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“Concepts and Measures: Empirical evidence on the interpretation of ESeC and other occupation-based social classifications”

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Abstract:

This paper discusses the linkage between ‘concepts’ and ‘measures’ across alternative occupation-based social classifications. We review empirical evidence from contemporary longitudinal survey data from the UK (British Household Panel Survey) and Sweden (Level of Living Survey), and discuss the properties of an array of alternative occupation-based social classifications.

Our assertion is that social scientists frequently over-estimate the linkage between concepts and measures in occupation-based social classifications. The simple point is that measures do correlate strongly with features of the concept(s) on which they are theoretically based - as is demonstrated in valuable studies of criterion validity. However, what the same measures never achieve is an exclusive correlation with their concepts, and nothing else – yet, we argue, this is what many authors have effectively assumed. The result is something of a fallacy – that measures do not distinctively measure the concepts that are attributed to them. This is highly pertinent to stratification research, where the conceptual basis of social classifications is often used in empirical hypotheses concerning stratification processes (esp. Chan and Goldthorpe 2007).

The ESeC classification (European Socio-economic Classification) is increasingly expected to be the most widely used occupation-based social classification across Europe and beyond in the next decade. This paper notes several favourable features of the ESeC derivation project and measure. However, it also cites the ESeC classification as a particularly problematic example of assumptions over the linkage between concepts and measures - embodied the ESeC project’s use of the slogan ‘One concept, one measure’ (Rose and Harrison 2007). Our analyses demonstrate emphatically that whilst ESeC may originate from one concept (employment relations), in empirical terms it measures many things (including employment relations, skill, socio-economic advantage, and social distance). These correlations have non-trivial implications for its interpretation and advocacy.

Whilst ESeC is an especially influential occupation-based measure, it is important to realise that the opportunities for analysing occupations are many and varied. Major internet resources, such as the files distributed by Ganzeboom (e.g. <http://home.fsw.vu.nl/~ganzeboom/pisa/>), and by the GEODE project (www.geode.stir.ac.uk), allow rapid access to extensive collections of resources. This paper features a short discussion showcasing the facilities of one such resource (the GEODE project, on which both authors have worked). It illustrates how this new internet facility (launched January 2007) allows social scientists ready access to numerous occupational datasets and new opportunities in exploiting occupation-based social classifications.

Accordingly, our analysis implements a wide selection of occupation-based social classifications (including the class schemes of ESeC, Wright, and the skill-based scheme advocated by Elias; and the stratification scales of ISEI and CAMSIS), as well as other indicators of occupational circumstances (including measures of the skill levels, income profiles, and gender segregation levels of jobs). By comparing

associations and correlations between these measures and key indicators of socio-economic circumstances, we emphasise how an array of alternative occupation-based measures overlap substantially in the factors which they empirically measure.

Of course, not only do social scientists have numerous alternatives in how they code occupational data, they also have numerous alternatives in the analytical methods they may use when studying processes related to occupational measures. In this paper we explore the impact of alternative statistical formulations in the exploitation of occupation-based social classifications. We focus on the particular example of the prediction of unemployment risks (which has been used by previous authors as a test of the measurement properties of alternative social classifications), and paying attention to selection effects associated with industry. We find that such effects diminish the overall impact of occupation-based social classifications, though they do not entirely diminish small measurement differences between schemes.

This paper concludes that there is work to be done in clarifying how we relate the concepts and measures of alternative occupation-based social classifications. We argue that the more favourable occupation-based social classifications are those that are explicit about their qualities as generalised summaries of stratification circumstances, and we challenge the important claim that the ESeC scheme can be taken as a clear measure of 'one concept'. However, our analyses also demonstrate that occupational information remains the best way to understand micro-social inequalities and processes of social stratification. Indeed, returning to the theme of this conference, we suggest that longitudinal processes of cumulative advantage (in terms of unemployment risks) are ideally understood through the careful interpretation of occupation-based measures and their correlates.

1. Introduction: Concepts and measures in social science research

This paper discusses the linkage between ‘concepts’ and ‘measures’ across alternative occupation-based social classifications. Our focus is the realm of survey-based quantitative research in sociology¹. In this field, empirical investigation commonly proceeds according to a model which hinges upon an assumed relationship between concepts and measures. Ordinarily, theories and questions of interest are laid out in terms of possible relationships between concepts, but are analysed in terms of relationships between measures. Several commentators have argued convincingly that it is through understanding empirical patterns in carefully operationalised measures that social researchers have the best opportunity to undertake research of a scientific character contributing to the testing and development of social theories (e.g. Steuer, 2003; Goldthorpe, 2007).

Measures in social survey research are therefore typically interpreted as potential (and potentially imperfect) indicators of the concepts of interest. Consequently, much methodological attention has been directed to the quality of survey measures across different domains of social science research. Literatures relevant to this discussion include prescriptive texts offering guidance on the qualities and mechanics of existing social science measures (e.g. Hoffmeyer-Zlotnik & Wolf, 2003; Rose & Pevalin, 2003; Shaw et al., 2007); focussed studies of the empirical properties and interpretations of existing measures (examples on occupation-based social classifications include Marshall et al., 1988; Chan & Goldthorpe, 2007; Rose & Harrison, 2007); and discussions covering procedures for choosing and identifying appropriate concepts to a relevant social science research question or theory (e.g. Goertz, 2006; Grusky & Kanbur, 2006; Goldthorpe, 2007)².

A complaint of some recent writers (e.g. Goertz, 2006) has been that social science methodologists have paid too much attention to the mechanics of measurements, to the neglect of underlying conceptualisations. On the one hand, it is easy to demonstrate that in the study of occupation-based social classifications, attempts to

¹ Although the use of occupation-based social classifications – the focus of this study – does extend to other social research methodologies. Indeed, challenges in relating concepts and measures in the domain of social classifications have also been prominent in empirical research based upon extended interviews and focus groups (e.g. Devine, 2004, chpt 1).

² Three literatures may be broadly distinguished. As well as concerns over which concepts should be focussed upon (conceptualisation) and how a measure should be operationalised from the original data (operationalisation), there are also many outputs concerned with how data should be collected in order to construct a measure (data collection). These three elements have distinctive features, but they are not independent of each other (indeed, the inter-dependence of conceptualisation, data collection and operationalisation is well illustrated in terms of National Statistics Institutes decisions on revisions to occupational classifications, whereby revisions to data collection instruments, revisions to tools for linking data resources, and revisions to substantive motivations in data collection, are often combined within the same methodological projects and reports – e.g. Rose & O'Reilly, 1997). This discussion is restricted to two features of methodological debate – conceptualisations and operationalisations – since the field of data collection is typically outwith the control of secondary social survey researchers.

link measures with concepts are very well advanced, since such studies have been a staple component of sociological publications since the earliest empirical studies (e.g. Armstrong, 1972; Hauser & Warren, 1997; Grusky & Weeden, 2006), and continue to generate numerous alternative reviews (for recent examples, see Wright, 2005; Oesch, 2006; Lambert et al., 2008). However, we suggest below that many contemporary reviews of concepts and measures in occupation-based social classifications do suffer from limitations in the extent to which they compare an adequate range of alternative measures, and in certain features of their interpretations of empirical patterns of measurement.

The first assumption in the use of occupation-based social classifications is that occupational circumstances of individuals (or indeed the occupations of their household sharers, their parents, and so forth) can be used to inform us about the experiences of individuals within a social structure of 'stratification' or 'class'. Although there are important concerns involving the relationship between occupations and other social divisions both within and between societies and time periods (e.g. Abbott, 2006), this first key assumption of the relevance of occupations has garnered overwhelming empirical support across the range of societies and time periods over which sociological research has spanned³.

A second assumption during the use of occupation-based social classification has been subject to far more methodological debate. It is that one or more set of rules ('translation codes') may be used to locate occupational positions into appropriate measures of 'social class' or 'stratification' positions. Classical approaches to measurement involve either grouping occupational titles into a small number of categorical locations (usually termed 'class' categories), or else scaling occupational titles with scores in one dimension of social inequality (usually referred to as 'status', 'prestige' or 'stratification' scales). Most contemporary research continues with one of these approaches⁴, and this is especially true of the many users of occupation-based social classifications who seek convenient measures without recourse to specialist methodological literatures. However, there is a great deal of inconsistency in contemporary survey research in how social scientists derive and exploit translation codes for occupation-based social classifications (Lambert et al., 2007), and there

³ There have been a number of well-publicised counter-claims over the value of researching occupational positions (e.g. Pakulski & Waters, 1996; Beck, 2000). These have highlighted the allegedly diminishing importance of occupational circumstances (and other economic structures) in defining social inequalities. Many such studies have been exposed as lacking in robust empirical foundations – and directly contrasted with empirical evidence which contradicts many of their claims (see for instance the review by Goldthorpe, 2007, Chapter 5). However, it is useful to recognise that many of these influential studies do include some commentary on the mediation of occupational influences (such as by age, gender and ethnic groups within a society) which is empirically persistent. Most multivariate analyses exploiting occupation-based social classifications do of course recognise such mediating influences (e.g. Svallfors, 2005; Morgan et al., 2006), a point which is perhaps not appreciated by critiques of research on occupational positions.

⁴ There have been a variety of alternative suggestions for measuring social inequalities on the basis of occupations which depart from such positions. These include advocacy of measurement scales involving multiple dimensions; of longitudinal measures of occupational trajectories or structures (Gershuny, 2002); and of categorisations which use much larger numbers of different categories (e.g. Weeden & Grusky, 2005).

continues to be much debate over what may be the best available classification for a given application.

The focus of this discussion is that different occupation-based social classifications have been claimed to be associated with different underlying conceptual accounts of ‘class’ and ‘stratification’. One widely used family of occupation-based social classification measures of ‘class’ have been claimed to represent ‘employment relations’ (i.e. the ‘EGP’ or ‘Goldthorpe’ scheme and the related NS-SEC and ESeC schemes – for a summary see Rose & Harrison, 2007). Another widely used family of class measures are claimed to represent, first and foremost, economic relations of production and conflict (i.e. the ‘Wright’ class scheme, see e.g. Wright, 2005). Features of these and other measures are that the translation rules for deriving a measure are specified in a manner which the authors intend to emphasise their own conceptual account of class or stratification. Subsequently, empirical differences between the properties of different schemes are ordinarily interpreted as indicators of differences attributed to the underlying concepts (esp. Marshall et al., 1988; Chan & Goldthorpe, 2007).

We argue in this paper that whilst occupation-based social classifications are powerful tools, there is a danger in that social scientists frequently over-estimate the linkage between concepts and measures in occupation-based social classifications. Some measures do correlate strongly with features of the concept(s) on which they are theoretically based. This has been demonstrated, for selected measures, in studies of ‘criterion validity’, which have reported correlations between occupation-based social classifications and alternative measures of underlying concepts. For instance, in the case of the EGP scheme, Evans and Mills (1998; 2000) have shown convincing patterns of association between that scheme and alternative indicators of employment relations and conditions. However, it is worth highlighting that many sociological studies have used alternative occupation-based social classifications which do not benefit from such consistent evidence of criterion validity, and correspondingly many measures may not be reliably assumed to correlate with their claimed properties.

However, regardless of the extent to which ‘criterion validity’ has been established, a simple but important point is that all measures of occupation-based social classification, in large degree by dint of their operationalisation through occupations, can be shown to correlate with numerous other concepts aside from those directly attributed to them (we demonstrate this below). Thus, occupation-based social classification never achieve an *exclusive* correlation with their concepts, and nothing else. Nevertheless, this is what many authors have, effectively, assumed⁵. The result is

⁵ This issue reflects an enduring misconception in the field of measurement in the social sciences (Prandy, 2002). Whilst it is true that occupation-based social classifications can capture empirical patterns of difference between different groups in relevant concepts, the relationship is asymmetric – it does not follow that the same concepts are distinguished through the measurement, and in fact this is very unlikely to happen when the occupation-based social classification involves a relatively large degree of aggregation, as is inherent to a parsimonious classification based upon occupational locations.

something of a fallacy – that measures do not (and cannot) distinctively measure the concepts that are attributed to them. This is highly pertinent to stratification research, where the conceptual basis of social classifications is often used in empirical hypotheses concerning stratification processes (esp. Chan and Goldthorpe 2007).

An instantiation of the lack of exclusivity between alternative occupation-based social classifications is well known to sociologists, although is not usually viewed from this perspective. The ‘Treiman constant’ refers to the empirical generalization that ‘occupations are ranked in the same order in most nations and over time’ (Hout & DiPrete, 2006, p2). A large volume of empirical studies have supported this claim, yet although this assertion has ordinarily been associated with scaling exercises concerned with hierarchies of advantage, it may equally be regarded as consistent with the view that alternative occupational measures tend in large part to measure the same structures of difference (esp. Ganzeboom, 2005).

Whilst most occupation-based social classifications have been directly linked with specific concepts of class and stratification, some alternative classifications have been claimed to represent more generalised social structures of inequality. These include ‘stratification’ scales derived from patterns of social interactions (Rytina, 2000; Bottero & Prandy, 2003). This position is also held for the status and prestige approaches associated with Ganzeboom and Treiman (e.g. Ganzeboom & Treiman, 2003)⁶. We conclude, below, that these attempts offer a better appreciation of occupation-based social classifications, although we also emphasise that for many purposes, the differences between the empirical properties of such measures makes little impact.

In this paper we review existing occupation-based social classifications. We discuss selected features of an array of alternative occupation-based social classifications, focussing upon empirical evidence from contemporary longitudinal survey data from the UK (British Household Panel Survey) and Sweden (Level of Living Survey, linked with administrative data). We focus upon claims made concerning the conceptualisation and operationalisation of the European Socio-Economic Classification (‘ESeC’), with particular attention to the relationship between the ESeC measure and patterns of subsequent experiences of unemployment (cf. Elias & McKnight, 2003; Goldthorpe & McKnight, 2006; Schizzerotto et al., 2006).

⁶ Though it is useful to distinguish the wider group of claims that occupation-based social classifications may represent a generalised structure of stratification (e.g. Prandy, Rytina, Ganzeboom, Trieman), from the sub-set of those claims which also assert that this occupational order is broadly fixed across different countries and time periods (e.g. Ganzeboom, Treiman). This latter claim has received much empirical support (cf. Hout and DiPrete 2006), but is not adopted by all advocates of measurements of a generalised structure stratification (cf. Lambert et al 2008).

2. Data

2.1 Micro-Data

Our analyses are based upon micro-data from random survey samples drawn in Britain and in Sweden in 1991. Since our analytical interest centres on the prediction of prospective unemployment, we required longitudinal micro-data. An implication of this requirement was that we worked with relatively small survey samples of individuals who were employed in 1991 and successfully re-interviewed in Britain (or traced in Sweden) over the period until 2002. This means that our survey micro-data is not necessarily the largest or most comprehensive dataset for the analyses of occupational structures around the period 1991⁷. Basic parameters of the data used are described in Appendix Tables A.1-A.3.

The British sample design using the British Household Panel Study (BHPS, Halpin, 2006; University of Essex & Institute for Social and Economic Research, 2007) begins with a nationally representative random sample of adults in 1991. We select only those adults aged 23-55 in 1991 with valid data on employment, since younger adults are argued to be increasingly likely to be in temporary and casual employment, and older adults as increasingly likely to voluntarily withdraw from the labour market within the period of the study observation (this age range was also used by Elias & McKnight, 2003). In Britain, the analysis is restricted only to the subsample of cases who were successfully re-interviewed every year from 1991 to 2002, and who also contributed complete responses on the work life history database (Halpin, 2006). This leads to approximately 50% attrition from the 1991 sample (compare Table A.1, which shows the data from the BHPS used in our analysis, and Table A.2, shows the full range of data that could potentially have been used). This attrition should be noted, although we argue that the BHPS is widely regarded as a high quality longitudinal survey where a complete case analysis can often be justified. Therefore, the analyses we undertake on the BHPS make the standard ‘missing at random’ assumption, that cases excluded from the sample are missing for reasons either outwith the scope of the analysis, or on the basis of factors which can be controlled for in the multivariate models (see Allison, 2002 for defence of this approach). In fact, similar data from the BHPS has also been used for comparable analyses by Elias and McKnight (2003); Goldthorpe and McKnight (2006); Schizzerotto et al. (2006) and Chan and Goldthorpe (2007).

The Swedish data is not affected by attrition in the same way, since the longitudinal follow up is achieved by administrative data. The data is based on the LNU (Levnadsnivåundersökningen/ Level of living Survey) survey⁸ of 1991, with a response rate of 79 %. Thereafter administrative data was merged with the survey records as part of a larger research project at the Swedish Institute for Social Research

⁷ Indeed in Britain alternative resources such as the Labour Force Survey, the Employment in Britain survey; and the Social Class in Modern Britain survey – all available via the UK Data Archive

<http://www.data-archive.ac.uk/> - all feature more extensive cross-sectional micro-data on occupations.

⁸ <http://www.sofi.su.se/LNU2000/english.htm>

(SOFI)⁹. The administrative records, which cover data on future spells of unemployment experienced by the 1991 LNU respondents, come from the ‘PRESO’ register of employment and unemployment events, which is maintained by the ‘AMS’ (Arbetsmarknadsstyrelsen / The National Labour Market Board). The approach combining administrative and survey data is used and described in a study by Korpi and Stenberg (2001). Since people in Sweden who become unemployed register themselves at AMS in order to get unemployment insurance, the coverage of the PRESO register of all unemployment will be close to complete (cf. Levin, 1996). Hence, we have summed all episodes of unemployment on PRESO for the LNU-respondents for the years 1992-2002.

2.2 Occupation-based social classifications

“Sensible taxonomies can rarely be judged true or false, only more or less useful for a given purpose” (Mills & Evans, 2002, p80).

Evans and Mills’ statement with regard to occupation-based social classifications would appear to command widespread agreement amongst sociologists. Yet it carries two implications which are seldom developed within validation studies of the properties of occupation-based social classifications such as Mills and Evans’, or indeed in wider empirical applications. These are that there may be numerous alternative occupation-based taxonomies worthy of empirical attention; and that different taxonomies may be more suitable in a given empirical analysis (distinguished for instance by national and temporal context, or by analytical focus). In practice, most studies of the properties of occupation-based social classifications have focussed on just one or two taxonomies. Most empirical analyses using occupation-based social classifications have used just one taxonomy, whereas those which have used more than one have typically used only two or three (e.g. Heath et al., 2003; Weeden & Grusky, 2005; Chan & Goldthorpe, 2007).

The total number of alternative occupation based-social classifications available to social scientists in any given context is much higher. In Britain for instance, Lambert et al noted that in 2005 alone, 6 new social classifications were proposed for contemporary analyses (Lambert et al., 2008). Although some decades ago Bechhofer (1969) urged researchers to stop adding to the already large number of alternative taxonomies, this advice was not followed either in Britain or elsewhere!

There are considerable practical difficulties involved in comparing more than a small number of occupation-based social classifications. We attempt this in our analyses below (Figures 2.1 – 4.2, discussed below). Our results are largely of a descriptive and preliminary character, but one clear problem is the difficulty of conveying the wide range of details and associations summarised in the analyses – which involve

⁹ We are grateful for the work done by Tomas Korpi in order for us to be able to use this data.

thousands of different permutations in the relationships between different social classifications and other relevant measures - in a coherent way.

A second practical difficulty involves facilities for operationalising occupation-based social classifications on the basis of 'source occupational information' (e.g. job titles) typically recorded by social surveys. A preferable model for a replicable research undertaking would involve using transparent translation codes on carefully preserved micro-data. However, the costs involved in implementing such codes (usually through bespoke software programming) are considerable for most social scientists. It is, moreover, easy to find numerous examples of research projects which do not keep strictly to such an approach to operationalisation (for an extended discussion see Lambert et al., 2007).

Nevertheless, it may be argued that the barriers to empirical researchers considering a wider range of occupation-based social classifications are diminishing¹⁰. Social researchers' capacities for exploiting internet provisions of occupational translation codes would ordinarily be expected to increase with improving computer literacy and software packages for data management. In addition, a recent project - involving the authors of this text - was specifically designed to improve social scientists' access to occupational information resources, such as translation codes for occupation-based social classifications. The GEODE project (Grid Enabled Occupational Data Environment)¹¹ involved developing web-pages and an open access internet 'portal' (a login web site - illustrated in Figure 1) which allows social scientists to search for and retrieve relevant information on occupation-based social classifications, as well as to deposit new occupational information resources in a coordinated manner. The range of facilities involved in this site - which includes a purpose built programme for linking micro-data files with selected occupation-based social classifications - are described on web-pages and working papers downloadable from the project website. The authors exploited resources from the GEODE site in order to access and implement the 31 different occupation-based social classifications covered in this paper. It is worthwhile to highlight to non-specialist users that the facilities on the GEODE web-site are not entirely finalised and user-friendly at time of writing, though the developers of this facility hope to continue improving its accessibility in response to users' feedback.

In this analysis, we depart from many previous reviews of occupation-based social classifications by comparing as wide a range of taxonomies as are available to us on our particular datasets. Our analyses proceed by operationalising 31 different occupation-based social classifications (these are drawn from thirteen traditions on occupational research - see the groups reported in Figures 2.1-3). The schemes - and the abbreviations we use in the figures - are described in Table 1. In both countries, occupational measures are based upon self-reported descriptions of current occupations 1991 (and self-reported descriptions of mother's and father's occupations when respondents were aged 14) coded to the UK and Swedish standardised

¹⁰ Motivations for considering wider ranges of classifications are also likely to grow, as secondary micro-data is increasingly available from a wider range of countries and time periods, which in turn feature different occupational data and potentially different classification schemes.

¹¹ See <http://www.geode.stir.ac.uk/>.

occupational classifications (for Britain, see OPCS, 1990). This data was subsequently translated to social classification schemes and other occupational measures using resources accessed from the GEODE website (Lambert, 2007), including measures derived from published texts (Chan & Goldthorpe, 2004; Oesch, 2006) and online occupational information provisions (including Leiulfstrud et al., 2005; Bihagen & Ohls, 2007; Ganzeboom, 2007; Lambert & Prandy, 2007).

European Socio-Economic Classification (E9, E6, E5, E2)

A particular interest in this study is in the ESeC classification (European Socio-economic Classification). This scheme is increasingly expected to be the most widely used occupation-based social classification across Europe and beyond in the next decade (Rose & Harrison, 2007). The ESeC scheme is broadly based upon the definitions used in the EGP classification, in which ‘employment relations’ are used to define a structure of occupational categories (see Rose & Harrison, 2007). Attractive features of the ESeC scheme include online facilities for implementing the scheme according to internationally standardised occupational classifications¹²; the development of the scheme during a collaborative project exploiting national expertise in occupational classifications and their engagement in a programme of research assessing aspects of the validity of the measurement¹³; and the engagement of the scheme with previous approaches to occupation-based social classifications, especially those of the EGP measures (cf. Rose et al., 2005). In fact, the most significant departures from the ESeC scheme and the EGP classifications lie in the mechanics of its operationalisation. For the period of our data (1991), specialist national operationalisations of EGP were available for both Britain and Sweden, whereas ESeC was operationalised using an internationally standardised classification to ESeC (using ISCO-88 3-digit occupations and employment status data). This meant the two schemes did not overlap in several cases – a consequence of which are differential patterns of association revealed between the schemes in our results (Figures 2.1 – 4.2).

Despite its strengths, the ESeC derivation project and measure does appear to have one significant drawback, insofar as it has adopted very strong assumptions over the linkage between its concepts and measures. This has been embodied in the use by the developers of ESeC project’s use of the slogan ‘One concept, one measure’ (Rose and Harrison 2007). The claim is that the ESeC scheme – being a measure based strictly upon concepts of employment relations – is superior to alternative occupation based social classifications because it is known to measure one distinctive property (employment relations). As discussed above, this property of unique measurement is unlikely to be the case for any occupation-based social classification. In fact, our analyses below demonstrate that whilst ESeC may originate from one concept (employment relations), in empirical terms it measures many things (including employment relations, skill, socio-economic advantage, and social distance).

¹² Resources are available at <http://www.iser.essex.ac.uk/esec/>; the ESeC translation codes have also been implemented into an ‘occupational matching’ programme within the GEODE web portal at www.geode.stir.ac.uk.

¹³ See especially <http://www.iser.essex.ac.uk/esec/events/conferences/2006/2006-01-19/>.

Skill levels (K4)

We use a 4-fold categorisation of the ISCO-88 scheme into skill levels typically associated with component jobs. This scheme, proposed by Elias (1996), excludes ISCO occupations in major groups 0 and 1 since they are considered ambiguous in their skill levels. Dumont (2006) has commented critically on the ability of ISCO based categorisations to identify different levels of skill in a reliable way.

Manual / Non-manual classification (MN)

An enduring analytical category in sociological commentaries is the simple dichotomy between occupations which are predominantly manual and non-manual in character. We classify occupations on the basis of a recoding scheme for ISCO88(COM) unit groups prepared by the authors and available for download from the GEODE web pages¹⁴.

Work Logic classifications (O17; O8; O4)

Oesch (2006) advocates alternative 17-, 8- and 4-category classifications of occupations which are differentiated in terms of the ‘work logic’ and technical content associated with jobs¹⁵. Oesch argues that this scheme reflects more salient features of contemporary occupational and social inequalities than do alternative classifications, because the work logics which define the scheme are sensitive to the social impact of recent occupational changes associated with recent processes of ‘tertiarisation’, ‘feminisation’ and ‘welfare statism’ in the European labour market. This scheme is operationalised by Oesch (2006, p222-4) for Britain, Switzerland, and Germany on the basis of a classification of ISCO-88 unit groups; and for Sweden on the basis of a classification of Swedish NYK-83 and SEI units (for all countries these units are cross-classified with data on employment status, number of employees, and educational levels). A Stata format variant transcription of these codes was prepared by the authors and is available for download from the GEODE web pages.

Wright class scheme (WR; WR9)

The class categorisations advocated by Wright (1985) are conceptualised as reflecting differences associated with a Marxist employment and stratification structure. The categories are notoriously difficult to derive for non-specialist data (cf. Marshall et al., 1988, chpt 3), since they require details of the autonomy, supervisory roles and

¹⁴ The coding schedule is available for inspection at www.geode.stir.ac.uk. This recoding involves the author’s own specification of ‘manual’ and ‘non-manual’ occupations. In our classification, all occupations in ISCO major groups 1 and 2 were coded as ‘non-manual’ (even though some occupations in major group 2, such as ‘athletes’ or ‘nursing professionals’, might be viewed by some as manual in nature). Occupations in major groups 3-9 were coded on a case by case basis. Our criterion for allocating jobs as ‘non-manual’ was that the jobs were judged by us to be to be wholly or largely achievable by individuals with limited physical capability; ‘manual’ jobs were those, in our interpretation, which could not readily be undertaken without a certain degree of physical capability.

¹⁵ The work logic components central to Oesch’s scheme share many features with the technical distinctions advocated in a study of Spanish occupations by Rodriguez (2008).

skills involved in a job. We use the macros provided by Leiulfsrud et al. (2005) which are derived for variables on the European Social Survey. For both the BHPS and LNU, there are limitations in the extent to which this macro is reliably implemented, since not all of the required differentiation in positions is available in either scheme.

CAMSIS scales (CM, CF, CM2, CF2, CG)

CAMSIS scale scores are argued to represent a generalised structure of stratification which is exhibited through relations of social interaction between the incumbents of occupational positions (Prandy & Lambert, 2003). However, Chan and Goldthorpe (2004; 2007) derive empirically equivalent classifications but interpret them as measures of a Weberian interpretation of social status. In either case, scores are assigned to occupations which are claimed to represent the average position of an occupational incumbent in the structure of stratification or status; these scores are empirically derived from a multidimensional model of social interaction, and there is some ambiguity over the extent to which any derivation may exclusively differentiate the dimension of stratification/status from other influences upon social interaction patterns in occupational unit holders (such as induced by gender segregation patterns, and institutionally connected occupations).

Wage scores (WG1, WG2, WG3)

These scores indicate measures of the average levels of income associated with relevant occupational positions. They are ordinarily interpreted as direct measures of relative economic advantage.

Average Wage Mobility (AWM)

Bihagen and Ohls (2007) have advocated a measure of occupational circumstances based upon empirical patterns of intra-occupational wage mobility. An analysis on Swedish data derived a scale score for Sweden which can also, via ISCO-88, be linked to occupations from other countries – with the obvious criteria that its reflection of occupational progression structures might not be thought to translate consistently across countries.

Gender Segregation index (GN)

Sociologists studying stratification and class inequalities often acknowledge the importance of occupational gender segregation in impacting our interpretation of occupational circumstances. For instance, Hakim (1998) has demonstrated that the gender segregation profile of jobs often relates to relations of occupational advantage and disadvantage; see also Charles and Grusky (2005).

Result 1: The inter-relationship of occupation-based social classifications

Few sociologists would dispute that most occupation-based social classifications are highly correlated with each other (and with relevant other measures), yet the current authors know of only a few instances where such correlations have been explicitly published. Therefore, in Figures 2.1-2.3 we reiterate this point by attempting to summarise an array of correlations (31*31 associations, for each combination of men and women in Britain and Sweden). We use graphical representations of the average magnitude of each association¹⁶ and plot correlation points organised according to groups of related occupation-based social classifications. The first and core result is that almost all occupation-based social classifications have moderate correlations between each other (the only outliers are the gender segregation index and the dichotomous employment status categorisation). Moreover, occupational classifications which putatively have quite different conceptual foundations often turn out to be strongly correlated with each other. Indeed, in some instances, conceptually different schemes are more closely correlated than conceptually similar schemes.

The above pattern of generalised similarity is the core result that we choose to emphasise. However, it would be wrong to claim that this generalised similarity has no structure within in. On the contrary, there are also significant patterns of difference in the magnitude of associations within Figure 2.1-2.3 which do suggest that different occupation-based social classifications are measuring somewhat different properties.

To understand the nature of differences in occupation-based social classifications, Figures 2.4-2.7 are used to summarise patterns of ‘criterion’ validity, and Figures 3.4-3.7 are used to summarize patterns of ‘construct’ validity¹⁷. The multiple plots in Figures 2.4-2.7 show how different social classifications correlate with alternative indicators of ‘employment relations and conditions’. Measures of employment relations and conditions have been widely used to assess the criterion validity of the EGP and ESeC schemes. Our analysis, like those of several other papers, is restricted by the relatively limited volume of data in the LNU and BHPS surveys which could be interpreted as proxy measures of employment relations and conditions (esp. cf. Birkelund et al., 1996; Evans & Mills, 2000), and the lack of comparability between the countries. Moreover, many of the associations are heavily influenced by the high correlations between the measure of type of labour contract and the ESeC and EGP classifications (our measure of labour contract is, in fact, defined according to the ESeC categories, as specified in Rose & Harrison, 2007). For the latter reason, the Figures 2.4b-2.7b use equivalent data to 2.4-2.7, but exclude the labour contract measures from analysis.

¹⁶ The averages (of the association statistics) do not have any particular substantive significance – they are merely a function of the number of different social classifications operationalised. They are used in these and other figures as a convenient device to simplify the graphs.

¹⁷ Here, following the use of Rose and Harrison (2007), criterion validity is interpreted as the extent to which a measure is correlated to things it is designed to be related to, whilst construct validity is interpreted as the extent to which a measure is related to things which it is theorised to be correlated with.

Again, the core interpretation from Figures 2.4-2.7 which we choose to emphasize is the degree of consistency between different occupation-based social classifications. Although this would naturally be expected given the correlations seen in Figures 2.1-2.3, it is nonetheless striking that patterns in employment relations and conditions tend to be shared, by and large homogeneously, across schemes.

The plots in Figures 3.4a, 3.4b, and 3.5 to 3.7 summarize the magnitude of association between the alternative social classifications and various measures of unemployment risks, educational levels, subjective health, and parental occupational advantage (all widely used measures of 'construct' validity, cf. Rose & Harrison, 2007). For the time being we will highlight only the first part of those figures, the darker bar plots indicating the magnitude of association between the measure and the social classification. At this point, we emphasize again the broad similarity in the order of magnitude between the schemes, and the apparent lack of systematic relationship between the conceptual foundations of the relevant schemes, and the magnitude of correlations (on the contrary, with the exception of the gender segregation measures which have very low correlations, we see that the magnitude seems to be related more strongly to the level of differentiation between categories – compare, say, G11 with G5 – than the conceptual origins of a measure).

In summary, these simple reviews of patterns of correlation between measures show first and foremost a great deal of similarity between measures.

2.3 Other variables in the analysis

Other measures used in our analysis are summarised in Tables A.1-A.3.

Unemployment

Our central interest was in studying patterns of unemployment risk. In both countries we operationalised several alternative measures of unemployment over the period 1991-2002¹⁸. We derived two binary indicators, of whether or not an individual reported experiencing any unemployment over the period, or at least 12 months worth of unemployment in the period (cf. Elias & McKnight, 2003), which we analysed using logistic or probit regressions. To consider the impact of the extent of unemployment experienced, we also attempted to operationalise measures reflecting those used by Schizzerotto et al (2006), which cover the cumulative length of

¹⁸ For both countries, the categorisation of any period as one of 'unemployment' involves administrative criteria (of looking for work in Britain, and registering unemployed in Sweden). It is worth mentioning that Sweden has a long history of active social policy for keeping unemployment low. In the 1990s for instance when unemployment rose drastically one way of lowering it was to invest in the educational system, hence many people who would be unemployed or escaped unemployment ended up in educational programs. Thus, the unemployment we measure is clearly 'open' unemployment

unemployment. For Britain only, we were able to construct a measure of unemployment incidence rate (proportion of time economically active in the period 1991/2002 which is spent in unemployment), and for both countries we were able to construct a measure of cumulative experience of unemployment (the log of the total number of days unemployed after 1991). Both variables have highly skewed distributions, for which reason we analysed them using Poisson and negative binomial regression models. In fact, the empirical associates of unemployment risks proved largely stable across different measures of unemployment (see Figure 3.1), as a consequence of which many of our analyses are restricted for convenience to one measure (whether or not the respondent experiences more than one year of unemployment within the period).

3. Empirical patterns: Construct validity and parsimony

The devices used for comparison in Figures 3.1 to 3.7 attempts to jointly evaluate two conflicting intentions in most uses of occupation-based social classifications. On the one hand, to accurately measure structures of difference; on the other hand, to summarise this parsimoniously through occupational records. The latter aim is often not explicitly acknowledged as a feature of social classifications, though any review of published analyses of schemes reveals that social researchers have a strong preference for the most simplified possible social classifications (often summarising complex class classifications through a simple dichotomisation).

In Figures 3.1-3.7 we summarise the strength of association, between social classifications for individuals¹⁹, and other variables, by using conventional association statistics and plots of predicted values, but we add an additional factor in Figures 3.4-3.7 by also summarising a widely used indicator of relative parsimony, the BIC statistic (Raftery, 1986)²⁰.

Firstly, in Figures 3.1-3.3, we show the magnitude of bivariate effects of alternative social classifications upon unemployment risks. This shows that the two social classifications focussed upon are only weakly predictive of unemployment risks, and, for a result which will be of relevant in section 4, we note that other measures related to occupational locations – industry of occupations – is much more clearly related to unemployment than the social classifications measured. Then, in Figures 3.4 to 3.7, we review more systematically the extend of the association between relevant constructs and alternative social classifications.

¹⁹ The plots of relationships with Father's social classifications shown in Figure 3.4c are discussed in Section 4.

²⁰ Some authors have been rightly sceptical that use of the BIC statistic can over-emphasise the importance parsimony. Since our analyses are entirely concerned with comparing relative degrees of parsimony this is not a relevant concern in this instance.

Result 2: The ambiguity of optimal social classifications

The sentiment cited above by Mills and Evans (2003), that different measures are preferable in different circumstances, is difficult to act upon for the range of outcomes covered in this analysis, since alternative occupation-based social classifications do not have clear strengths and weaknesses in any outcome. Typically, we see that the association decreases, but parsimony improves, when related categorical measures reduce the number of categories, and we generally see that metric measures are often more promising in combining a moderate degree of association with above average parsimony. We also see that high-category categorisations, such as the Oesch 17-class scheme, and the Wright 12-class version, appear on national samples to have little to recommend them, since they lack parsimony but also do not feature notable additional association. However, despite these small differences, the order of magnitude is otherwise quite similar between different schemes, which might suggest that any measure would be adequate. Moreover, there are numerous small variations between gender and country which, if used to select alternative measure, might compromise the coherence of a comparative analysis.

There are many interesting relationships within these patterns which are worthy of further commentary. Most obviously given our focus on ESeC, is the similarity between the ESeC and EGP schemes, but the relative strengths of the latter, at least in its 11 and 7 category versions, over comparable ESeC classifications in both countries. This suggests that in this periods, ESeC may be an adequate but imperfect alternative to EGP categorisations.

4. Empirical properties: Understanding social processes

Hitherto, the results presented have concentrated upon bivariate or limited multivariate associations between occupation-based social classifications and putatively related measures. Of course, not only do social scientists have numerous alternatives in how they code occupational data, they also have numerous alternatives in the analytical methods they may use when studying processes related to occupational measures. Indeed, there are good grounds for anticipating that the story revealed when comparing occupation-based social classifications may change significantly when more complex analytical relationships are considered.

One reason this may occur reflects simple demographic structures and their instability across time and between genders. For instance, some occupation-based social classifications have categories or positions which are dominated by one or another gender and/or by people at certain career stages. Entry into different locations in the classification is therefore partly determined by gender, age and time period; if these themselves are correlated to the outcome of interest (such as poor health) we could have a classically spurious interpretation of occupational effects. A subsequent

hypothesis may therefore be that the differences between occupation-based social classifications in discriminating other measures would themselves diminish when such endogenous processes are accounted for. Needless to say, however, there is little certainly over how much endogeneity could – or should – be accounted for.

One relatively succinct way in which to try control for such effects is to concentrate upon the relative strengths of parental occupation-based social classifications (on the assumption that parental occupations are in large part independent of many of the individual level differences which may influence the properties of occupation-based social classifications. Therefore, the hypothesis that differences between occupation-based social classifications are in part a misleading function of endogenous occupational locations, would hold that differences between the influence of parental occupational positions would diminish compared to those between own occupational positions. We attempt to evaluate this in Figure 3.4c. Unfortunately, the magnitude of parental effects on current unemployment are too slight for an unambiguous interpretation. However, if anything the evidence runs against our hypothesis of diminishing differences between schemes, since the graphs show traces of differences between measures which resemble scaled down versions of the same differences between individual level occupations.

The second, more conventional approach to accounting for spurious effects is to develop a multivariate model for all factors which might influence unemployment risks. In the case of simple socio-demographic measures this can conventionally be achieved by a univariate regression analysis. Figures 4.1 and 4.2 (Model 1) show the differences between 8 selected social classification schemes for men in these groups. However a more complex specification may be required to account for the possible role of industry in predicting unemployment. It may be expected that different industries would carry quite different risks of unemployment, which to an extent is embodied by our measure of 3 industrial sections and its influence on unemployment risks shown in Figure 3.2²¹. Should we wish to differentiate the concept of industry from that of occupation-based social classification, we could simply enter industry of job in a regression model (Model 2 of Figures 4.1 and 4.2), however, this would still be flawed since we would have a model with endogenous predictors. A further alternative, therefore, would be to estimate a selection model in which the prediction of unemployment risks is undertaken within an industry group, after a previous related model is estimated predicting entry to the relevant industry. These are summarised in Models 3 and 4 of Figures 4.1 and 4.2. Our hypothesis was that the (already small) differences between occupation-based social classifications seen in the simpler analyses summarised in Figures 3.4-3.7, would diminish further when additional multivariate factors were accounted for. However, inspection of Figures 4.1 and 4.2 reveals that this does not particularly occur.

Result 3: Persistence of small differences between conceptually distinct occupation-based social classifications

²¹ Of course, this 3-category measurement of the concept of industrial sector may seem inadequate, though a 9-category industrial classification led to similar results.

Our third core result runs counter to our own initial expectations. Differences between different occupation-based social classifications which can be given a conceptual interpretation do not diminish to insignificance when other factors are controlled for. On the contrary, there is a small premium to the EGP scheme, and to a lesser extent to the ESeC scheme, in predicting unemployment risks which does not seem to be related to the endogeneity of industry, life course stage and gender to class position. Contrary to the main thrust of our argument in this paper, this suggests that some level of difference between measures of social classifications do genuinely reflect conceptual foundations of the measurements.

5. Conclusions

Sociologists make widespread use of occupation-based social classifications such as social class schemes and stratification scales. They frequently use these measures as summary indicators of individuals' overall life chances or advantages. Contrary to certain speculative social commentaries, our results confirm, along with numerous other empirical analyses, the continued relevance of occupation-based social classifications to understanding life chances and advantages.

The focus of our analyses was on the degree to which the properties that alternative occupation-based social classifications measure, are related to the differences between the concepts which underlie the alternative schemes. We found that an array of alternative occupation-based measures overlap substantially in the factors which they empirically measure. By showing high degrees of similarity between schemes in their correlations with each other and with other related factors, we argued that the extent to which different schemes measure different concepts is minimal. On the other hand, through finding small persistent differences in the properties of different classifications, we also find that while conceptually founded measurement differences between schemes may be minimal, they do exist.

Important questions concern what which can recommend from this review. Firstly, with regard to the ESeC classification, we can emphasise that it is unrealistic to assert that the ESeC categorisation clearly measures concepts of employment relationships in a manner that is different from other alternative schemes. On the contrary, our analyses suggest that the ESeC scheme, along with all the other classifications reviewed, is first and foremost a measure of a generalised structure of stratification. In this respect, a stratification scheme which itself describes itself as such a generalised structure is arguably a more favourable option.

As the ESeC scheme is an influential and significant endeavour in occupation-based social classifications, we can conclude that there is work to be done in clarifying how we relate the concepts and measures of alternative occupation-based social classifications.

Table 1: Occupation-based social classifications				
<i>(grouped according to conceptual foundations)</i>				
Abbr.	GB	SW	Comments	
1	ES5	Y	Y	Employment status, 5 categories. (Employee; supervisor/manager; self-employed > 10 empy.; self-emp. 1-10 empy.; self-emp. no employees)
2	ES2	Y	Y	Employment status, 2-categories. (Employee; self-employed)
3	E9	Y	Y	ESeC (full version). 9-categories:
4	E6	Y	Y	ESeC (reduced 6-category version). As ESC9 but merges categories 1 and 2; 3 and 6; 4 and 5 (see Rose and Harrison 2007, p464)
5	E5	Y	Y	ESeC (reduced 5-category version). As ESC6 but merges categories 5 and 6 (see Rose and Harrison 2007, p464)
6	E3	Y	Y	ESeC (reduced 3-category version). As ESC5 but merges categories 2 and 3; 4 and 5 (see Rose and Harrison 2007, p464)
7	E2	Y	Y	ESeC (reduced 2-category version). Separates ESeC 1 and 2 salariat, from all other classes (see Rose and Harrison 2007, p464)
8	G11	Y	Y	EGP (11-category version). Erikson, Goldthorpe, Portacero class scheme (see Erikson and Goldthorpe 1992, p38-9 for categories and versions)
9	G7	Y	Y	EGP 7-category scheme (Erikson and Goldthorpe 1992, p38-9)
10	G5	Y	Y	EGP 5-category scheme (Erikson and Goldthorpe 1992, p38-9)
11	G3	Y	Y	EGP 3-category scheme (Erikson and Goldthorpe 1992, p38-9)
12	G2	Y	Y	EGP 2-category scheme (separates Service classes I and II from others)
13	K4	Y	Y	Elias Skill levels. 4-category definition of skill levels associated with ISCO-88 occupations (see Elias 1996)
14	WR	Y	Y	Wright class scheme (12-categories). Derived using ISCO-88 occupations via algorithm of Leisufrud et al (2005). British derivation requires imputations on job autonomy using managerial status questions.
15	WR9	Y	Y	Wright class scheme (9-categories). As WR, but recoding into 9 categories by merging workers and supervisors within skilled categories.
16	O17	Y	Y	Oesch 'work logics' class scheme (17 categories). Oesch (2006, p222), derived from ISCO-88 plus employment status data.
17	O8	Y	Y	Oesch class scheme (8 categories). Oesch (2006, p68).
18	O4	Y	Y	Oesch class scheme (4 categories). Oesch (2006, p82-3).
19	MN	Y	Y	Manual / Non-Manual dichotomy (using ISCO-88 recode)
20	CM	Y	Y	Male CAMSIS scale scores, national scales / units
21	CF	Y	Y	Female CAMSIS scale scores, national scales / units
22	CM2		Y	Male CAMSIS scales scores, national scales / ISCO
23	CF2		Y	Female CAMSIS scales scores, national scales / ISCO
24	CG	Y		Chan-Goldthorpe Status-scale scores (dimension 1 from Chan and Goldthorpe 2004)
25	ISEI	Y	Y	ISEI : International Socio-Economic Status scale from ISCO88 (using Ganzeboom et al 2003, 2007)
26	SIOP	Y	Y	SIOPS : Standard International Occupational Prestige Scale scores, ISCO88 (using Ganzeboom et al 2003, 2007)
27	AWM	Y	Y	Average Wage Mobility score: Estimated average wage mobility for occupational units in Sweden (see Bihagen and Ohls 2006). For Britain, scores are calculated from Swedish data via ISCO88
28	WG1		Y	Average wage of occupation - in Sweden, predicted by OLS controlling for age, gender, 1999 data
29	WG2		Y	Average Wage of occupation - in Sweden, predicted by OLS controlling for age, gender, 2003 data
30	WG3	Y		Average Wage of occupation - for male full time wage of occupation in Britain, using 1992 Labour Force Survey at SOC-90 2-digit level
31	GN1	Y	Y	Gender segregation index. Average percent of women in each occupational unit group. For Britain, averages for SOC-90 unit groups in 1991, using Hakim (1998).

Table A.1 Descriptive statistics for British analytical sample
Adults aged 23-55 interviewed in 1991 with full life history data to 2002

by gender and age at interview in 1991

	Males				Females			
	23-33	34-44	45-55	<i>n</i> (<i>N</i>)	23-33	34-44	45-55	<i>n</i> (<i>N</i>)
Employee (10+ hrs/wk)	75	72	67	1142	64	62	63	1208
Self-employed	12	17	19	249	4	8	7	111
Not working (or < 10hrs)	13	11	15	206	37	30	31	650
				(1597)				(1969)

by gender and employment status in 1991

	Males				Females			
	Empye.	S-E	N/W	%mg	Empye.	S-E	N/W	%mg
Pct. married or cohabiting	82	84	69	0	78	87	82	0
Mean (sd) school leaving age (truncated at age 26)	17.9 (3.1)	17.8 (3.2)	17.3 (3.1)	2	17.8 (3.1)	18.4 (3.5)	17.0 (2.6)	1
Highest qualifications (%):				3				1
Low school or below	21	24	38		23	21	42	
Higher school level	33	34	30		38	32	33	
Vocational	18	17	10		12	20	10	
Degree/Diploma	25	22	17		27	27	14	
Mean work experience yrs, to 1991	19.6	21.7	17.8	4	16.0	16.5	13.1	3
Mean work experience yrs, in current job, to 1991	5.7	7.4	n/a	0	4.2	6.7	n/a	0
Unemployment 1991-2002				0				0
Pct any Un. in period	27.5	22.5	68.4		23.2	16.2	31.2	
Pct cumulative Un. >= 1 yr	8.8	8.8	47.1		5.5	7.2	12.3	
Un. Incidence (time Un / time Un or working)*100	3.4	2.3	33.8		2.3	2.1	10.6	
Mean Un duration (ln.days in Un. between 1991-2002)	1.5	1.2	4.4		1.2	0.9	1.7	

%mg = Percent of all valid case with missing data on this variable (0 by definition for unemployment on analytical file)

Table A.2 Descriptive statistics for British random sample

Adults aged 23-55 interviewed in 1991

by gender and age at interview in 1991

	Males				Females			
	23-33	34-44	45-55	n (N)	23-33	34-44	45-55	n (N)
Employee (10+ hrs/wk)	72	67	64	1980	58	62	60	1897
Self-employed	12	19	19	482	4	6	7	178
Not working (or < 10hrs)	16	14	17	448	38	31	34	1095
				(2910)				(3170)

by gender and employment status in 1991

	Males				Females			
	Empye.	S-E	N/W	%mg	Empye.	S-E	N/W	%mg
Pct. married or cohabiting	79	83	64	0	77	85	76	0
Mean (sd) school leaving age (truncated at age 26)	17.8 (3.0)	17.6 (3.1)	17.2 (3.1)	4	17.8 (3.1)	18.3 (3.3)	16.8 (2.5)	2
Highest qualifications (%):				5				2
Low school or below	24	26	36		25	20	45	
Higher school level	32	31	28		36	36	30	
Vocational	17	17	12		12	16	10	
Degree/Diploma	22	20	16		25	25	12	
Mean work experience yrs, to 1991	17.8	19.9	16.6	10	14.9	15.5	12.8	9
Mean work experience yrs, in current job, to 1991	5.8	8.0	n/a	0	4.3	6.3	n/a	0
Unemployment 1991-2002				45				38

%mg = Percent of all valid case with missing data on this variable

Unemployment: observed percentages for random sample are equal to those of analytical sample

Table A.3 Descriptive statistics for Swedish random sample

Adults aged 23-55 interviewed in 1991

by gender and age at interview in 1991

	Males				Females			
	23-33	34-44	45-55	n (N)	23-33	34-44	45-55	n (N)
		col. %				col. %		
Employee (10+ hrs/wk)	70	71	70	1224	55	69	69	1046
Self-employed (10+ hr/wk)	7	14	14	202	2	5	6	66
Not working or < 10hrs	23	15	16	316	44	27	25	519
				(1742)				(1631)

by gender and employment status in 1991

	Males				Females			
	Empye.	S-E	N/W	%mg	Empye.	S-E	N/W	%mg
% married or cohabiting	74	78	57	0	76	79	79	0
Mean (sd) years of educ. (truncated at 24yrs)	11.9 (3.3)	11.7 (3.1)	11.6 (3.6)	0*	11.8 (3.0)	11.9 (2.9)	11.4 (3.2)	0*
Highest qualifications (%):								
Lower gymnasium	68	73	69	0	70	71	75	0
Higher gymnasium	19	19	24		20	15	19	
Academic	13	8	7		10	14	5	
Mean work experience yrs, to 1991	18.9	21.3	15.9	0*	16.6	19.7	13.1	0*
Mean work experience yrs, in current job, to 1991	10.3	n/a	n/a	14*	9.0	n/a	n/a	11*
Unemployment 1991-2002								
Pct any Un. in period	35.9	43.1	54.7	0	38.9	45.4	51.6	0
Pct cumulative Un. >= 1 yr	25.6	27.2	41.3		29.3	36.4	39.1	
Mean Un duration (ln.days in Un. between 1991-2002)	2.3	2.7	3.6		2.3	3.1	3.4	

%mg = Percent of all valid case with missing data on this variable

* For work experience: total work experience data is missing for 5% of non-working sample, but is present for all employees / self-employed. Current job work experience is only interpretable for current employees, and is missing for 14% / 11% of the sample of male / female current employees.

Figures referred to in the text

Figure 1: Screenshot of the GEODE portal www.geode.stir.ac.uk

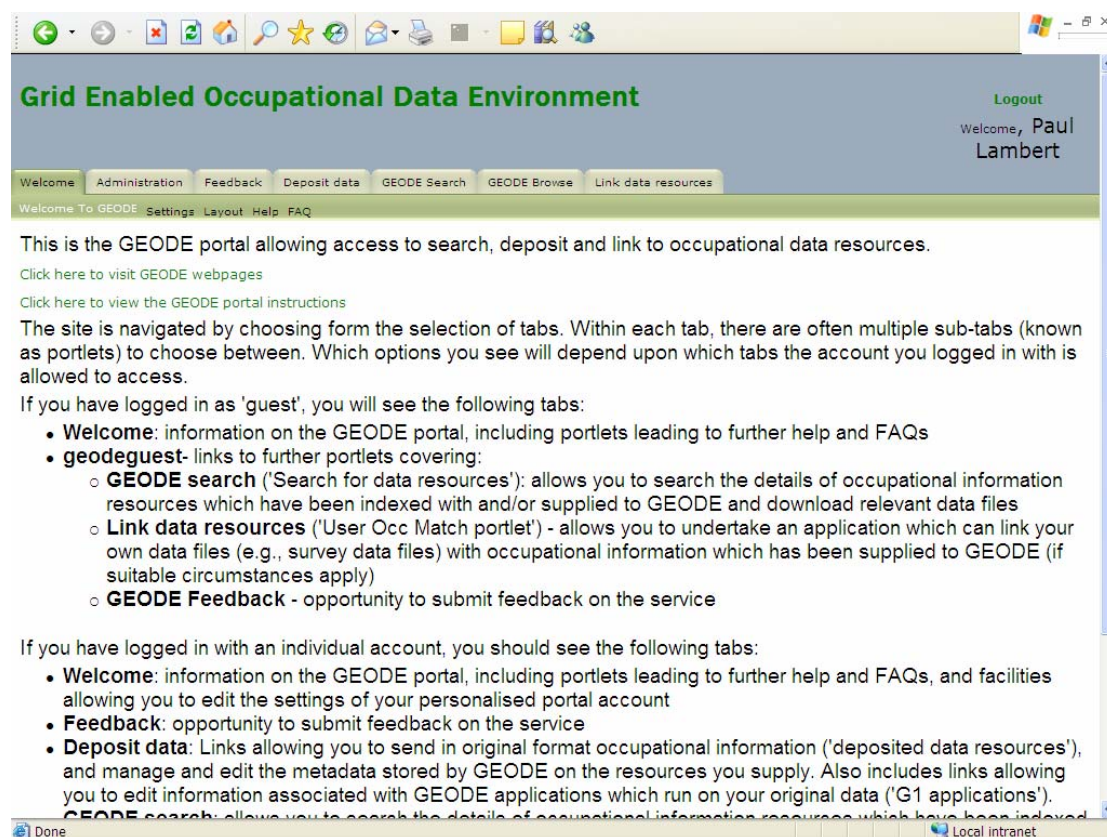
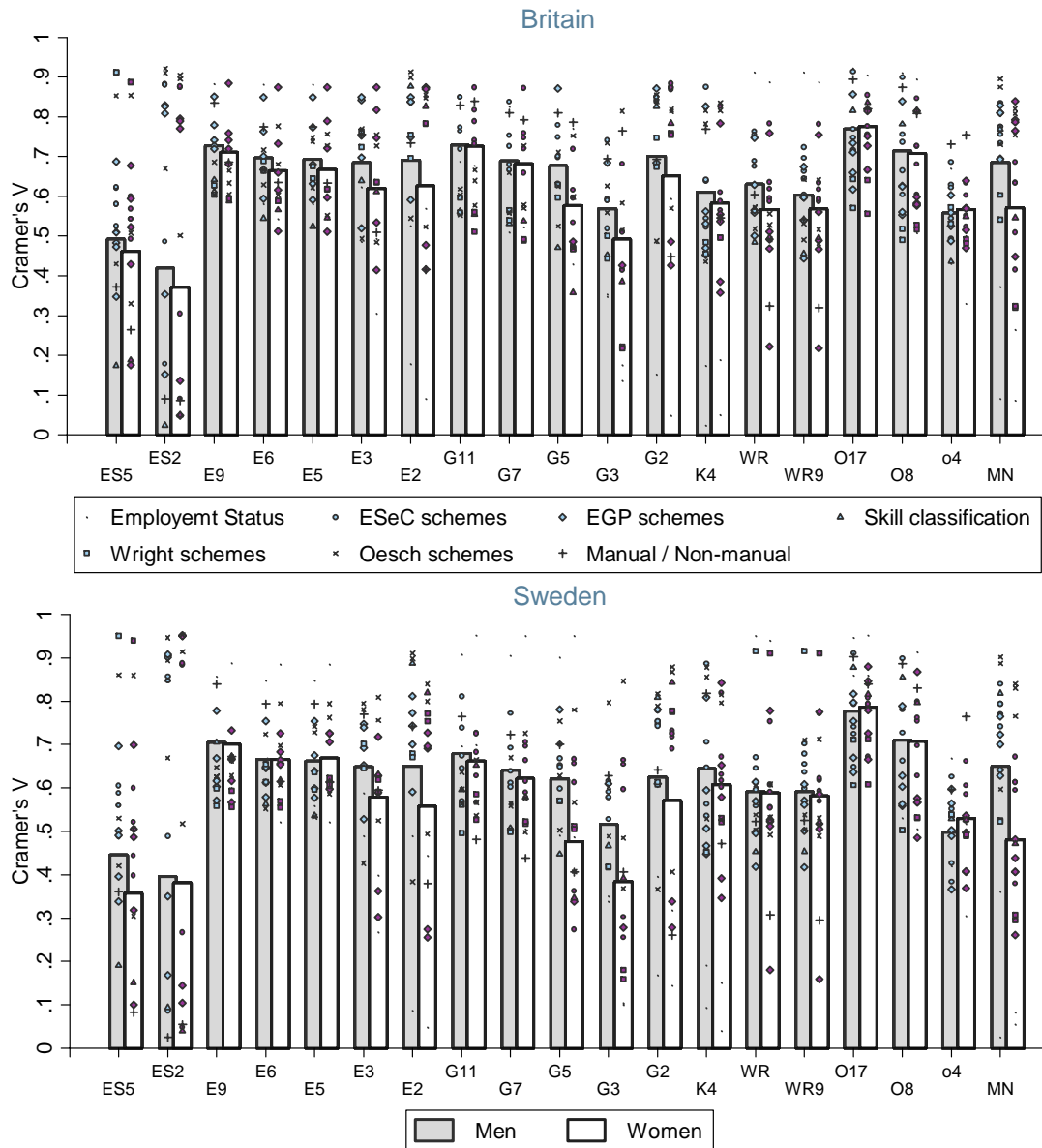


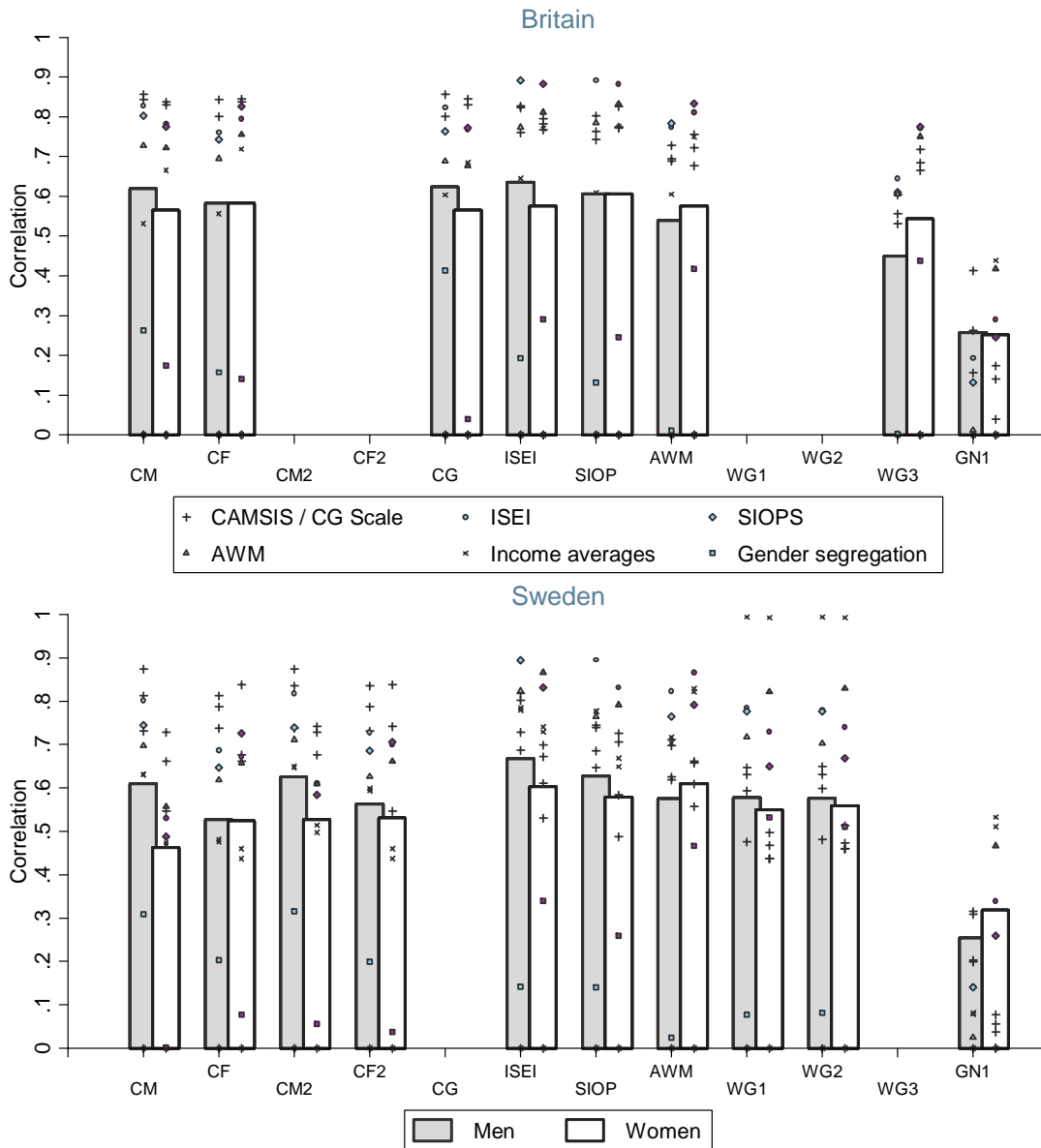
Figure 2.1: Association statistics for categorical schemes
 Categorical - Categorical relations, Cramer's V statistics



Source: Data and schemes as Table 1.
 Bars show average association between all types of measures, for men and women.
 Points show individual associations with alternative schemes (excluding perfect correlations).
 Occupation-based social classifications as listed in Table 3.1.

Figure 2.2: Association statistics for metric scales

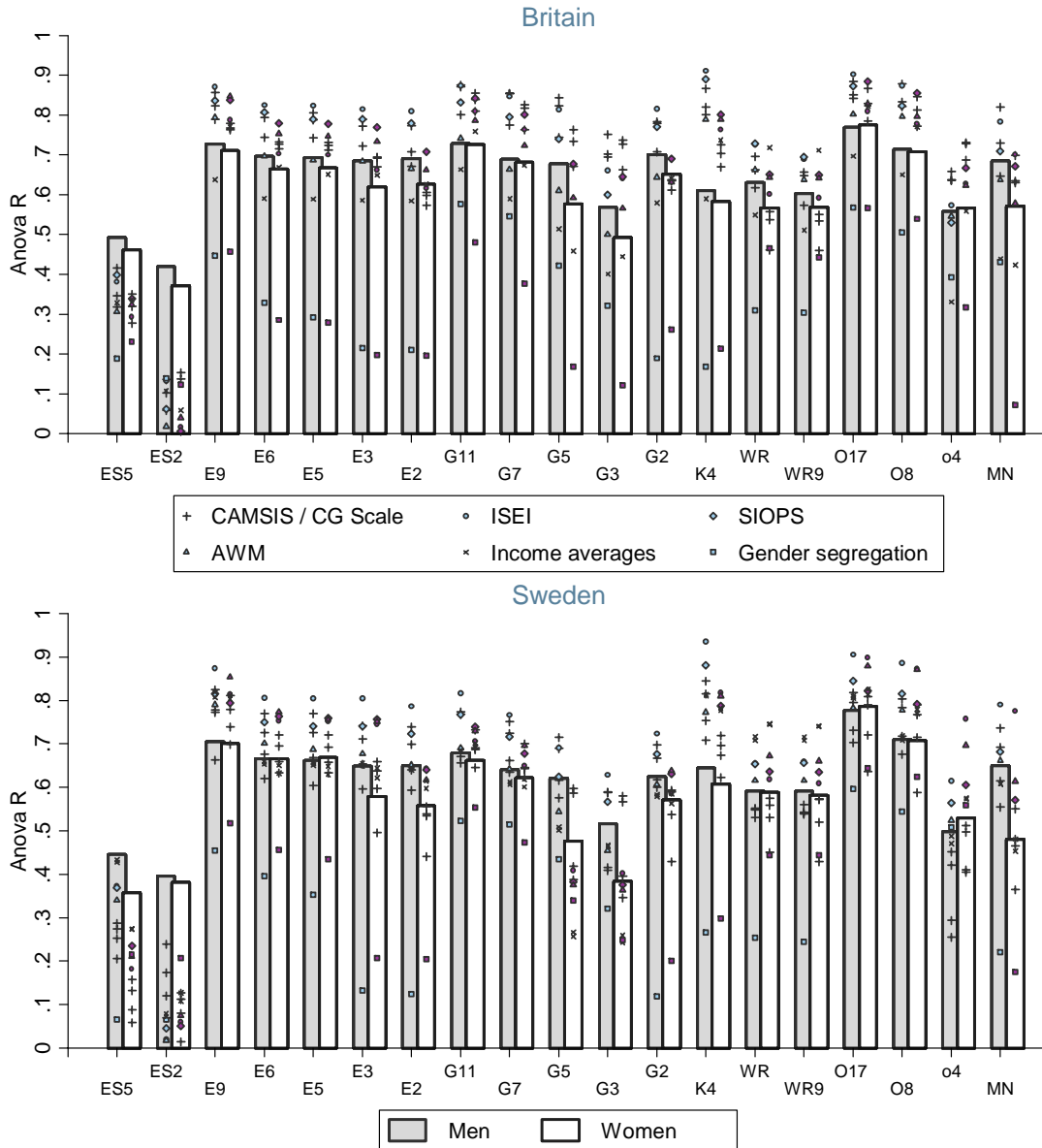
Metric-Metric relations, Linear correlations



Source: Data and schemes as Table 1.
 Bars show average association between all types of measures, for men and women.
 Points show individual associations with alternative schemes.
 Occupation-based social classifications as listed in Table 3.1.

Figure 2.3: Association statistics (3)

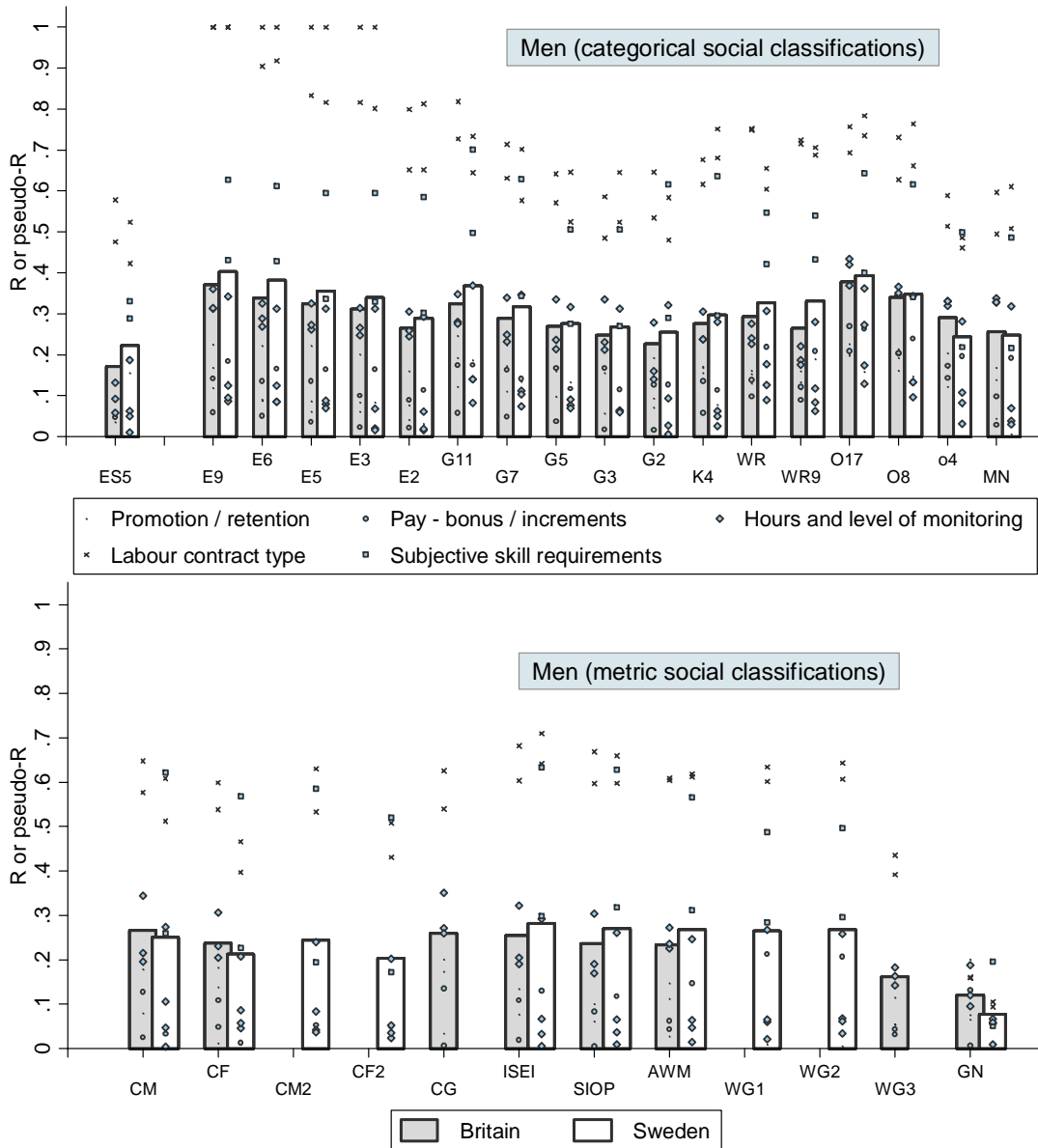
Categorical-Metric relations, Anova R



Source: Data and schemes as Table 1.
 Bars show average association between all types of measures, for men and women.
 Points show individual associations with alternative schemes.
 Occupation-based social classifications as listed in Table 3.1.

Figure 2.4: Employment Relations and Conditions

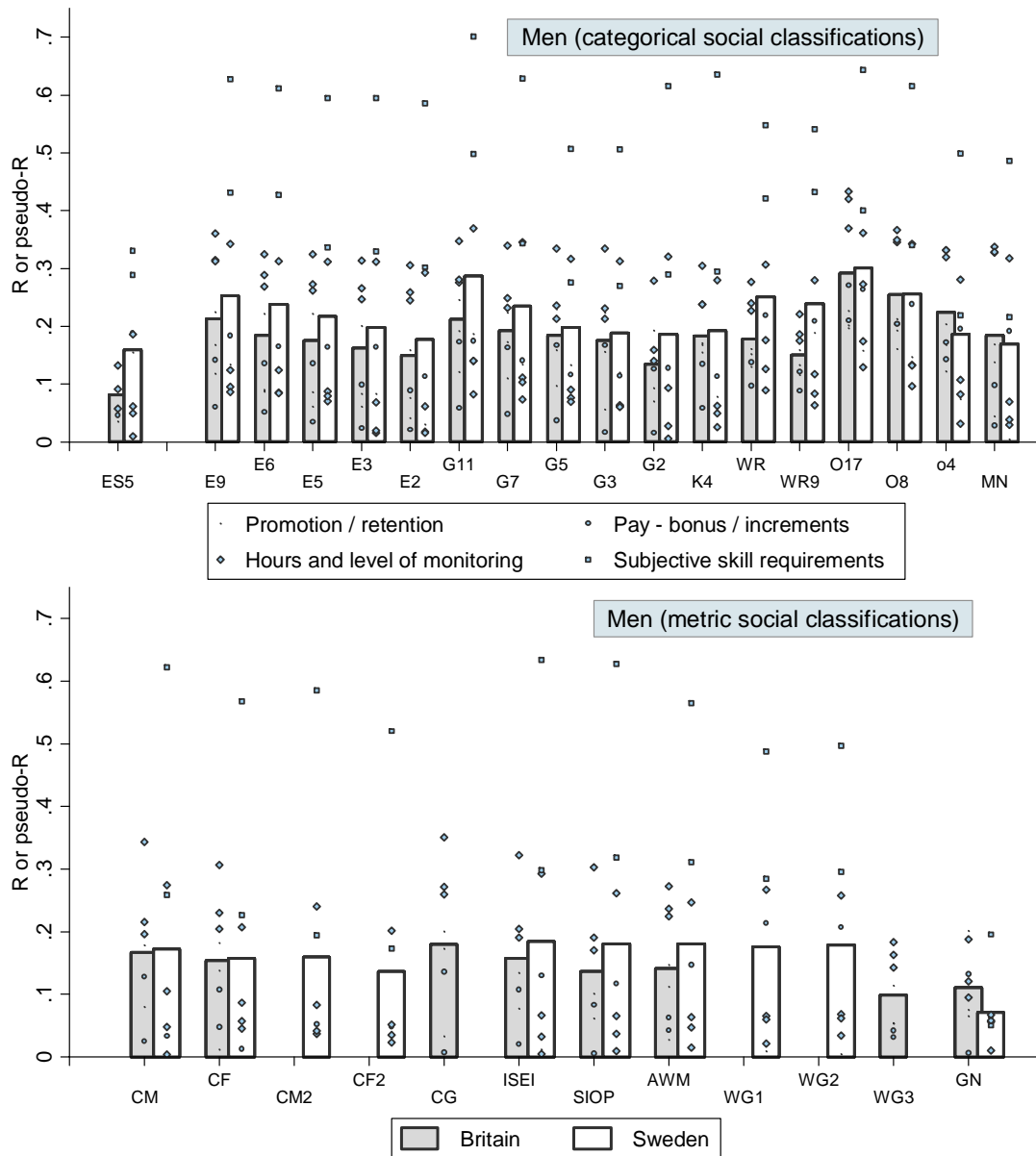
Associations with alternative social classifications



Source: Data and schemes as Table 1. Employees only.
 Points show regression correlation for alternative schemes in predicting ERC measures.
 (Pseudo-R for categorical, R for metric ERC's). Bars show indicative averages for all ERCs.
 Occupation-based social classifications as listed in Table 3.1.

Figure 2.4b: Employment Relations / Conditions (excluding contract data)

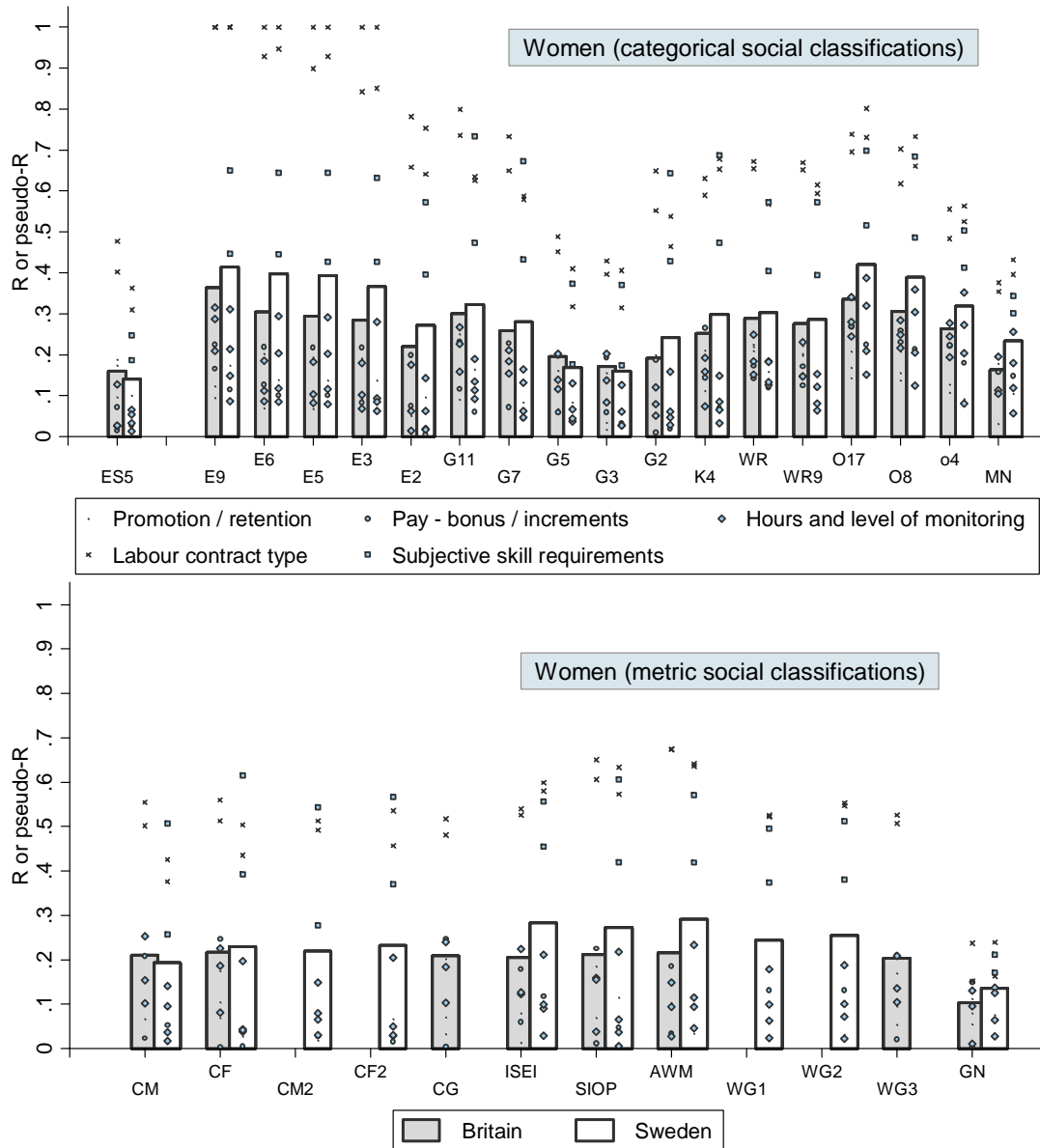
Associations with alternative social classifications



Source: Data and schemes as Table 1. Employees only.
 Points show regression correlation explained by alternative schemes in predicting ERC measures.
 (Pseudo-R for categorical, R for metric ERC's). Bars show indicative averages for all ERCs.
 Occupation-based social classifications as listed in Table 3.1.

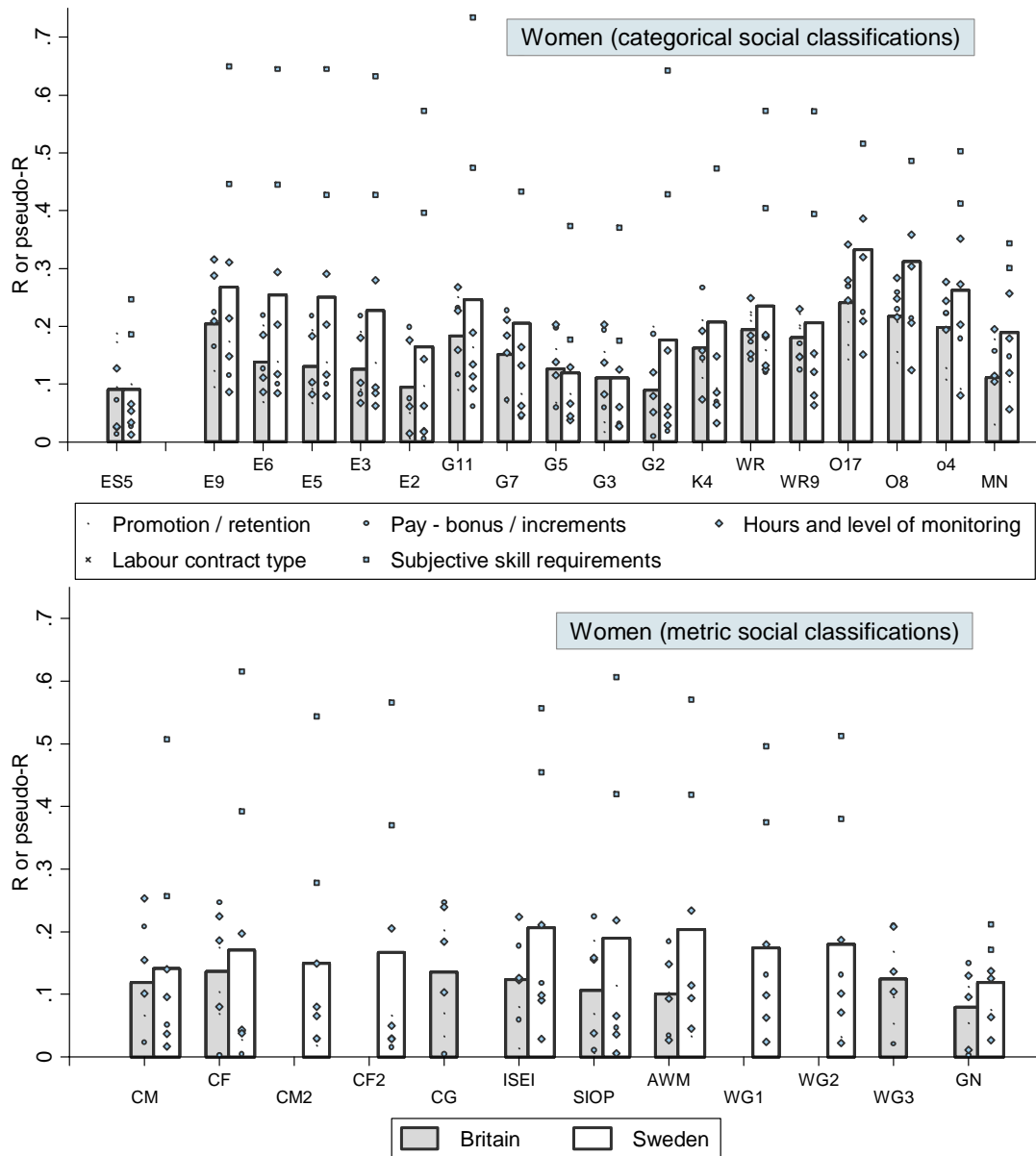
Figure 2.5: Employment Relations and Conditions

Associations with alternative social classifications



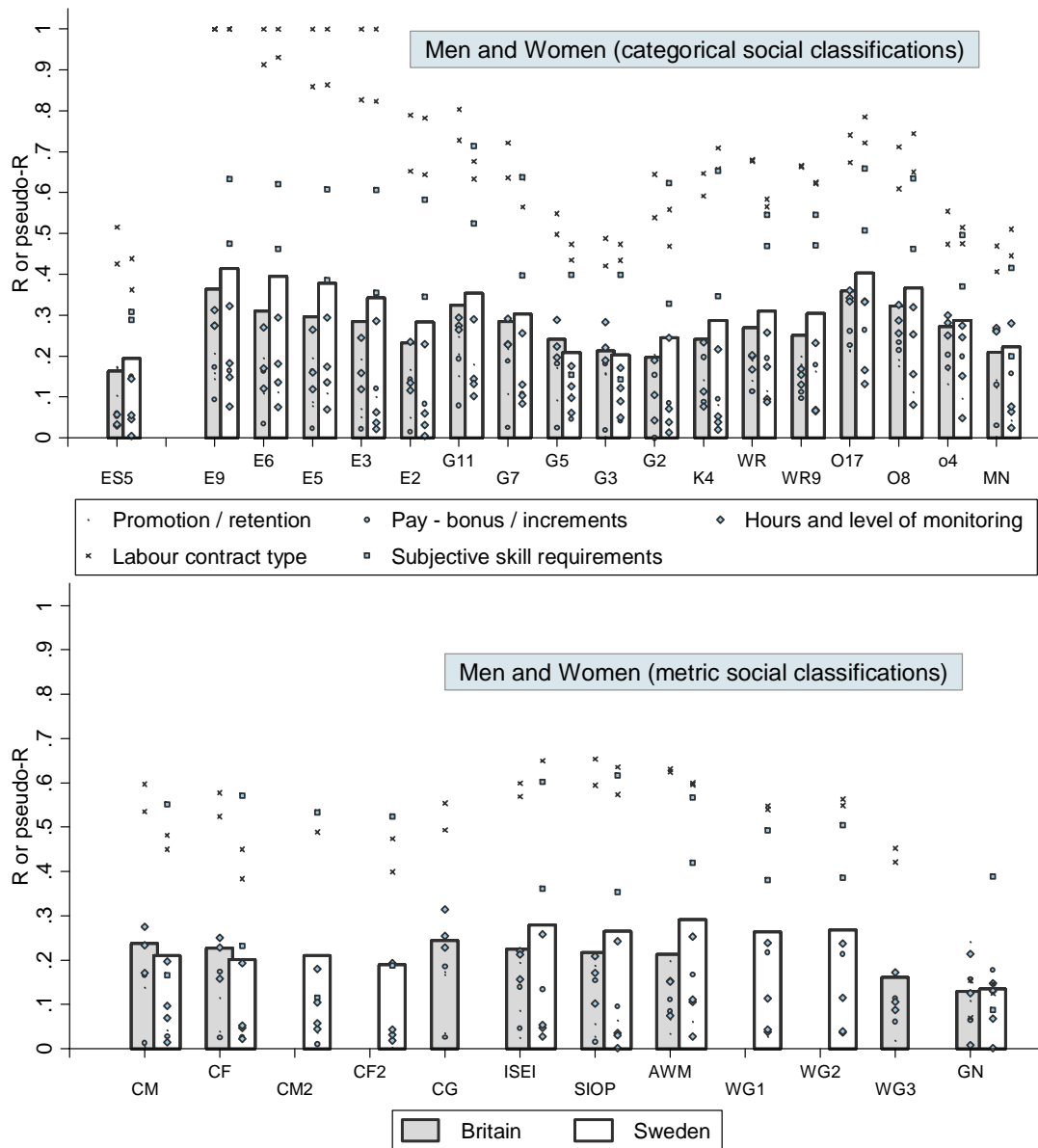
Source: Data and schemes as Table 1. Employees only.
 Points show regression correlation by alternative schemes in predicting ERC measures.
 (Pseudo-R for categorical, R for metric ERC's). Bars show indicative averages for all ERCs.
 Occupation-based social classifications as listed in Table 3.1.

Figure 2.5b: Employment Relations / Conditions (excluding contract data)
Associations with alternative social classifications



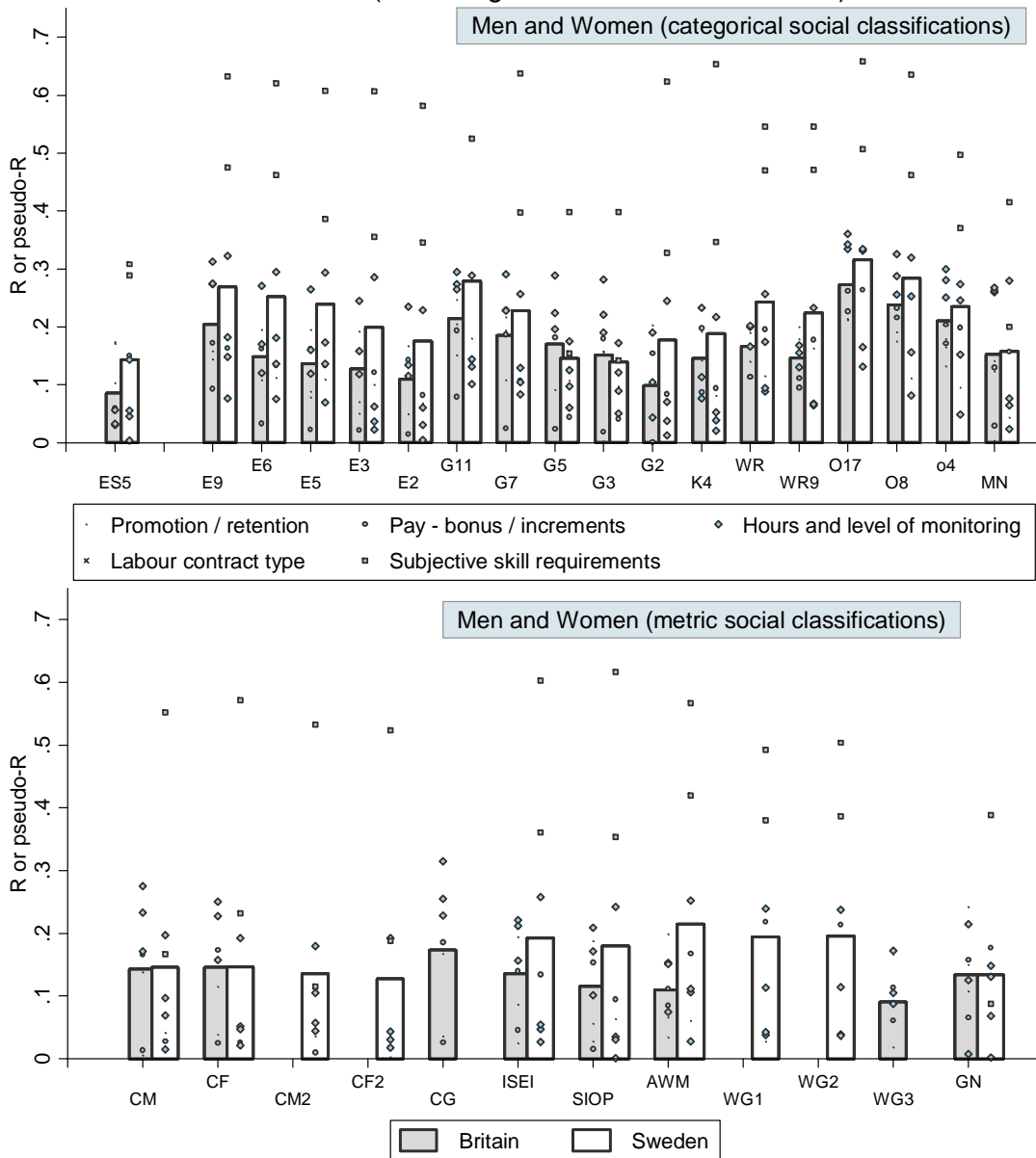
Source: Data and schemes as Table 1. Employees only.
Points show regression correlation by alternative schemes in predicting ERC measures.
(Pseudo-R for categorical, R for metric ERC's). Bars show indicative averages for all ERCs.
Occupation-based social classifications as listed in Table 3.1.

Figure 2.6: Employment Relations and Conditions
Associations with alternative social classifications



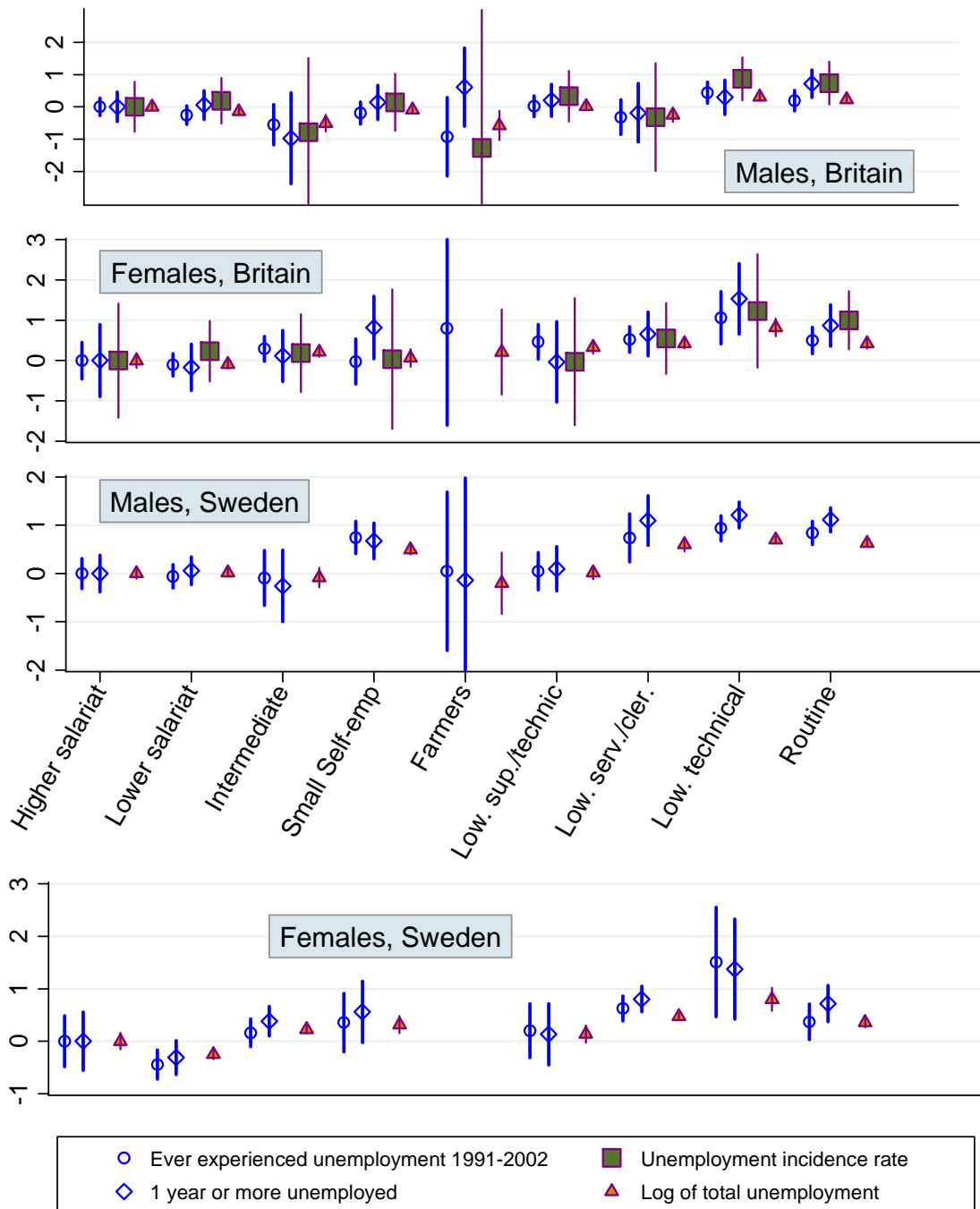
Source: Data and schemes as Table 1. Employees only.
Points show regression correlation by alternative schemes in predicting ERC measures.
(Pseudo-R for categorical, R for metric ERC's). Bars show indicative averages for all ERCs.
Occupation-based social classifications as listed in Table 3.1.

Figure 2.6b: Employment Relations / Conditions (excluding contract data)
Associations (excluding labour contract measures)



Source: Data and schemes as Table 1. Employees only.
Points show regression correlation by alternative schemes in predicting ERC measures.
(Pseudo-R for categorical, R for metric ERC's). Bars show indicative averages for all ERCs.
Occupation-based social classifications as listed in Table 3.1.

Figure 3.1: Predictions of Unemployment risk, 1991-2002
 Comparison intervals for ESeC categories, by unemployment measure



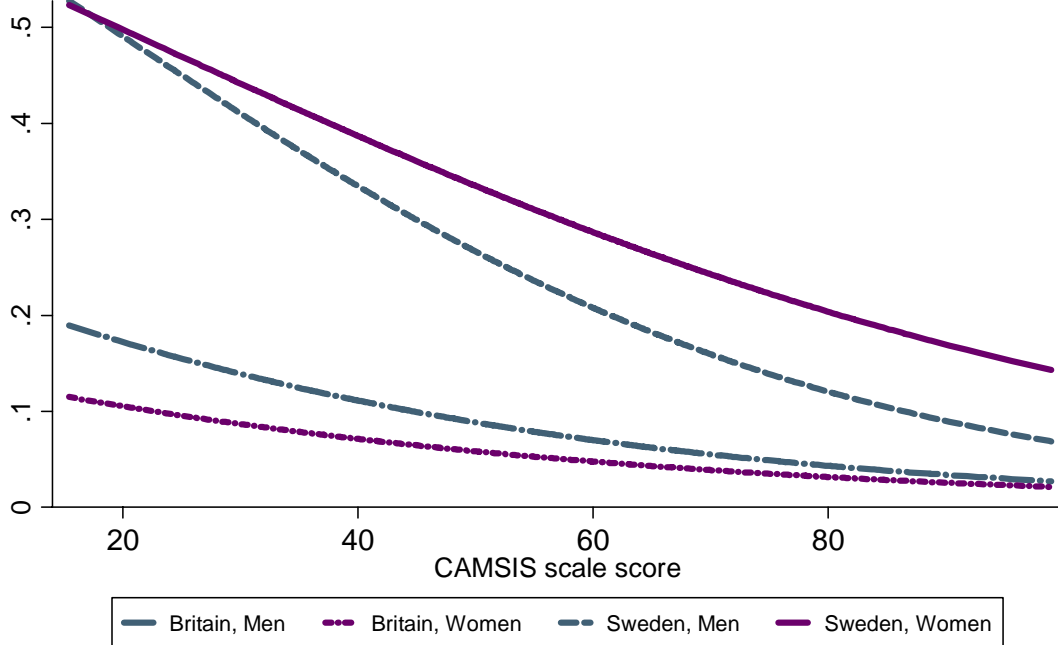
Source: LNU and BHPS 1991-2002, adults 23-55yrs in work 1991, N=2709 Britain, 2538 Sweden. Graph shows regression coefficients of ESeC categories, and quasi-variance comparison intervals. Null models - ESeC categories are only predictors. Unweighted data.

Figure 3.2: Unemployment by Industry categories
Experiences 1 year or more of unemployment



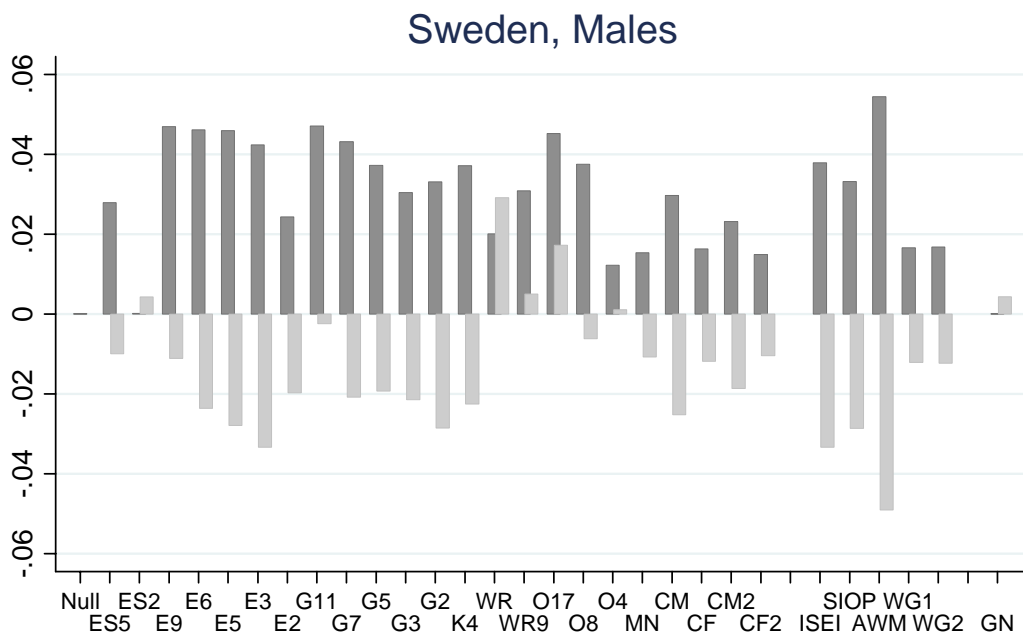
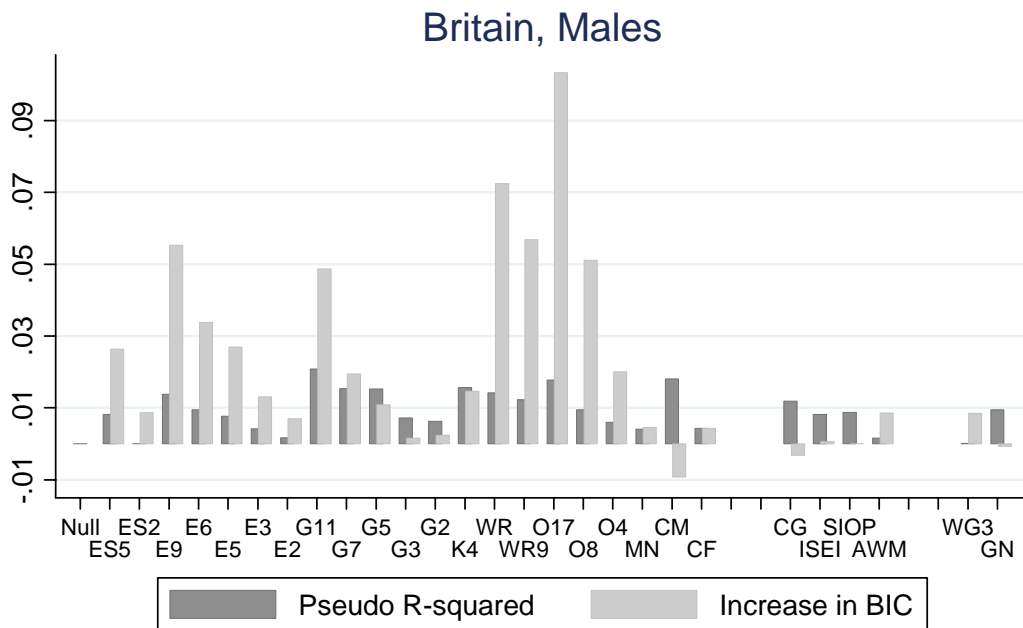
Source: As Figure 3.1, LNU, 1991-2002 and BHPS 1991-2002, all adults aged 23-55 in work in 1991. Graph shows regression coefficients of Industry category dummies, with 'quasi-variance' comparison intervals.

Figure 3.3: Unemployment by CAMSIS scale score
Probability that experiences 1 year of more unemployment within 1991-2002



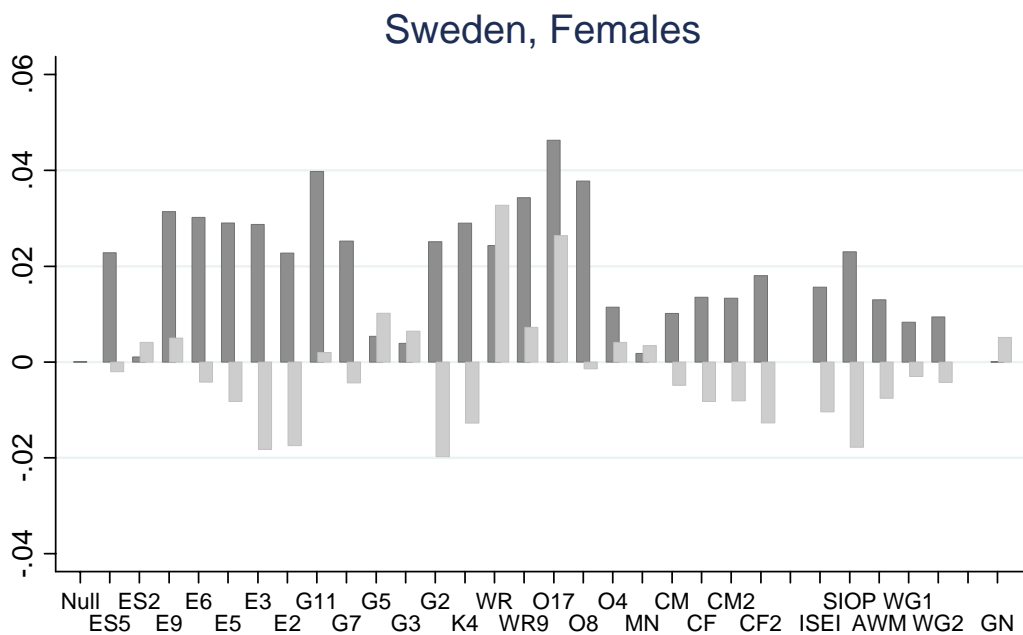
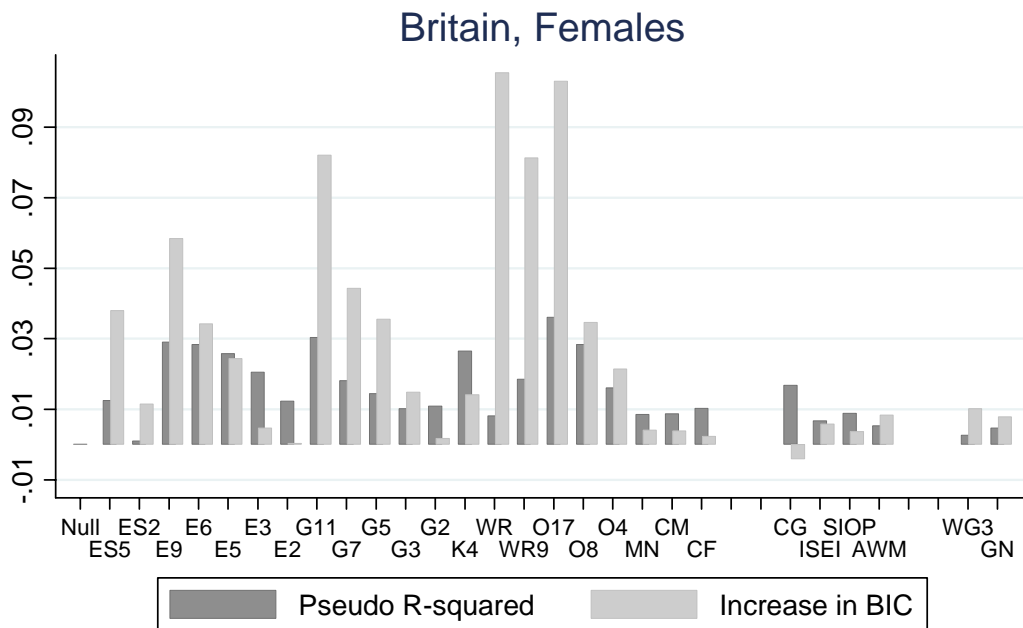
Source: As Figure 3.1, LNU, 1991-2002 and BHPS 1991-2002, all adults aged 23-55 in work in 1991. Graph shows regression predicted values. Confidence intervals omitted for clarity.

Figure 3.4a: R-2 and BIC for predicted unemployment risk
 Explanatory power of schemes in predicting 1+ year Unemp., 1991-2002



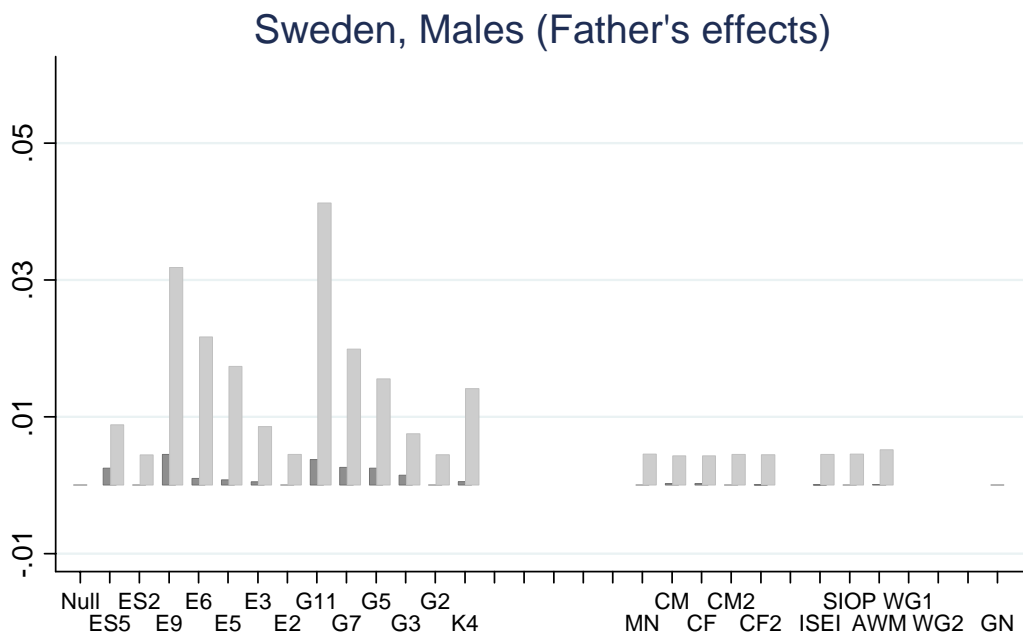
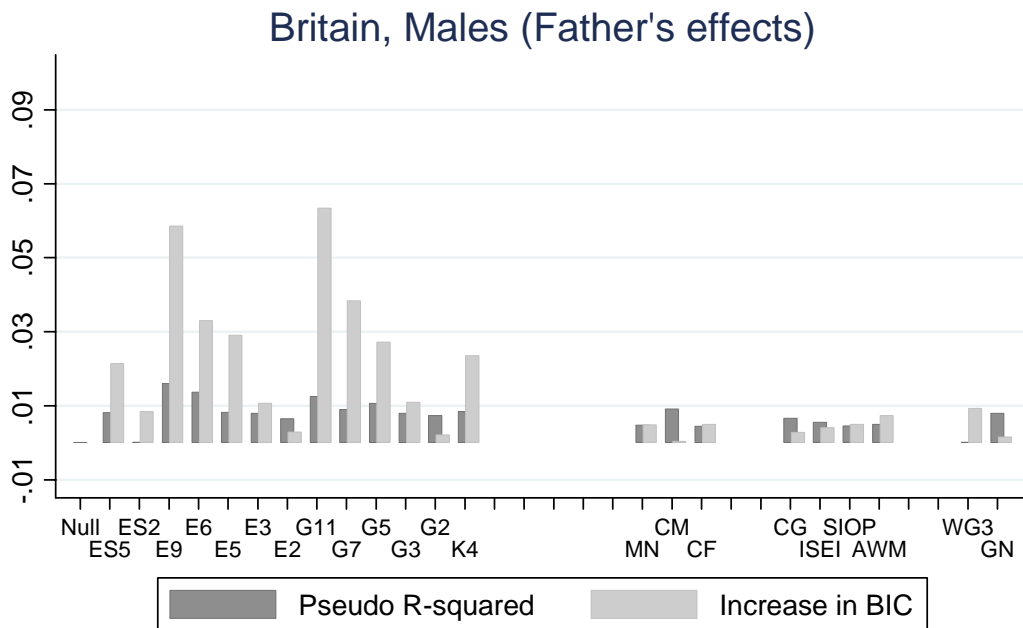
Source: BHPS and LNU 1991-2002, males aged 23-55 in work in 1991, N=1390 Britain, 1426 Sweden. Graph shows pseudo-R² for logit model including only the occupation-based social classification and scaled BIC statistic $(BIC - \text{Null BIC}) / \text{Null BIC}$. Unweighted data.

Figure 3.4b: R-2 and BIC for predicted unemployment risk
 Explanatory power of schemes in predicting 1+ year Unemp., 1991-2002



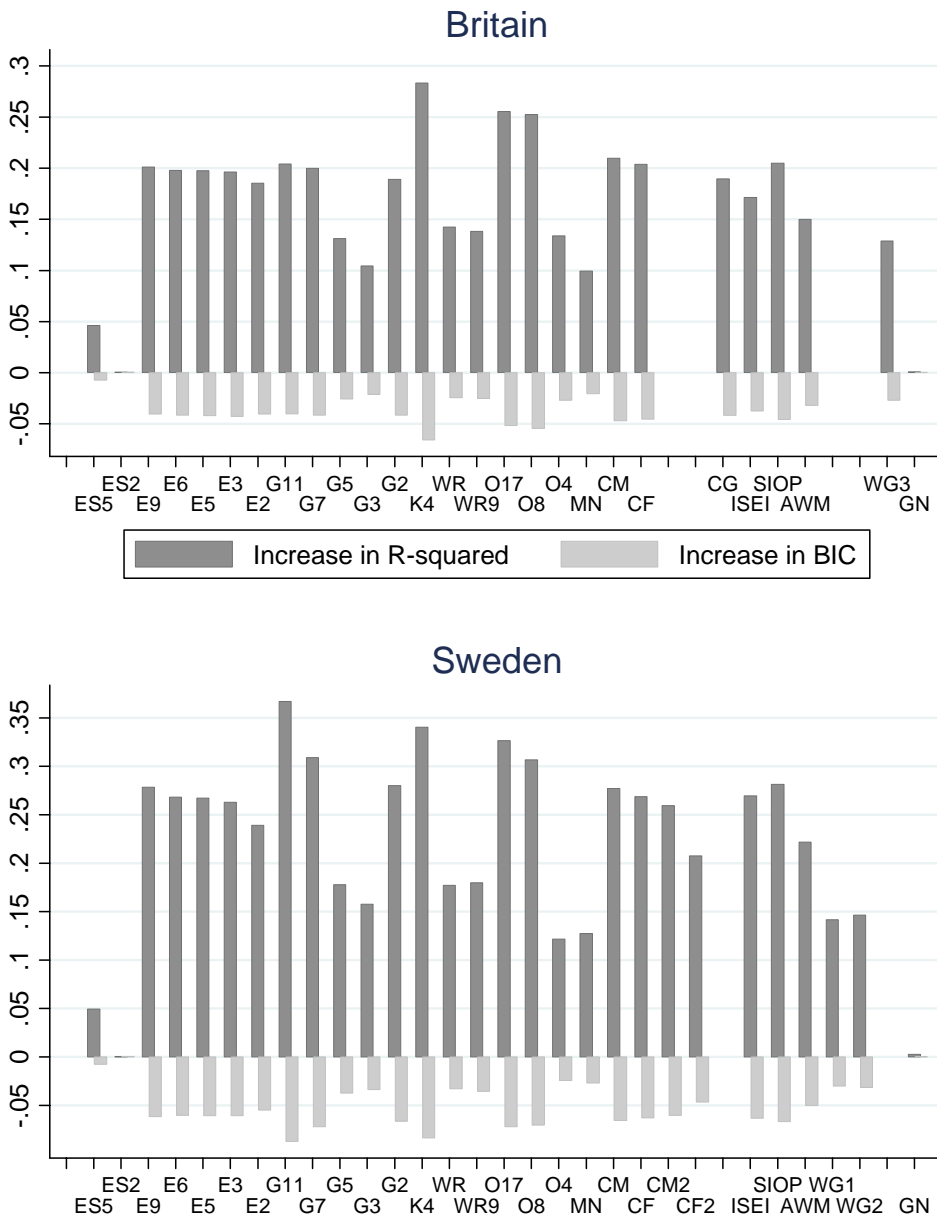
Source: LNU and BHPS 1991-2002, females aged 23-55 in work in 1991, N=1319 Britain, 1112 Sweden. Graph shows pseudo-R2 for logit model including only the occupation-based social classification and scaled BIC statistic $(BIC - \text{Null BIC} / \text{Null BIC})$. Unweighted data.

Figure 3.4c: R-2 and BIC for predicted unemployment risk
 Explanatory power of father's scheme (1+ year Unemp., 1991-2002)



Source: As Figure 3.4a, males with valid parental occ data, N=1249 Britain, 1402 Sweden.
 Graph shows pseudo-R2 for logit model including only the occupation-based social classification and scaled BIC statistic $(BIC - \text{Null BIC} / \text{Null BIC})$. Unweighted data.

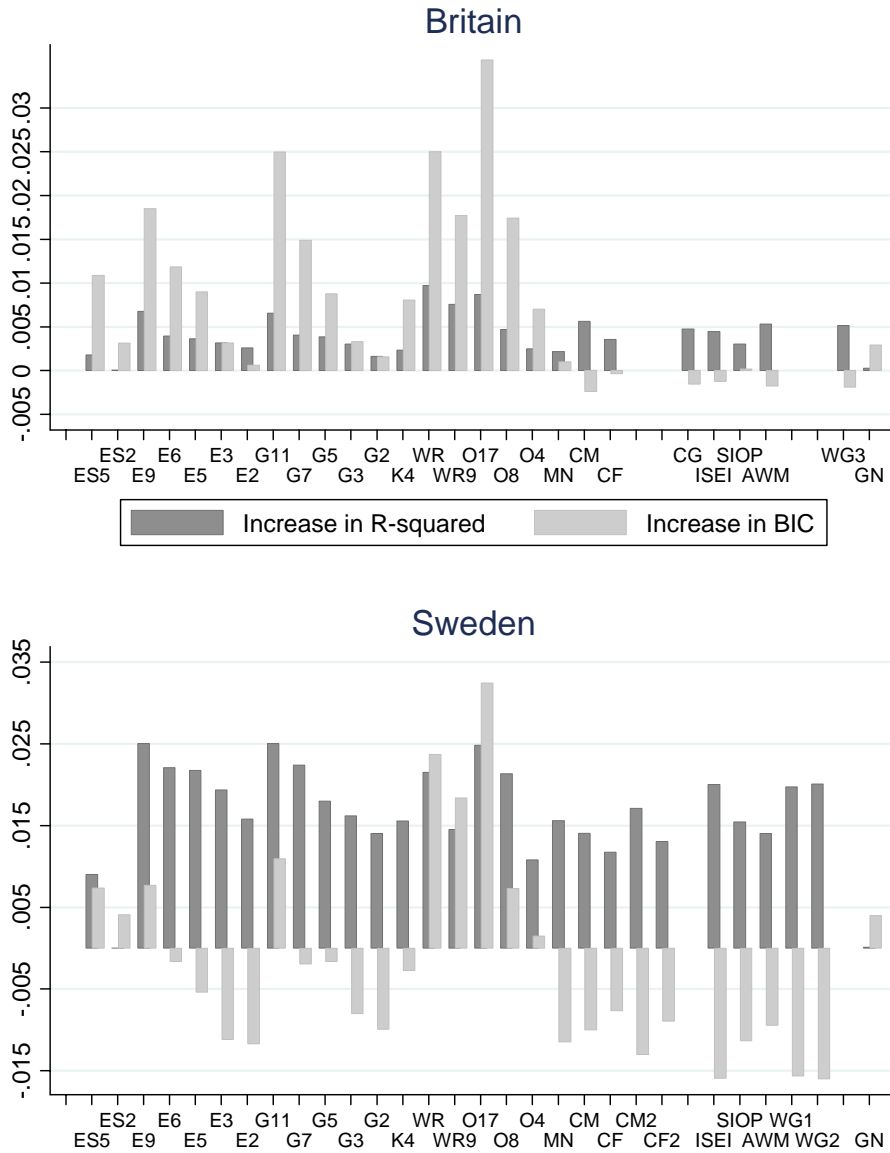
Figure 3.5: R-2 and BIC for Years of Education
 Explanatory power of schemes in predicting years of education



Source: BHPS and LNU 1991-2002, adults aged 23-55 in work in 1991, N=2568 Britain, 2504 Sweden.
 Model 1: Education = quadratic age + gender ; Model 2: Education = (Model 1) + occupation-based social classification
 Graph shows improvement in R2 for OLS regression, Model 2 v's Model 1,
 plus scaled BIC statistic (Model 2 BIC - Model 1 BIC / Model 1 BIC). Unweighted data.

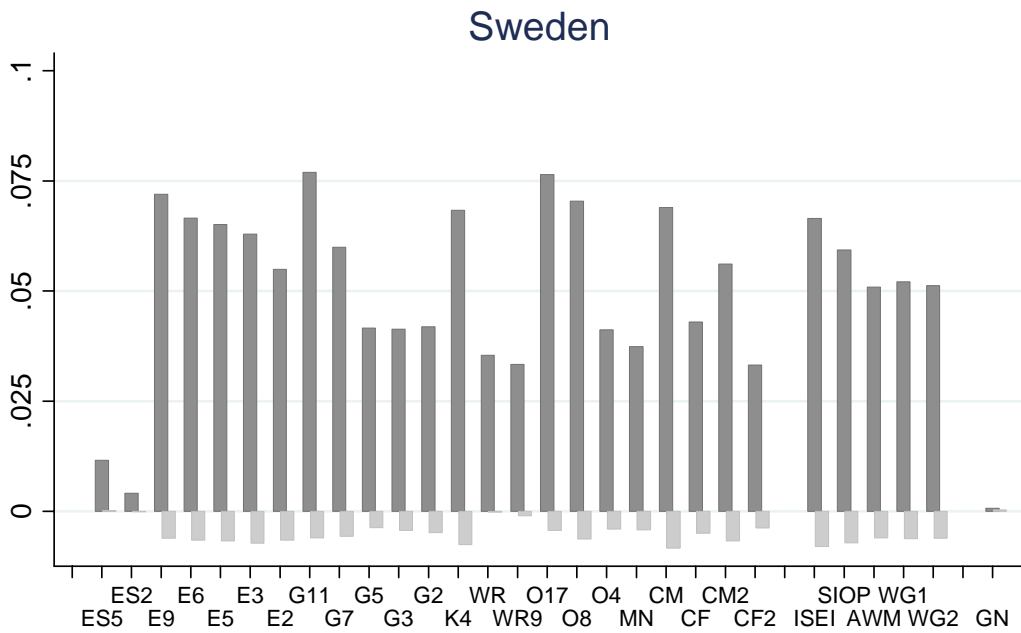
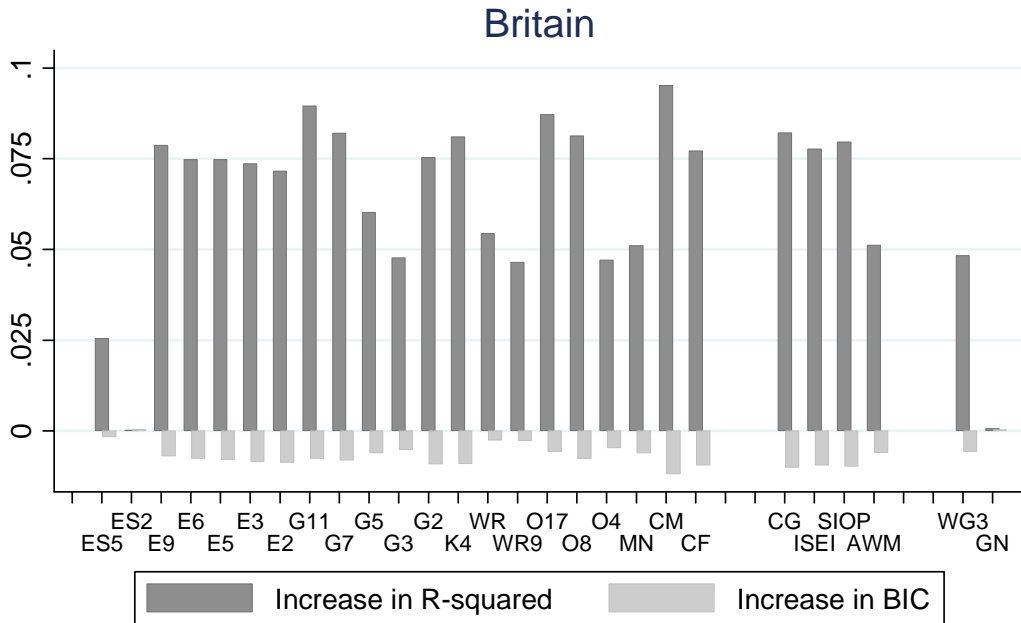
Figure 3.6: R-2 and BIC for Poor Subjective Health

Explanatory power of schemes in predicting poor subjective health



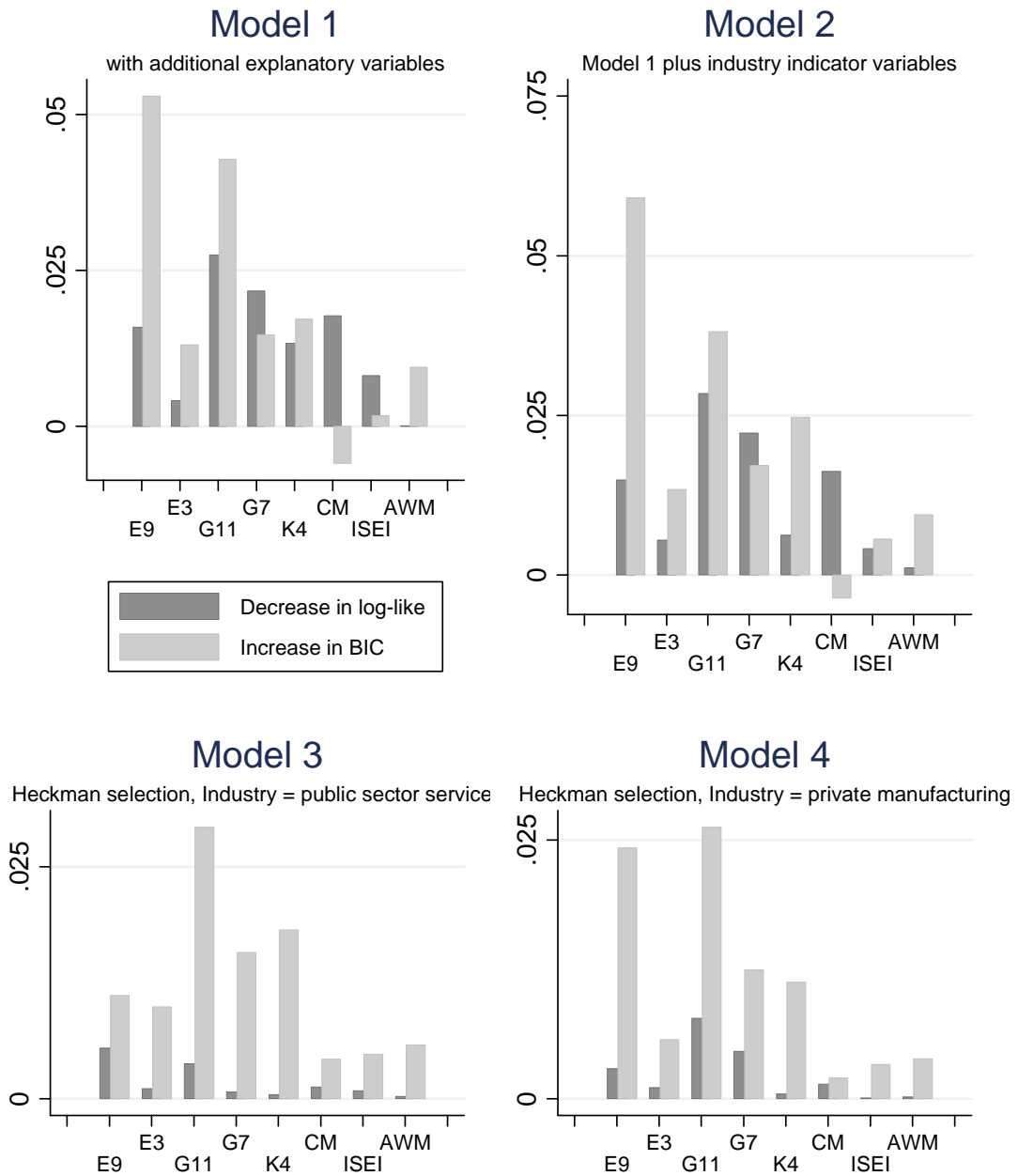
Source: BHPS and LNU 1991-2002, adults aged 23-55 in work in 1991, N=2568 Britain, 2504 Sweden.
 Model 1: Health = quadratic age + gender + age*gender; Model 2: Health = (Model 1) + occupation-based social classification
 Graph shows improvement in Pseudo R2 for Logistic regression, Model 2 v's Model 1, plus scaled BIC statistic (Model 2 BIC - Model 1 BIC / Model 1 BIC). Unweighted data.

Figure 3.7: R-2 and BIC for Fathers ISEI
 Explanatory power of schemes in predicting father's ISEI



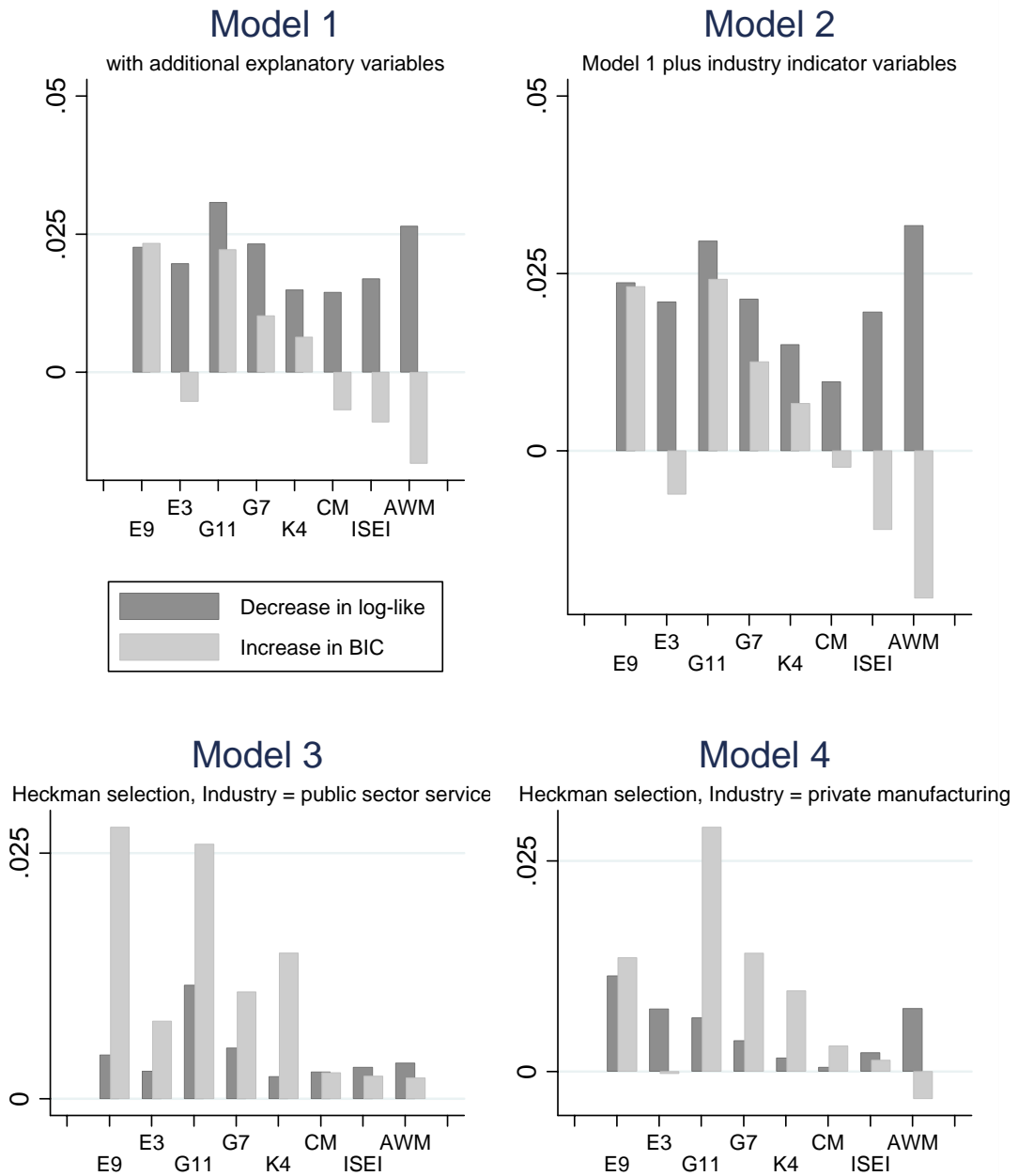
Source: BHPS and LNU 1991-2002, adults aged 23-55 in work in 1991, N=2568 Britain, 2504 Sweden. Model 1: ISEI = linear age + gender ; Model 2: ISEI = (Model 1) + occupation-based social classification. Graph shows improvement in R2 for OLS regression, Model 2 v's Model 1, plus scaled BIC statistic (Model 2 BIC - Model 1 BIC / Model 1 BIC). Unweighted data.

Figure 4.1: Unemployment risks (British men)
 Explanatory power of schemes, given alternative additional controls



Source: BHPS, males aged 23-55 in work in 1991, N=1319.
 Outcome variable: Whether experienced one year or more of unemployment 1991-2002
 Graphs show incremental explanation associated with occupation-based social classification
 Models 3 and 4 selection equation predictors: age, education, total work experience, region
 Models 3 and 4 process equation predictors: marital status, education, work experience in current job
 Graph shows improvement in log-likelihood in model with and without occupation-based social classifications plus scaled BIC statistic (Model BIC - null Model BIC / null Model 1 BIC). Unweighted data.

Figure 4.2: Unemployment risks (Swedish men)
 Explanatory power of schemes, given alternative additional controls



Source: LNU, males aged 23-55 in work in 1991, N=1112.
 Outcome variable: Whether experienced one year or more of unemployment 1991-2002
 Graphs show incremental explanation associated with occupation-based social classification
 Models 3 and 4 selection equation predictors: age, education, total work experience, region
 Models 3 and 4 process equation predictors: marital status, education, work experience in current job
 Graph shows improvement in log-likelihood in model with and without occupation-based social classifications plus scaled BIC statistic (Model BIC - null Model BIC / null Model 1 BIC). Unweighted data.

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