eirich, G. M. (2006). Cumulative advantage as a mechanism for inequality: A review of theoretical and empirical developments. *Annual Review of Sociology, 32*, 271-297.

Evans, C. R., Williams, D. R., Onnela, J. P., & Subramanian, S. V. (2018). A multilevel approach to modeling health inequalities at the intersection of multiple social identities. *Social Science and Medicine, 203*, 64-73.

Ganzeboom, H. B. G., de Graaf, P. M., & Treiman, D. J. (1992). A standard international socio-economic index of occupational status. *Social Science Research, 21*, 1-56.

Hoffmeyer-Zlotnik, J. H. P., & Warner, U. (2014). *Harmonising Demographic and Socio-Economic Variables for Cross-National Comparative Survey Research*. Berlin: Springer.

Jenkins, S. P. (2011). *Changing Fortunes: Income Mobility and Poverty Dynamics in Britain*. Oxford: Oxford University Press.

Lambert, P. S., & Bihagen, E. (2014). Using occupation-based social classifications. *Work, Employment and Society, 28*(3), 481-494.

Lambert, P. S., & Griffiths, D. (2018). *Social Inequalities and Occupational Stratification: Methods and Concepts in the Analysis of Social Distance*. Basingstoke: Palgrave

McCall, L. (2005). The Complexity of Intersectionality. *Signs: Journal of Women in Culture and Society, 30*(3), 1771-1800.

Pollock, G. (2007). Holistic trajectories: a study of combined employment, housing and family careers by using multiple-sequence analysis *Journal of the Royal Statistical Society Series A, 170*(1), 167-183.

Prandy, K. (1986). Similarities of Life-style and the Occupations of Women. In R. Crompton & M. Mann (Eds.), *Gender and Stratification* (pp. 137-153). Cambridge: Polity Press.

Rose, D., & Harrison, E. (Eds.). (2010). *Social Class in Europe: An Introduction to the European Socio-economic Classification* London: Routledge.

Rose, D., Pevalin, D., & O'Reilly, K. (2005). *The NS-SEC: Origins, Development and Use*. Basingstoke: Palgrave Macmillan.

Shaw, M., Galobardes, B., Lawlor, D. A., Lynch, J., Wheeler, B., & Davey Smith, G. (2007). *The Handbook of Inequality and Socioeconomic Position: Concepts and Measures*. Bristol: Policy Press.

Treiman, D. J. (1977). *Occupational Prestige in Comparative Perspective*. New York: Academic Press.

Tumin, M. M. (1967). *Social Stratification: The Forms and Functions of Inequality*. New Jersey: Prentice-Hall.

University of Essex, & Institute for Social and Economic Research. (2018). *Understanding Society: Waves 1-8, 2009-2017 and Harmonised BHPS: Waves 1-18, 1991-2009. [data collection]. 11th Edition*: UK Data Service, SN: 6614, http://doi.org/10.5255/UKDA-SN-6614-12.

van Leeuwen, M. H. D., & Maas, I. (2011). *HISCLASS: A Historical International Social Class Scheme*. Leuven: Leuven University Press.

Walby, S. (2007). Complexity Theory, Systems Theory, and Multiple Intersecting Social Inequalities. *Philosophy of the Social Sciences, 37*(4), 449-470.

Weeden, K. A., & Grusky, D. B. (2012). The Three Worlds of Inequality. *American Journal of Sociology, 117*(6), 1723-1785.

Weldon, S. L. (2006). The Structure of Intersectionality: A Comparative Politics of Gender. *Politics and Gender, 2*(2), 235-248.

Wielgoszewska, B. (2018). *Understanding University Graduates' Social Mobility Trajectories: How Does the Route Affect the Outcome?* (PhD), University of Edinburgh.

Tables referred to in the text

Table 1: Selected features of six popular measures of social stratification position

	% with valid data			*Correlations*100 with household income; health; arts consumption*		
	(i)	(ii)	(iii)	(i)	(ii)	(iii)
Measures operationalised as one-dimensional scales						
CAMSIS	57	87	96	36; 6; 23	35; 14; 28	38; 13; 27
ISEI	56	88	97	39; 7; 21	36; 13; 26	40; 14; 25
Household equivalised income			100			--; 17; 26
Measures operationalised as categorisations (number of categories)						
NS-SeC (7)	57	87	96	41; 8; 11	38; 14; 15	43; 15; 15
RGSC (6)	57	87	96	37; 8; 11	35; 13; 14	39; 14; 14
Housing tenure (3)			99			30; 16; 11

Notes: Distributional data calculated for the UKHLS, wave E (2013), all adult respondents (aged 16-101), unweighted. (i) individual level measures using current occupation; (ii) individual level measures using current or last occupation; (iii) household level measures, using current or last occupation of the household member who has most influence on household economic situation 'Health' refers to whether or not self-rated health is described as 'fair' or 'poor'. 'Arts consumption' refers to self-reported volume of arts events attended in the last year (UKHLS measure 'arts2freq').

Table 2: Variations in the empirical performance of stratification measures in predicting health, with different adaptations to longitudinal context

	Percent change in association between stratification measure and health, 1995 to 2013				*Pooled data: 2013*stratification interaction parameter, as percent of main effect*			
	(i)	***(ii)***	***(iii)***	***(iv)***	***(i)***	***(ii)***	***(iii)***	***(iv)***
CAMSIS	2	2	-9	-8	30*	25*	28*	30*
ISEI	4	4	13	3	32*	47**	47**	40**
Equivalised household income	5	5	21	18	56**	40**	37**	38**
NS-SeC (7)	2	2	-14	-6	120**	20	22	30*
RGSC (6)	4	4	4	-39	44**	41**	35*	-9
Housing tenure (3)	6	6	31	34	2800**	46**	45**	51**

Notes: Data as Table 1 for 2013, and using UK's British Household Panel Survey, wave E (1995). (i) No adjustment (original measures). (ii) Mean standardisation within year. (iii) Controls for age and life course stage (if married/cohabiting, children in household, living with either parent, age and gender). (iv) Stratification measure calculated from historical profile over last 5 years (weighted cumulative sum of measure over 5 years), with controls as (iii). Left panel shows change in bivariate association (i) and (ii), or change in partial association net of controls (iii) and (iv). Right panel shows how much the model estimated effect of stratification increased by for 2013. In approaches (ii), (iii) and (iv), effect proportional scaling of categorical measures was deployed. */** p-value for interaction is 0.05-0.01 / < 0.01.

Table 3: Adapting stratification measures to account for intersectional social inequalities and for a longitudinal context

	Characteristics of the health-CAMSIS association patttern					
	Partial R2	% decline in predicted poor health, CAMSIS score 50 to 75, for...		Time effect: 2013*CAMSIS interaction parameter, as percent of main effect of CAMSIS, with...		
		White male, 30-40yrs	*Black afr. female, 45-60yrs*	*No adjustment for time*	*Temporal z-score*	*Longitudinal cumulative measure*
(i) No adjustment for intersectionality	0.019	42	42	21*	17	16
(ii) Main effects only	0.019	43	42	23*	18	20*
(iii) Main effects and 2-way interactions	0.020	38	27	40	31	37
(iv) Random effects for inequality category	0.018	0	6	23*	19	20*
(v) Model (iii) plus group random effects	0.020	38	27	41	32	37
(vi) Standardisation within inequality category	0.017	38	38	18	14	16

Notes: Data and symbols as per Table 2 (UKHLS, 2013 and BHPS, 1995). Left panel shows different depictions of health-stratification relationship given different adaptations to intersectional inequalities. Right panel repeats controls (ii) and (iv) for the pooled data interaction parameter from Table 2.