Occupational earning potential: A new measure of social hierarchy applied to Europe

Daniel Oesch[1], Oliver Lipps[2,5], Roujman Shahbazian[3,4,6], Erik Bihagen[4], Katy Morris[1]

[1] University of Lausanne, [2] FORS, [3] Uppsala University, [4] Stockholm University, [5] University of Bern, [6] University of Munich

Abstract

Social stratification is interested in unequal life chances and assumes the existence of a hierarchy of more or less advantageous occupations. Yet occupations are not easily translated into a linear hierarchical measure. Influential scales combine multiple indicators and lack intuitive interpretation. We present a new scale based on occupations' earnings potential (OEP). The OEP scale measures the median earnings of occupations and expresses them as percentiles of the overall earnings structure: If machine mechanics earn the national median wage, their OEP is 50. We construct national OEP scales using annual microdata pooled over several decades for Germany, Sweden, Switzerland, the UK and US. Consistent with the Treiman constant, these national scales are highly correlated over time (r=0.90) and across countries (r=0.80), justifying the use of one common OEP scale. When applied to another European database, the common OEP scale explains a quarter of the variance in earnings – and performs as well for countries used to construct the scale as for countries not used. Moreover, it is associated with the causes (education) and consequences (social mobility) that theory expects it to be. OEP provides a simple, clear and parsimonious indicator of economic advantage that can be meaningfully interpreted.

This version: 10 October 2024

1. Introduction

Social stratification is interested in the unequal distribution of life chances and assumes the existence of a hierarchy – a hierarchy rooted in the division of labour that needs to be made visible. To the extent that some occupations offer more advantageous positions in the division of labour than others – judges rather than janitors, managers rather than machinists –, they have been widely used to construct measures of labour market hierarchy. The use of occupations in stratification research has been enhanced by their visibility. Unlike income and wealth, occupations are publicly known to and understood by others. Just by seeing a person at work, we know the occupations of waiters and plumbers, teachers and doctors. People are therefore much less reluctant to disclose their occupation than their income, and occupational information is widely available in public registers and social surveys (Hauser and Warren 1997, Song and Xie 2023).

However, occupations are unwieldy categorical indicators that do not easily translate into a measure of social hierarchy. One solution is to treat stratification as multidimensional and to aggregate occupations into a large number of micro-classes (Weeden and Grusky 2005, Jonsson et al. 2009) or a small number of big social classes, as in the EGP class scheme and its European version ESeC (Erikson and Goldthorpe 1992, Rose and Harrison 2010). Another solution is to align occupations along one single dimension of socio-economic advantage and to create a linear hierarchical scale. Both approaches have advantages and disadvantages, and scholars may legitimately prefer one to the other depending on the research question (Connelly et al. 2016).

Our paper proposes a measure that fully exploits the scalar approach. Scales have the advantage of simplicity, easy interpretation and parsimony as they transform dozens of occupations into a single continuous variable that can be analysed with linear rather than multinomial models. Influential scales include the SIOPS scale based on occupational prestige

(Treiman 1977) and the CAMSIS scale based on intermarriage patterns across occupations (Prandy and Lambert 2003). In the European social sciences, the most widely used occupational scale is the International Socio-Economic Index of Occupational Status, more commonly referred to as ISEI (Ganzeboom et al. 1992). ISEI has proved extremely useful for empirical research, but we argue it can be enhanced in several regards. Although based on optimal scaling, it is in effect a weighted average of an occupation's education and income. Including both the antecedent (education) and the consequence (income) of an occupation, this synthetic scale was created on a limited survey basis and lacks an intuitive interpretation.

As a result, this paper presents a new scale that is a simpler, clearer and more parsimonious alternative to ISEI. Our scale avoids the vague concept of socio-economic status. Instead, it expresses the hierarchical position of an occupation solely on the basis of its earning potential, following earlier work on national scales (Sobek 1995, Kalmijn 1994, De Graaf and Kalmijn 2011).[1] An occupation's earning potential (OEP) is determined by the median earnings of full-time employees in that occupation. We provide an intuitive measure of OEP by expressing its values relative to the earnings distribution of the entire workforce. If the median earnings in a given occupation are identical to the median earnings of the whole workforce (percentile 50), then the value for this occupation's earning potential is 50. By the same logic, an occupation with an OEP score of 75 means that the earning potential of this occupation – measured by its median earnings – is equal to the 75th earnings percentile of the whole workforce. Anchoring OEP values in the overall earnings distribution gives them a meaningful interpretation.

[1] Earlier scales for the UK (Kalmijn 1994) and the Netherlands (De Graaf and Kalmijn 2001) also determined the economic status of occupations based on their labour income. However, by expressing values as z-scores ranging from -2 to 2, these scales lack an intuitive interpretation. In the US, a historical scale based on median percentiles, called the Occupational Income Score (OCCSCORE), was constructed using the 1950 census to approximate incomes in older censuses going back to 1850 (Sobek 1995; for a critique, see Saavedra and Twinam 2020).

The OEP scale is constructed on the basis of pooled annual data for full-time employed men and women in five distinct Western countries over several decades, using Britain's Understanding Society 1991-2023, Germany's Socio-Economic Panel 1984-2021, Swedish tax register data 1970-2021, Switzerland's Labour Force Survey 1991-2022 and the U.S. Current Population Survey 1970-2023. We first create a harmonised OEP index for each country and decade. The comparison of the correlations of OEPs between countries and decades allows us to examine the stability in occupational earnings rankings across space and time. As the correlation coefficients are high between our harmonized country-decade OEPs (r=0.82 across 105 country-decades), we construct a joint cross-country scale of OEP based on the period 2000-2021.

We submit the OEP scale to tests of construct and criterion validity. Construct validity involves testing whether OEP measures the concept it is intended to measure on different data, namely variance in earnings. We do so by comparing the predictive power of OEP across European countries, using the 2010 and 2015 European Working Conditions Surveys. Criterion validity involves testing whether OEP is associated with the causes (education) and consequences (social mobility) that the theory expects. Using yet another data source – the European Social Survey – we show that ascending levels of education are associated with rising occupational earning potential and compare the extent of intergenerational mobility in Europe using OEP and ISEI. The results show that the OEP alone explains a quarter of the variance in earnings for countries (and data) for which the scale was not developed – substantially more than ISEI. By contrast, ISEI explains more variance in intergenerational mobility than OEP.

2. Theoretical framework

Occupations underpin social stratification

A central source of social inequality is the division of labour, which is reflected in the occupational structure. Workers in different occupations control different amounts of productive resources, which places them in asymmetrical social relations with one another. It has therefore been argued that occupation is the single most important indicator of social stratification, "a measure that is highly associated with one's ability, characteristics, and training, and from which others can infer one's social prestige" (Song & Xie 2023: 2). A person's occupation also tends to delimit future economic prospects. Even for people not in employment such as the unemployed, homemakers or retirees, past occupation provides information about their social and economic standing (Hauser and Warren 1997).

However, occupational classifications distinguish dozens, sometimes hundreds of units, making it necessary to aggregate occupational information into a more parsimonious indicator. While there is a consensus in stratification research to use occupations as the building blocks when measuring people's position in the social hierarchy, it is less clear as to whether stratification should be represented in categorical or continuous terms. Influential scholars have argued that occupations cannot be easily ordered on one single dimension because differences involved are of "kind as well as level" (Goldthorpe 2010: 316).

At the same time, empirical studies suggest that different measures of class and status – whether categorical or continuous – are highly correlated because they share a common underlying hierarchical dimension (Bihagen and Lambert 2018, Lambert and Bihagen 2014). The same reason explains the strong correlation between different scales of prestige, social status, socio-economic status and social distance. While they may have different theoretical starting points (Lambert 2024), they do not seem distinct empirically (Meraviglia et al. 2016, Song and Xie 2023). The stability of occupational prestige rankings over time and across countries has been termed the "Treiman constant" (Hout and DiPrete 2006, Treiman 1977), and this stability seems to apply more broadly to hierarchical measures of occupations.

Going beyond ISEI

In European social sciences, by far the most influential occupation-based scale is ISEI (Ganzeboom et al. 1992, Ganzeboom and Treiman 1996). Between 2000 and 2023, the *European Sociological Review* published no less than 108 articles – an average of 5 per year – that either used or referenced ISEI. While ISEI has proven to be extremely fruitful for research, it also has some problematic features.

Conceptually, ISEI aims to scale occupations in such a way as to best mediate the impact of education on income. Going back to Duncan (1961), ISEI is a kind of latent variable that converts education into income (Ganzeboom et al. 1992). In practical terms, this is equivalent to a weighted sum of mean education and mean income for each occupational group, taking into account the influence of age (Ganzeboom et al. 1992: 12).[2] The weighted sum of education and income leads to values that do not lend themselves to intuitive interpretation. Neither minimum nor maximum values (calibrated to numbers between 16 and 90) nor changes in these values have any concrete meaning. For this reason, Bukodi, Dex and Goldthorpe (2011) argued that synthetic (or composite) scales should be abandoned in favour of disaggregated (or analytical) scales of the occupational hierarchy.

In addition, by including education and income, ISEI integrates both the antecedents of entering an occupation (education) and the consequences of being in a given occupation

[2] In technical terms, ISEI scores are derived using optimal scaling techniques, that is, the scaling of the detailed occupational categories that minimises the direct effect of education on income and maximises the indirect effect of education on income through occupation, controlling for age.

(income). However, many researchers are interested in how education translates occupational attainment. By removing education from the construction of the scale, one avoids the problem of including education on both sides of the equation – as an independent variable (education) and as a dependent variable (ISEI).

Empirically, ISEI was built on a database that most users ignore, namely 31 surveys for 16 countries, conducted between 1968 and 1982, only including men (Ganzeboom et al. 1992, Ganzeboom and Treiman 1996). Although the original version is still mostly used by researchers, including the main architect of ISEI (Meraviglia, Ganzeboom and De Luca 2016), there is a new version of ISEI-08 based on men and women using 2002-07 International Social Survey Programme (ISSP) data (Ganzeboom 2010). However, ISEI-08 uses household income (along with education) to rank occupations rather than the more obvious alternative of individual labour income.

Focussing on occupations' earning potential

Building on these arguments, we propose an alternative that is simpler, clearer and more parsimonious. Our aim is to innovate in three ways: Conceptually, by ranking occupations according to a single, well-defined criterion, namely earnings. Statistically, by using an intuitive metric that relates the percentile rank of the median earnings of occupations to the entire earnings distribution. Empirically, by using extensive annual labour market data for five different Western countries over several decades.

Conceptually, occupations are bundles of tasks that are associated – because of differences in skill requirements, but also state regulation and collective bargaining – with different levels of earnings (Autor et al. 2003, Tåhlin 2007). We therefore rank occupations according to their median earnings, as commonly done in the literature on upgrading and polarization of the employment structure (e.g. Wright and Dwyer 2003, Fernandez-Macias and Hurley 2017). This approach invites the objection that other job characteristics such as skill requirement, work autonomy, promotion prospects or job security also matter for labour market inequalities and should also be incorporated in the measure. While this is certainly the case, earnings are undoubtedly a key indicator of advantage and are positively correlated with a number of other indicators of job quality (Muñoz de Bustillo et al., 2011, Oesch and Piccitto 2019). While the use of different indicators of advantage should lead to similar empirical conclusions, earnings have the advantage of being easier to observe and measure.

Using only one indicator and omitting education may come at an empirical cost. However, it has the advantage of measuring a clearly defined phenomenon, earnings potential, which lends itself to a substantive interpretation. We thus deliberately steer away from synthetic scales and the ambiguous notion of 'socio-economic status', which has been measured by education and income (Duncan 1961, Ganzeboom and Treiman 1996), but is seen in the Weberian tradition as referring to prestige, social recognition and social status (Chan and Goldthorpe 2007, Gidron and Hall 2017). Of course, depending on the research question, one may legitimately prefer a synthetic scale such as ISEI or an analytical scale that ranks occupations based on years of education – and use the cohort-specific index developed by Song and Xie (2023) for historical US data, 1850-2018. However, we would argue that it is more consequential for stratification research to know the rewards associated with being in an occupation (earnings) rather than the inputs required to enter that occupation (education).

Given our focus on earnings, one might wonder why we do not use the direct measure of individuals' earnings. This question is all the more relevant given that income measures have come to dominate stratification research (Barone et al. 2022) and annual earnings have been shown to be better proxies for lifetime earnings than occupation or education (Brady et. al. 2018, Kim et. al. 2018, Shahbazian and Bihagen 2022). Our response involves a theoretical and practical argument.

Theoretically, we argue that occupations are defined by a set of tasks and skills and therefore come with an earning potential, regardless of whether incumbents fully realise this potential. Even if some lawyers and medical doctors decide to forego the high earnings typical of their profession by working for an NGO, the occupation's earning potential is high. Similarly, while some assemblers and truck drivers may achieve high earnings through night-shifts and week-end work, the occupation's earning potential remains limited. Our indicator therefore captures earning potential rather than realised earnings.

In practice, occupation has the advantage over earnings that it is much easier to measure in surveys. While many people are reluctant to share information about their earnings, this is not the case for occupation. Its public nature is illustrated by the fact that people's occupations used to be listed in telephone books and city directories. Occupations are thus much less sensitive to the problems of refusal, recall and reliability than income, resulting in much lower item non-response (Hauser and Warren 1997). Furthermore, when respondents have no earned income because they are still in education, working as a homemaker or are retired, occupational aspirations (for young adults outside the labour force) and former occupation (for homemakers and the retired) provide a proxy for people's position in the social hierarchy – and can be expressed by the occupation's earnings potential.

One scale or several scales?

Based on the Treiman constant, our theoretical premise is that the stability in the occupational structure between countries and over time justifies the use of a single OEP scale rather than several time- and country-specific scales. The validity of this premise requires testing: It may be preferable to use several scales for the analysis of different countries and/or long time periods. Nevertheless, the vast majority of occupation-based stratification measures – whether categorical class schemes such as EGP and ESeC or continuous scales such as ISEI and SIOPS

– have relied on one single measure covering many countries over long periods of time.[3] A study of historical occupational income scores in the US finds substantial changes over time (Saavedra and Twinam 2020), but the time frame is much longer than in our analysis (1850-2000).

There are several practical advantages to using a single scale. The most important is that trends over time and/or differences between countries are much easier to interpret if they are based on the same scale. If different scales are used instead, the results may be unduly influenced by artefactual breaks in measures or artefactual differences between countries. Similarly, the use of different scales with panel data may show changes for individuals in exactly the same occupation simply because the scale's value for that occupation has changed. Moreover, constructing scales separately for each country and each decade is demanding in terms of occupational and earnings data. For these reasons, a single measure seems preferable and the empirical analysis will tell whether this is justified.

The same argument applies to gender. Since the OEP scale is based on men and women working full-time, it may give more weight to men than to women, who often work part-time. Yet we can only compare the positions of men and women in the social hierarchy if we use the same scale, whereas gender-specific scales make it difficult to detect gender inequalities. It is an empirical question of construct and criterion validity whether a common OEP scale performs equally well for men and women.

[3] Two notable exceptions are the historical CAMSIS scales (Lambert et. al. 2013) and the cohort scales of occupational percentile ranks (Song and Xie 2023).

3. Data and methods

The construction logic of the OEP

We determine the earning potential of an occupation by its percentile position in the overall earnings distribution of the full-time employed workforce. This is calculated by comparing the median earning of the occupation in question to the earnings of the entire full-time employed labour force. If the median earning of secretaries in Germany is identical to the median earning of Germany's workforce as a whole (p50), secretaries are assigned a value of 50. Likewise, an OEP value of 80 for engineers tells us that the median earning of engineers exceeds that of 80 percent of full-time workers in Germany. On a scale from 1 to 100, percentile positions thus reflect where occupations' median earnings fall within the overall earnings distribution. By anchoring occupational earning potential in the earnings distribution, absolute levels and relative changes in OEP can be interpreted meaningfully.

Data and measures

We construct the OEP by using data from five affluent Western countries that have different institutions governing the education system, labour market and welfare state: Germany, Sweden, Switzerland, the United Kingdom and the United States. For each country, we select a national database with large samples (N>10,000) and detailed measures of occupations and individual earnings for as many common years as possible. This leads us to select the German Socio-Economic Panel 1984-2021, Swedish tax registry data 1970-2021, the Swiss Labour Force Survey 1991-2022, the UK Understanding Society (British Household Panel Survey & UK Household Longitudinal Study [see ISER 2023a, b]) 1991-2023 and the US Current Population Survey 1970-2023.

Our two key variables are occupations and earnings. In a first step, we translate each country's national occupational classification into the corresponding ISCO-88 3-digit codes. This translation makes the comparison across countries and over time possible. Among others, it involves converting ISCO-68 and ISCO-08 classifications into ISCO-88, using the *iscogen* module in Stata (Jann 2019). Making sure that each occupation has at least 20 valid observations in each country, we create 76 harmonized occupations across the five countries that span all the decades (we return in a second step to the full set of occupations at the 4-digit level).

As for earnings, we use the inflation-corrected pre-tax labour income of men and women aged 25-60 who work full-time (at least 35 hours per week) as employees, thus excluding the self-employed whose incomes owe as much to entrepreneurial logics as to their occupation's earning potential. As Swedish registers have no detailed information on working hours, we exclude individuals whose annual earnings are below 100,000 SEK (approximately 10,000 Euros) and who are therefore unlikely to be in full-time employment. Our goal is to calculate the typical earnings of a given occupation rather than the life-time earnings of a given individual. Some occupations such as athletes and flight attendants are dominated by young workers, while others, such as judges and corporate managers, are dominated by older workers.

Only using full-time employees aged 25-60 with non-missing values on occupation and earnings still leaves us with very large analytical samples. For the sole period 2000-2021/3, there are 119,086 valid observations in Germany, approximately 72 million in Sweden's tax registry, 334,083 in Switzerland, 170,808 in the UK and 1,403,380 in the US.

Country-decade OEPs and their correlations over time

We begin by calculating OEP values for 76 harmonised occupations in each decade and country. These country-decade OEP scales allow us to determine the correlation between the OEP scores over time within a given country and between countries in a given decade, as well as between different decades in different countries.

The correlation matrix for the three decades of the 1990s, 2000s and 2010s within and between the five countries is shown in Table 1. The correlation coefficients are consistently high, fluctuating around r=0.90 within countries over time and r=0.80 between country pairs in the same or different decades. No correlation coefficient is lower than r=0.72, with the correlation averaged over all 105 country-decade pairs being r=0.82. This means that the OEP of one country-decade predicts two thirds of the variance of the OEP of another country-decade (r2=0.68). The high degree of stability is also confirmed when looking at longer time ranges: The OEP measured in the decade of the 1970s correlates with the OEP measured in the 2020s correlates with r=0.75 in Sweden and with r=0.85 in the US.

These correlations over 50 years correspond to the average correlation of two IQ tests taken by the same person in two different sessions within the same month (Ritchie 2015: 23). Nevertheless, some researchers may take the Treiman constant literally and wonder why the correlations are not closer to one. There are at least three factors at play. First, occupations are prone to measurement error, based on how people describe their jobs and how the underlying algorithms convert job titles into occupational classifications. These classifications, in turn, differ across countries and decades, and breaks in classifications can lead to artefactual differences (notably from ISCO-88 to ISCO-08 as well as the crosswalks used in the CPS). Second, none of the surveys used were designed to be representative at the occupational level. Despite the large number of observations, some variance across countries and decades in occupational median earnings will reflect sampling error. Finally, there is real variation between countries and within countries over time that affects the position of occupations in the earnings distribution. Differences between countries may reflect differences in skill requirements, legal regulations, union power, and collective bargaining agreements. Differences over time may reflect changes in task intensity associated with technological innovation, as well as the expansion and contraction of public spending.[4]

Table 1: Correlation coefficients (Pearson's *r*) in OEP values, across countries and over decades

	CH, 1990s	CH, 2000s	CH, 2010s	DE, 1990s	DE, 2000s	DE, 2010s	SE, 1990s	SE, 2000s	SE, 2010s	UK, 1990s	UK, 2000s	UK, 2010s	US, 1990s	US, 2000s	US, 2010s
CH, 1990s	1														
CH, 2000s	0.98	1													
CH, 2010s	0.95	0.97	1												
DE, 1990s	0.83	0.84	0.85	1											
DE, 2000s	0.81	0.82	0.83	0.92	1										
DE, 2010s	0.81	0.82	0.83	0.88	0.94	1									
SE, 1990s	0.74	0.75	0.78	0.76	0.80	0.79	1								
SE, 2000s	0.74	0.75	0.78	0.85	0.84	0.87	0.87	1							
SE, 2010s	0.72	0.73	0.77	0.84	0.83	0.86	0.85	0.98	1						
UK, 1990s	0.77	0.77	0.79	0.86	0.83	0.81	0.79	0.87	0.84	1					
UK, 2000s	0.75	0.78	0.79	0.83	0.81	0.79	0.82	0.85	0.82	0.93	1				
UK, 2010s	0.78	0.80	0.81	0.86	0.81	0.79	0.74	0.81	0.79	0.90	0.93	1			
US, 1990s	0.78	0.81	0.80	0.78	0.76	0.75	0.81	0.82	0.81	0.81	0.85	0.81	1		
US, 2000s	0.81	0.82	0.81	0.79	0.79	0.74	0.82	0.81	0.79	0.83	0.86	0.81	0.94	1	
US, 2010s	0.78	0.79	0.78	0.81	0.79	0.75	0.84	0.84	0.82	0.84	0.88	0.83	0.93	0.98	1

Creating one single OEP scale

We interpret the strong correlations as evidence in favour of the Treiman constant and its theoretical premise of a high degree of stability in the occupational hierarchy across space and time. Importantly, it allows us to construct and use one single OEP scale rather than resorting

[4] Indeed, among the few occupations in Sweden that have markedly increased their OEP scores in recent decades are mining occupations. This increase is probably due to technological progress, which has made mining less labour-intensive, but more capital- and skill-intensive. On the other hand, there has been a marked decline in Sweden in the OEP of various teaching occupations over the last fifty years.

to multiple time- and country-specific OEP scales. We create a single OEP scale based on data from all five countries for the years 2000/1 to 2021/23, using the same analytical sample of full-time employees aged 25-60. We calculate the OEP values for both ISCO-88 and ISCO-08 at four different levels of occupational information: ISCO 1-digit, 2-digit, 3-digit, 4-digit. This gives us maximum flexibility to apply OEP to different datasets. For small occupations with less than 20 valid country earnings observations, we impute values from the less detailed ISCO level, that is from ISCO 1-digit to ISCO 2-digit, from ISCO 2-digit to ISCO 3-digit or from ISCO 3-digit to ISCO 4-digit.[5]

Once we have calculated the OEP values for each country, we average them across the five countries to derive a common OEP scale at the 1-digit, 2-digit, 3-digit and 4-digit levels of ISCO-88 and ISCO-08 each. Table 2 shows the correlation matrix of all the scales at the level of ISCO-08 3-digit. If we focus on the key correlation between the general OEP scale with the country-specific OEP scales, we obtain high values of between *r*=0.93 and *r*=0.96. This suggests that the general and national OEP measure the same phenomenon and that we do not lose any information by using the general OEP scale instead of the national OEP.

Table 2: Correlation coefficients in OEP values between country scales for 2000/1-2021/3

	General OEP	OEP-CH	OEP-DE	OEP-SE	OEP-UK	OEP-US
General OEP						
OEP-CH	0.95					
OEP-DE	0.95	0.92				
OEP-SE	0.94	0.84	0.90			
OEP-UK	0.92	0.86	0.88	0.86		
OEP-US	0.93	0.86	0.85	0.86	0.89	

[5] To give an example, if there are not enough observations at the ISCO 3-digit level for "234 Special education teaching professionals", the OEP score will be imputed from the ISCO 2-digit level of "23 Teaching professionals".

The values of the OEP scale for all occupations at the ISCO-08 3-digit level are shown in Table A.1 in the appendix (note, however, that values are available for ISCO-88 and ISCO-08 at each level from 1 to 4-digit). The ISCO-08 3-digit occupations with the lowest earning potential are domestic cleaners and helpers with an OEP of 11, followed by waiters, market salespersons and ticket cashiers with an OEP of 12. This means that only around ten percent of the workforce earns less than the median worker in these occupations. The occupations with the highest earning potential are managing directors with an OEP of 93, medical doctors with 91, IT managers with 90 and legal professionals with 87. Approximately ten percent of the labour force is paid more than the median employee in these managerial and professional occupations.

Analytical strategy: testing the scale's validity

We subject the OEP scale to three tests of validity. First, we examine *construct validity*, which involves testing on different data whether our OEP scale measures the concept it is intended to measure, namely earnings. We use a new data source, the European Working Conditions Survey (EWCS) 2010 and 2015, and compare the variance explained by the general OEP for countries used to construct the scale with countries not used to construct the scale. We contrast these results with those obtained using ISEI.

We then provide two tests of *criterion validity* that examine whether the OEP scale is associated with the causes – education – and consequences – social mobility – that earlier findings and theories in stratification research expects it to be associated with. Using European Social Survey data 2002-2020, we first calculate the occupational returns to education in terms of OEP and then analyse intergenerational mobility, again comparing the results obtained with OEP and ISEI.

4. Results

Explained variance in earnings

We begin with an analysis of the variance in earnings explained by the different scales of the OEP. For this purpose, we pool the two rounds of the EWCS that have detailed information on earnings and occupations, 2010 and 2015, and restrict the analytical sample to employed workers aged 25 to 60 years who work full-time. Because of large differences in top earners in the two surveys 2010 and 2015, we set all earnings in the top percentile equivalent to the earnings of the 99th percentile.

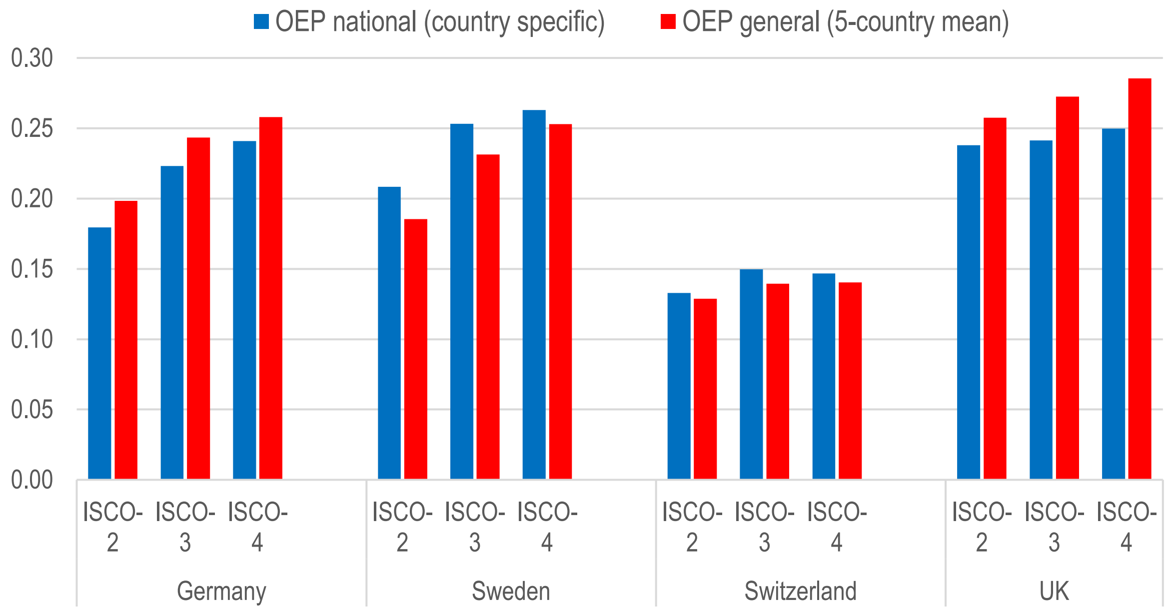
Figure 1 compares the explained variance in earnings by the country-specific OEP and the general OEP at different levels of ISCO-08 for the four European countries used to construct the scales. Only in Sweden does the national scale explain more variance than the general scale. There is no difference for Switzerland, but the general scale performs better than the national scale in Germany and the UK. Averaging the OEP scores across five countries thus improves the measurement of the earning potential of occupations in these two countries.

When comparing the r2 of the OEP scale measured at different levels of occupational detail, we see that the OEP measured at the most detailed ISCO 4-digit level performs best. The general OEP scale at ISCO-08 4-digit accounts for 29 percent of variance in earnings in the UK, 26 percent in Germany, 25 percent in Sweden and 14 percent in Switzerland (where there is only one EWCS round with just 426 observations).[6] However, differences between OEP at the 4-digit, 3-digit and 2-digit level are small and suggest that even the two more aggregated scales

[6] Some readers may prefer to see correlations (Pearson's *r*) rather than variance explained (r2). These correlations between the general OEP and earnings are strong, ranging between *r*=0.37 (Switzerland), *r*=0.50 (Sweden), *r*=0.51 (Germany) and *r*=0.53 (UK).

account for 20 to 25 percent of explained variance in earnings. This is good news because many datasets only report occupational information at the level of ISCO 2- or 3-digit.

Figure 1: Variance in earnings explained by OEP-scale as measured by r2



Data: EWCS 2010, 2015 (only 2015 for Switzerland). Analytical sample: employed workers aged 25-60, working full-time (or >30h per week). N(Germany): 2089. N(Sweden): 1116. N(Switzerland): 426. N(UK): 1215.

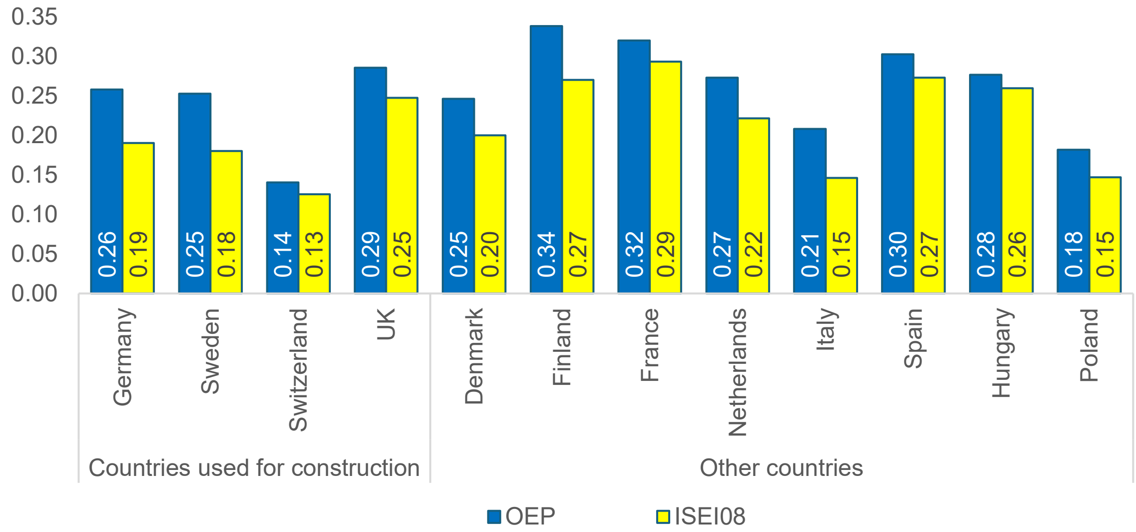
Our general OEP scale was calculated using data from the four European countries shown in Figure 1 and the United States. The questions are whether OEP also works for other European countries and whether it performs as well as ISEI, the most widely used hierarchical scale in sociological research. Figure 2 addresses these two questions by comparing the variance in earnings explained by the general OEP and ISEI-08 (both based on ISCO-08 4-digit) between two groups of countries: the four European countries used to construct the OEP and a selection of eight European countries not used, namely two Continental Western European, two Eastern European, two Mediterranean and two Scandinavian. To avoid the impression of cherry-picking, we show the full results for all countries included in the EWCS in the Appendix (see Table A.2).

Figure 2 shows that OEP explains between 20 and 30 percent of the variance in earnings for countries for which the scale was not developed. The general OEP performs as well for European countries used to construct the scale as it does for the other countries. This means that by simply assigning OEP scores to occupations at the 4-digit level, we can explain about a quarter of the variance in earnings between workers. In terms of construct validity, this suggests that the OEP measures what it is supposed to measure.

Although constructed on the basis of a single indicator, OEP explains more variance in earnings than ISEI, which uses education and income while controlling for age. For the twelve European countries shown in Figure 2, OEP explains 28 percent of variance compared to 23 percent for ISEI-08. The advantage of OEP holds both when comparing OEP to ISEI-08 (both measured at ISCO-08) and when comparing OEP to ISEI-88 (both measured at ISCO-88, see Figure A.1 in the appendix).

For some readers, it may be the similarity rather than the difference between OEP and ISEI that is striking. Both scales perform particularly well for Finland, France and Spain, but explain less variance for Italy, Poland and Switzerland. This similarity is due to the high correlation between OEP and ISEI: In the EWCS data, the correlations are r=0.90 between OEP and the new ISEI-08 (measured at ISCO-08 4-digit) and r=0.81 between OEP and the old ISEI (measured at ISCO-88 4-digit). Consistent with the Treiman constant, these strong correlations suggest that while OEP and ISEI may be based on different concepts and data, they measure very similar occupational hierarchies.

Figure 2: Variance in earnings explained by OEP and ISEI-08 as measured by r2



Data: EWCS 2010, 2015 (only 2015 for Switzerland). OEP and ISEI are based on ISCO-08 at the 4-digit level.

Since the OEP is constructed on the basis of full-time earnings only, a second question arises: Does it work as well for women as for men, knowing that the former often work part-time? Figure A.2 in the appendix compares the variance explained in earnings by OEP for full-time employed men and women, using the same countries as above. These results show that, on average, OEP accounts for more variance in women's earnings (28 percent) than in men's earnings (25 percent). However, it is again the similarity that is striking. When we calculate the male and female full-time earnings distributions separately in order to create distinct OEP scales for men and women, we find that these male and female OEP scales correlate very strongly: r=87 in Germany, r=0.96 in Sweden, r=0.92 in Switzerland, r=0.86 in the UK and r=0.95 in the US. The implication is that occupations sit in very similar positions within the male and female earnings distributions in the five countries.

Occupational returns to education

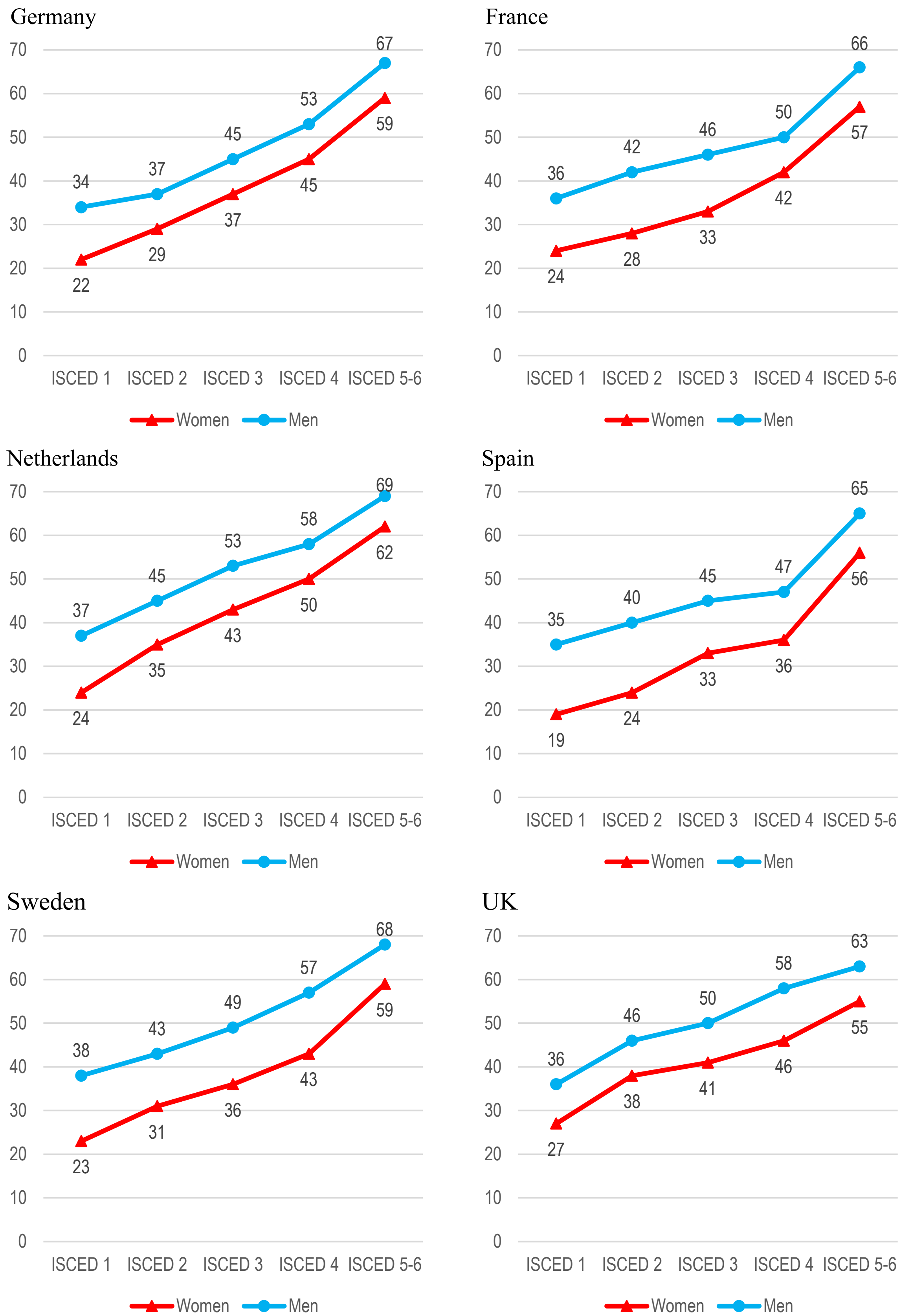
We move on to criterion validity by testing whether the OEP scale is associated with a prime cause that theory expects occupational attainment to be associated with, namely education. The analysis of occupational returns to education shows the added value of using an indicator of occupational advantage not based on education. It allows researchers to use education as the independent variable and OEP as the dependent variable and thus to estimate a regression that includes education on only one side of the equation. We use the ESS 2002-2020 and limit the analytical sample to full-time workers aged 40-60 who have therefore had time to reach mature occupational positions. We distinguish five ascending ISCED-categories of education: 1 primary, 2 lower secondary, 3 upper secondary, 4 post-secondary, and 5-6 tertiary education. We then estimate the following linear regression where these five categorical levels are interacted with gender, while controlling for age:

$$y(OEP) = \beta_1 + \beta_2(educ) + \beta_3\,(gender) + \beta_4(educ * gender) + \beta_5(age) + \varepsilon$$

Figure 3 shows the predicted values of OEP for men and women by education for three European countries used to construct OEP and three additional European countries. The selection of countries is inconsequential because the results are very similar. The OEP scale is everywhere strongly associated with education: For each additional level, the earnings potential of occupations increases by almost ten percentiles. Across Europe, workers succeed in transforming higher levels of education into occupational positions with higher median earnings.

Figure 3 also shows everywhere a gendered pattern. While the occupational earning potential rises linearly with education, the rise is steeper for women than men because women start out at much lower levels. In the European countries shown in Figure 3, workers with only primary education were employed in occupations around the 19-27th earning percentiles for women and the 34-38th earning percentiles for men. In contrast, the gap closes for workers with tertiary education where women were employed in occupations with an earning potential in the 55-62rd percentiles as compared to the 63-69th earning percentiles for men.

Figure 3: OEP by educational level for employed men and women aged 40-60



Data: ESS 2002-2020, employed full-time workers aged 40-60. OEP based on ISCO-08 at the 4-digit level.

Mobility in the occupational hierarchy

Stratification research has traditionally placed a strong emphasis on the analysis of social mobility (DiPrete 2020). In a last test of criterion validity, we therefore use the OEP scale to predict intergenerational mobility. For this purpose, we use the first five rounds of the European Social Survey 2002-2010, in which respondents were asked about their father's and mother's occupation at the age of 14, with occupations being coded at the ISCO-88 4-digit level.[7] We restrict the analytical sample to respondents aged 40 to 60 (and thus in mature occupational positions). This corresponds to the baby boomer generation, born between 1942 and 1970.

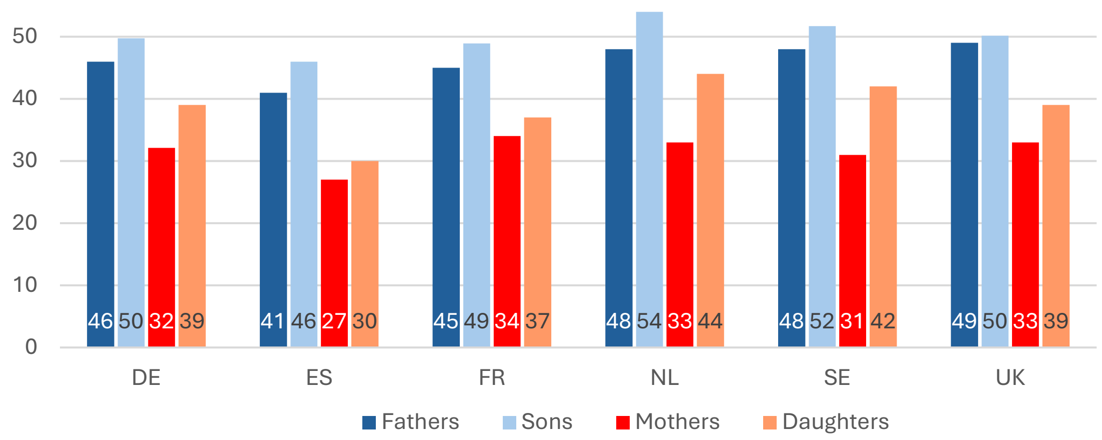
We begin by comparing the mean OEP of sons and daughters with the mean OEP of fathers and mothers. Figure 4 shows the results for the same six European countries as before and points to clear-cut upward absolute social mobility. In all six countries, baby boomer men worked in an occupation with a higher earning potential than their fathers, as did baby boomer women compared to their mothers. Averaged across our six countries, men in the child generation had an OEP of 50 (compared with 46 for their fathers) and women in the child generation an OEP of 39 (compared with 32 for their mothers). This finding reflects occupational upgrading over the period studied: Sons gained 4 percentiles relative to their fathers and daughters 7 percentiles relative to their mothers. Despite the faster catch-up process, baby boomer women continued to be in occupations with much lower earning potential than baby boomer men.

The country comparison shows that the mean OEP was considerably higher, for both the parental and child generation, in the Netherlands (the country with the highest occupational attainment) than in Spain (the country with the lowest attainment among our six countries). In

[7] The detailed coding of parental occupations was carried out by Harry Ganzeboom and collaborators at the Free University of Amsterdam and is only available for the first five rounds of the ESS, 2002-2010. Our analysis only includes the OEP of daughters for whom we also observe an OEP for their mothers, and only sons for whom we observe an OEP for their fathers.

the cohort born in 1942-1970, middle-aged men had an OEP of 54 in the Netherlands as compared to 46 in Spain, and middle-aged women had an OEP of 44 in the Netherlands as compared to 30 in Spain. This finding reflects the earlier shift towards higher-skilled and higher-paid occupations in the Dutch labour market. But then again, the similarities between countries are more striking than the differences.

Figure 4: OEP of sons and daughters (aged 40-60) and their parents, Europe 2002-2010



Data: ESS 2002-2010, all individuals aged 40-60 (and thus born in 1942-1970). OEP based on ISCO-88 4-digit.

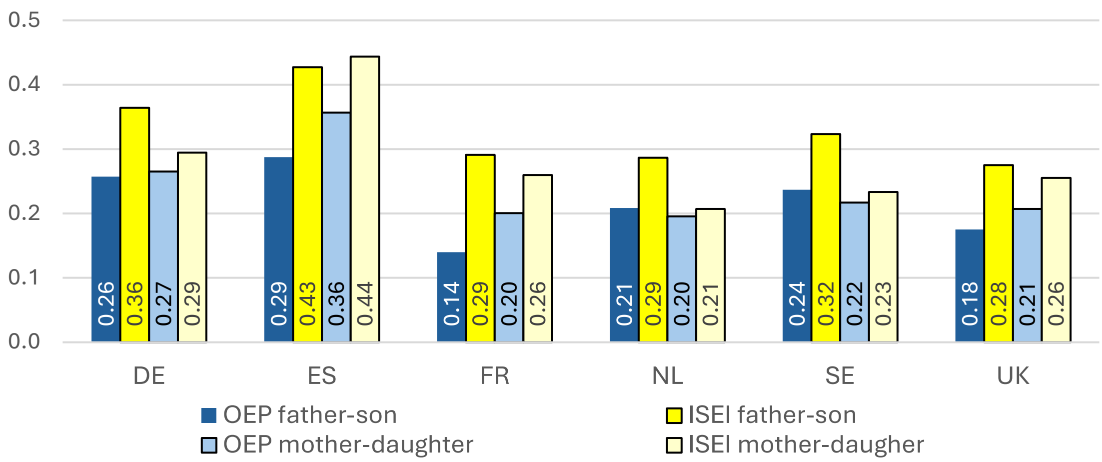
In a final analysis, we examine the link between parents' occupational earning potential and children's occupational earning potential. We do so by correlating fathers' OEP with sons' OEP and mothers' OEP with daughters' OEP, using the same analytical sample as above (men and women aged 40-60 in ESS 2002-10). Since ISEI was developed with the analysis of intergenerational mobility in mind (Ganzeboom and Treiman 1996), we compare the results for OEP with those of ISEI.

Figure 5 shows the correlation coefficients for the same selection of countries as before. The correlations are systematically higher for ISEI than OEP. Based on all countries in the ESS sample, the occupations of fathers and sons are correlated at r=0.26 for OEP and r=0.35 for

ISEI, and the occupations of mothers and daughters at r=0.26 for OEP and r=0.33 for ISEI.[8] Whether we use ISEI or OEP, the correlations are highest in Spain and Germany, and lowest in France and the Netherlands. But once again, a casual observer would probably be more impressed by the similarity than by the differences between countries.

The effect size of OEP is not negligible. A correlation coefficient of 0.26 indicates that having parents with an OEP of 77 (university teacher) rather than 25 (refuse worker/garbage collector) is associated with children having occupations whose earning potential is 13.5 percentiles higher (0.26*52). Although the correlations for ISEI are a third higher than for OEP, the interpretation of ISEI points is less straightforward.

Figure 5: The association between parents' and children's occupational attainment



Data: European Social Survey 2002-2010, individuals aged 40-60 (and thus born 1942-1970). ISCO-88 4-digit.

Our results for the OEP are very similar to those of Björklund and Jäntti (1997: 1014) in their comparison of fathers' predicted income based on occupation and sons' actual income, finding r=0.23 for Sweden and r=0.33 for the US. Clearly, the association between parents'

[8] Information on parents' occupations at the ISCO-08 4-digit level is available for a few countries in ESS rounds 2012 (seven countries) and 2014 (two countries). When pooling these data for all countries over the two rounds, the correlation between fathers and sons is r=0.29 for OEP and r=0,39 for ISEI-08, whereas the correlation between mothers and daughters is r=0.31 for OEP and r=0.38 for ISEI.

occupation and children's occupations is stronger when measured with a combination of education and earnings rather than earnings only. As intergenerational transmission is stronger for education than earnings (Hällsten 2020), OEP shows more societal fluidity than ISEI. This suggests that some of the apparent occupational immobility in the ISEI may reflect educational rather than labour market outcomes.

Conclusion

Social stratification is interested in the unequal distribution of life chances and assumes the existence of a hierarchy – a hierarchy rooted in labour markets that needs to be made visible. To this purpose, our paper has proposed a new scale that ranks occupations according to their earning potential. While information on people's earnings is sensitive and often difficult to obtain, occupations tend to be publicly known and more readily available.

We measure the hierarchy of occupations' earning potential for five countries over several decades using large annual micro-data sets. These national OEP scales turn out to be very stable over time, with high correlations both within countries over time (r=0.90) and between countries (r=0.80). This allows us to derive a single OEP scale by averaging the five national scales for the period 2000/1-2021/3. When applied to another database (EWCS 2010, 2015), the common OEP scale explains more variance in earnings than the national scales for Germany and the UK. Only in Sweden does the national scale perform better. The common OEP scale travels well to other European countries, explaining as much variance in earnings for countries used to construct the scale (such as Germany and the UK) as for countries not used (such as France and Spain), namely about a quarter. The strong similarity of the occupational earnings hierarchy in space and time is an interesting finding in itself, as it extends the scope of the Treiman constant beyond occupational prestige.

The Treiman constant also explains the strong results for ISEI. Despite being based on surveys conducted between 1968 and 1982 (for ISEI) or between 2002 and 2007 (for ISEI-08), it remains an empirically valid measure, explaining over twenty percent of variance in European earnings in 2010-15. ISEI is a composite scale using age-corrected education and income, whereas OEP is a disaggregated scale based on earnings only. Yet they provide similar results because they are highly correlated, reflecting the same underlying occupational hierarchy.

In the analysis of intergenerational mobility, ISEI explains more variance than OEP. This is not surprising given the strong transmission of education between parents and children (Hällsten 2020, Mastekaasa and Birkelund 2023, Strømme and Wiborg 2024). While the OEP scale allows us to see how occupational earnings are correlated across generations, social mobility is a multidimensional phenomenon that cannot be fully captured by any single measure (Breen et. al. 2016, Mood 2017). Other indicators such as education, class, individuals earnings and wealth are also crucial for the study of intergenerational mobility and social stratification.

Not using education in the OEP may come at a cost when analysing mobility. However, this cost is outweighed by three key advantages of OEP: parsimony, clarity and ease of interpretation. Parsimony refers to the fact that OEP requires only one single input measure, namely earnings. Greater parsimony also translates into greater conceptual clarity as the construction logic of OEP can be explained in one single sentence: OEP measures occupations' median earnings and expresses them as percentiles of the overall earnings structure. There is no need to invoke a concept with multiple interpretations such as socio-economic status, and no need to read a statistical appendix to understand the scale's construction logic. Our results on the link between education and OEP illustrate the clarity of this approach: the earning potential of occupations increases with education for both men and women. However, at each educational level, men have higher OEP than women – and the gender gap is largest at low levels of education. Men are thus more likely to be in higher-paid occupations at all levels of education, but the gender gap narrows at higher educational attainment.

Unlike synthetic scales, OEP has the key advantage of expressing results in a metric that lends itself to a substantive interpretation. In the last two decades, social scientists have moved beyond the strategy of simply highlighting the sign of a coefficient (positive or negative) and its statistical significance, instead focussing on the effect size and its *social* significance (Bernardi et al. 2016). By using percentiles of the earnings structure, the OEP has a concrete meaning that can be conveyed in socially significant terms. Two examples illustrate this. With an OEP of 90, lawyers have a median earning that exceeds the earnings of 90 percent of the workforce. Workers with tertiary education take on occupations that are 20 percentiles higher in the earnings structure than the occupations reached by workers with only upper secondary education.

Finally, we would like to highlight three avenues of research where OEP could be fruitful. One avenue concerns the occupational aspirations of people who are not (yet) in the labour force, typically young people before entering the labour market or the unemployed before finding a job. In this context, the OEP provides a measure of the financial attractiveness of jobs which young people and jobseekers from different origins and educational levels aspire to. A second avenue concerns the study of careers and *intragenerational* mobility. Many surveys provide retrospective data on respondents' previous occupations, but rarely on their previous earnings. By assigning occupations their typical earning potential, OEP makes it possible to identify upward, downward and sideways labour market trajectories over the life course. A third avenue concerns *intergenerational* mobility. People know the occupation of their parents and grandparents, sisters and brothers, but rarely their earnings. In the absence of earnings, the OEP provides hierarchical measures of people's social origin and social destination. Thanks to its linear metric, OEP allows for easier statistical analysis – and interpretation – of social mobility than the "complex world of log-linear modelling" (Blanden 2013: 44).

Of course, for many research questions, scholars may prefer to use categorical class measures, such as EGP or micro-classes, or scales that reflect differences in education, prestige or intermarriage patterns. In this sense, OEP is a new addition to the toolbox of social stratification in the Western world, providing a simple, clear and parsimonious measure of life chances that can be meaningfully interpreted.

References

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics*, *118*(4), 1279-1333.

Barone, C., Hertel, F. R., & Smallenbroek, O. (2022). The rise of income and the demise of class and social status? A systematic review of measures of socio-economic position in stratification research. *Research in Social Stratification and Mobility*, *78*, 100678.

Bernardi, F., Chakhaia, L., & Leopold, L. (2017). 'Sing me a song with social significance': the (mis) use of statistical significance testing in European sociological research. *European Sociological Review*, *33*(1), 1-15.

Bihagen, E., & Lambert, P. (2018). Can class and status really be disentangled?. *Research in Social Stratification and Mobility*, *58*, 1-10.

Björklund, A., & Jäntti, M. (1997). Intergenerational income mobility in Sweden compared to the United States. *American Economic Review*, *87*(5), 1009-1018.

Blanden, J. (2013). Cross-country rankings in intergenerational mobility: a comparison of approaches from economics and sociology. *Journal of Economic Surveys*, *27*(1), 38-73.

Brady, D., Giesselmann, M., Kohler, U., Radenacker, A. (2018). How to measure and proxy permanent income: Evidence from Germany and the U.S. *Journal of Economic Inequality*, 16(3), 321-345.

Breen, R., Mood, C., & Jonsson, J. O. (2016). How Much Scope for a Mobility Paradox? The Relationship between Social and Income Mobility in Sweden. *Sociological Science* 3:39–60.

Bukodi, E., Dex, S., & Goldthorpe, J. H. (2011). The conceptualisation and measurement of occupational hierarchies: a review, a proposal and some illustrative analyses. *Quality & Quantity*, *45*, 623-639.

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,* 9, 1-14.

De Graaf, P. M. & Kalmijn, M. (2001). Trends in the intergenerational transmission of cultural and economic status. *Acta Sociologica* 44(1), 51–66.

DiPrete, T. A. (2020). The impact of inequality on intergenerational mobility. *Annual Review of Sociology*, *46*, 379-398.

Duncan, O. D. (1961). A socioeconomic index for all occupations. In : Reiss, A. J. (ed.) *Occupations and Social Status*. New York: Free Press of Glencoe, pp. 109-138.

Erikson, R. & Goldthorpe, J. (1992). *The Constant Flux*. Oxford: Clarendon Press.

Fernández-Macías, E., & Hurley, J. (2017). Routine-biased technical change and job polarization in Europe. *Socio-Economic Review*, *15*(3), 563-585.

Hällsten, M. (2020). Scaling Occupations in Intergenerational Research - an Evaluation with Swedish Register Data. *SocArXiv,* 24 Jan. 2020. https://doi.org/10.31235/osf.io/uxy9q

Hauser, R. M., & Warren, J. R. (1997). Socioeconomic Indexes for Occupations: A Review, Update, and Critique. *Sociological Methodology* 27(1):177–298.

Hout, M., & DiPrete, T. A. (2006). What we have learned: RC28's contributions to knowledge about social stratification. *Research in Social Stratification and Mobility*, *24*(1), 1-20.

Ganzeboom, H. B. (2010). A new International Socio-Economic Index (ISEI) of occupational status for the International Standard Classification of Occupation 2008 (ISCO-08) constructed with data from the ISSP 2002–2007. Paper presented at the Annual Conference of The International Social Survey Programme, Lisbon

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

Ganzeboom, H. B., & Treiman, D. J. (1996). Internationally comparable measures of occupational status for the 1988 International Standard Classification of Occupations. *Social Science Research*, *25*(3), 201-239.

Gidron, N., & Hall, P. A. (2017). The politics of social status: Economic and cultural roots of the populist right. *British Journal of Sociology*, *68*, 57-84.

Goldthorpe, J. H. (2010). Class analysis and the reorientation of class theory: the case of persisting differentials in educational attainment. *British Journal of Sociology*, *61*, 311-335.

ISER (2023a). Understanding Society: Waves 1-13, 2009-2022 and Harmonised BHPS: Waves 1-18, 1991-2009, University of Essex [Data Collection]. https://doi.org/10.5255/UKDA-SN-6614-19.

ISER (2023b). Understanding Society: Waves 1-13, 2009-2023 and Harmonised BHPS: Waves 1-18, 1991-2009: Special Licence Access. University of Essex [Data Collection]. https://doi.org/10.5255/UKDA-SN-6931-16.

Jann, B. (2019). iscogen: Stata module to translate ISCO codes. Available from http://ideas.repec.org/c/boc/bocode/s458665.html.

Jonsson, J. O., Grusky, D. B., Di Carlo, M., Pollak, R., & Brinton, M. C. (2009). Microclass mobility: Social reproduction in four countries. *American Journal of Sociology*, *114*(4), 977-1036.

Kalmijn, M. (1994). Assortative mating by Cultural and Economic Occupational Status. *American Journal of Sociology* 100, 422-52.

Kim, C., Tamborini, C.R. & Sakamoto, A. (2018). The Sources of Life Chances: Does Education, Class Category, Occupation or Short-Term Earnings Predict 20-Year Long-Term Earnings? *Sociological Science*, 5, 206-233.

Lambert, P. (2024). Sociological measures of inequality. *Oxford Open Economics 3* (Supplement_1), 167-175

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

Lambert, P. S., Zijdeman R. L., Van Leeuwen M. H. D, Maas, I. & Prandy, K. (2013) The Construction of HISCAM: A Stratification Scale Based on Social Interactions for Historical Comparative Research, *Historical Methods: A Journal of Quantitative and Interdisciplinary History*, 46(2), 77-89.

Mastekaasa, A., & Birkelund, G. E. (2023). The intergenerational transmission of social advantage and disadvantage: comprehensive evidence on the association of parents' and children's educational attainments, class, earnings, and status. *European Societies*, 25(1), 66-86.

Meraviglia, C., Ganzeboom, H. B., & De Luca, D. (2016). A new international measure of social stratification. *Contemporary Social Science* 11, 1-29.

Mood, C. (2017). More than Money: Social Class, Income, and the Intergenerational Persistence of Advantage. *Sociological Science* 4: 263-287

Muñoz de Bustillo, R., Fernández-Macías, E., Esteve, F., & Antón, J. I. (2011). E pluribus unum? A critical survey of job quality indicators. *Socio-Economic Review*, *9*(3), 447-475.

Ritchie, S. (2015). *Intelligence: All that matters*. London: John Murray.

Rose, D. & Harrison, E. (2014). *Social Class in Europe: An Introduction to the European Socio-Economic Classification*. London: Routledge.

Saavedra, M. & Twinam, T. (2020) A machine learning approach to improving occupational income scores. *Explorations in Economic History*, 75, 101304.

Shahbazian, R., & Bihagen, E. (2022). Does Your Class Give More than a Hint of Your Lifetime Earnings?: Assessing Indicators for Lifetime Earnings Over the Life Course for Sweden. *European Sociological Review*, *38*(4), 527-542.

Sobek, M. (1995). The Comparability of Occupations and the Generation of Income Scores. *Historical Methods*, 28(1), 47-51.

Song, X., & Xie, Y. (2023). Occupational Percentile Rank: A New Method for Constructing a Socioeconomic Index of Occupational Status. *Sociological Methods & Research*.

Strømme, T. B., & Wiborg, Ø. N. (2024). Social origins and educational attainment: The unique contributions of parental education, class, and financial resources over time. *British Journal of Sociology* 1-20.

Tåhlin, M. (2007). Class clues. *European Sociological Review*, *23*(5), 557-572.

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

Weeden, K. A., & Grusky, D. B. (2005) The Case for a New Class Map. *American Journal of Sociology* 111(1), 141–212.

Appendix

Table A.1: OEP-values of occupations (ISCO-08 3-digit level)

ISCO-08 code and label	OEP value
11. Commissioned armed forces officers	87.2
21. Non-commissioned armed forces officers	78.6
30. Armed forces occupations, other ranks	55.2
31. Armed forces occupations, other ranks	63.0
100. Managers	80.6
110. Chief executives, senior officials and legislators	87.2
111. Legislators and senior officials	84.6
112. Managing directors and chief executives	92.8
120. Administrative and commercial managers	84.0
121. Business services and administration managers	82.8
122. Sales, marketing and development managers	85.6
130. Production and specialized services managers	79.4
131. Production managers in agriculture, forestry and fisheries	67.3
132. Manufacturing, mining, construction and distribution managers	77.2
133. Information and communications technology services managers	89.6
134. Professional services managers	72.0
140. Hospitality, retail and other services managers	52.2
141. Hotel and restaurant managers	39.8
142. Retail and wholesale trade managers	54.8
143. Other services managers	76.0
200. Professionals	71.2
210. Science and engineering professionals	78.6
211. Physical and earth science professionals	77.8
212. Mathematicians, actuaries and statisticians	84.0
213. Life science professionals	69.8
214. Engineering professionals (excluding electrotechnology)	80.2
215. Electrotechnology engineers	83.6
216. Architects, planners, surveyors and designers	66.8
220. Health professionals	73.2
221. Medical doctors	91.2
222. Nursing and midwifery professionals	55.0
223. Traditional and complementary medicine professionals	42.3
224. Paramedical practitioners	70.0
225. Veterinarians	78.7
226. Other health professionals	57.8
230. Teaching professionals	62.2
231. University and higher education teachers	77.4
232. Vocational education teachers	67.8
233. Secondary education teachers	69.0
234. Primary school and early childhood teachers	52.4
235. Other teaching professionals	59.4
240. Business and administration professionals	74.2
241. Finance professionals	80.0
242. Administration professionals	69.8
243. Sales, marketing and public relations professionals	78.5
250. Information and communications technology professionals	80.0
251. Software and applications developers and analysts	80.6
252. Database and network professionals	77.3
260. Legal, social and cultural professionals	64.8
261. Legal professionals	86.8
262. Librarians, archivists and curators	50.6
263. Social and religious professionals	58.2
264. Authors, journalists and linguists	66.5
265. Creative and performing artists	58.0

300. Technicians and associate professionals	55.2
310. Science and engineering associate professionals	63.0
311. Physical and engineering science technicians	62.6
312. Mining, manufacturing and construction supervisors	66.8
313. Process control technicians	56.2
314. Life science technicians and related associate professionals	50.8
315. Ship and aircraft controllers and technicians	84.6
321. Medical and pharmaceutical technicians	42.8
322. Nursing and midwifery associate professionals	42.2
323. Traditional and complementary medicine associate professionals	19.0
324. Veterinary technicians and assistants	25.5
325. Other health associate professionals	36.2
330. Business and administration associate professionals	58.0
331. Financial and mathematical associate professionals	56.6
332. Sales and purchasing agents and brokers	65.3
333. Business services agents	59.4
334. Administrative and specialized secretaries	49.9
335. Government regulatory associate professionals	61.6
341. Legal, social and religious associate professionals	43.8
342. Sports and fitness workers	45.5
343. Artistic, cultural and culinary associate professionals	40.5
351. IT operations and user support technicians	65.8
352. Telecommunications and broadcasting technicians	52.7
400. Clerical support workers	37.6
411. General office clerks	43.8
412. Secretaries (general)	35.3
413. Keyboard operators	26.1
420. Customer services clerks	37.0
421. Tellers, money collectors and related clerks	42.8
422. Client information workers	26.6
431. Numerical clerks	46.0
432. Material recording and transport clerks	38.0
441. Other clerical support workers	36.6
500. Services and sales workers	23.0
510. Personal services workers	20.6
511. Travel attendants, conductors and guides	41.4
512. Cooks	20.8
513. Waiters and bartenders	12.4
514. Hairdressers, beauticians and related workers	13.2
515. Building and housekeeping supervisors	27.0
516. Other personal services workers	24.8
521. Street and market salespersons	12.0
522. Shop salespersons	24.4
523. Cashiers and ticket clerks	12.2
524. Other sales workers	18.8
530. Personal care workers	17.6
531. Child care workers and teachers' aides	13.4
532. Personal care workers in health services	19.6
541. Protective services workers	54.0
610. Market-oriented skilled agricultural workers	20.8
611. Market gardeners and crop growers	21.6
612. Animal producers	15.6
613. Mixed crop and animal producers	27.5
621. Forestry and related workers	31.9
622. Fishery workers, hunters and trappers	32.5
631. Subsistence crop farmers	21.6
632. Subsistence livestock farmers	21.6
633. Subsistence mixed crop and livestock farmers	21.6
634. Subsistence fishers, hunters, trappers and gatherers	21.6
700. Craft and related trades workers	43.8

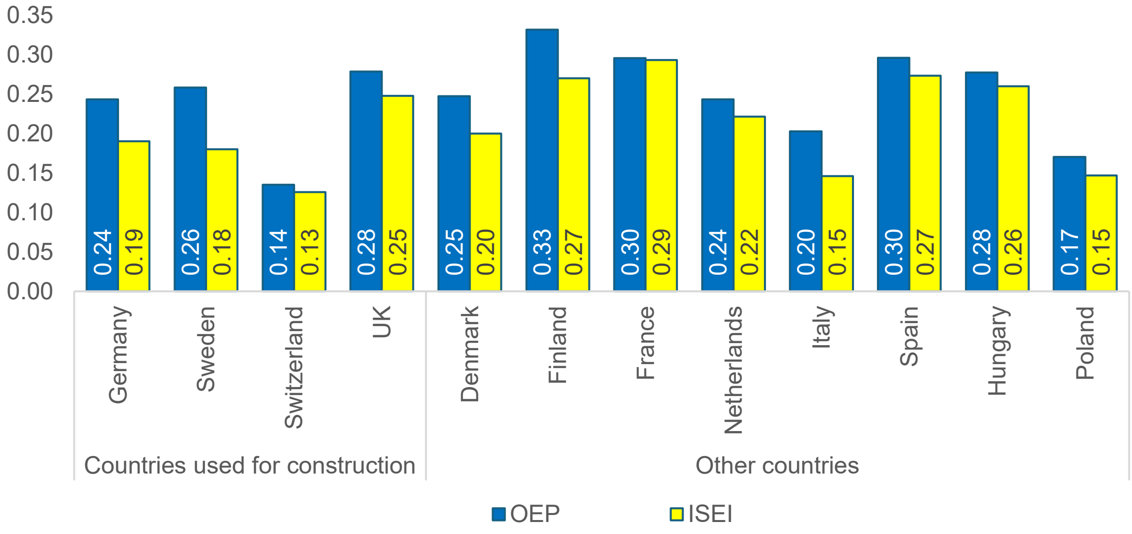
711. Building frame and related trades workers	41.6
712. Building finishers and related trades workers	45.4
713. Painters, building structure cleaners and related trades workers	33.8
720. Metal, machinery and related trades workers	46.6
721. Sheet and structural metal workers, moulders and welders	41.6
722. Blacksmiths, toolmakers and related trades workers	45.0
723. Machinery mechanics and repairers	48.6
731. Handicraft workers	35.4
732. Printing trades workers	43.8
740. Electrical and electronics trades workers	53.0
741. Electrical equipment installers and repairers	53.6
742. Electronics and telecommunications installers and repairers	50.4
751. Food processing and related trades workers	24.8
752. Wood treaters, cabinet-makers and related trades workers	32.2
753. Garment and related trades workers	21.3
754. Other craft and related workers	41.8
800. Plant and machine operators and assemblers	37.0
810. Stationary plant and machine operators	34.2
811. Mining and mineral processing plant operators	57.0
812. Metal processing and finishing plant operators	43.5
813. Chemical and photographic products plant and machine operators	45.5
814. Rubber, plastic and paper products machine operators	32.8
815. Textile, fur and leather products machine operators	15.6
816. Food and related products machine operators	27.8
817. Wood processing and papermaking plant operators	39.2
818. Other stationary plant and machine operators	30.0
821. Assemblers	31.5
830. Drivers and mobile plant operators	38.8
831. Locomotive engine drivers and related workers	65.2
832. Car, van and motorcycle drivers	26.6
833. Heavy truck and bus drivers	38.8
834. Mobile plant operators	38.6
835. Ships' deck crews and related workers	52.3
900. Elementary occupations	19.0
910. Cleaners and helpers	11.4
911. Domestic, hotel and office cleaners and helpers	10.8
912. Vehicle, window, laundry and other hand cleaning workers	18.0
921. Agricultural, forestry and fishery labourers	14.4
930. Labourers in mining, construction, manufacturing and transport	25.6
931. Mining and construction labourers	33.6
932. Manufacturing labourers	21.0
933. Transport and storage labourers	31.6
941. Food preparation assistants	12.8
951. Street and related services workers	17.0
952. Street vendors (excluding food)	17.0
961. Refuse workers	25.8
962. Other elementary workers	24.3

Table A.2: Variance in earnings (r2) explained by OEP and ISEI-08

Country	OEP	ISEI-08
Austria	0.25	0.23
Belgium	0.23	0.20
Bulgaria	0.15	0.12
Croatia	0.30	0.31
Cyprus	0.23	0.16
Czech	0.22	0.18
Denmark	0.25	0.20
Estonia	0.26	0.20
Finland	0.34	0.27
France	0.32	0.29
Germany	0.26	0.19
Greece	0.23	0.18
Hungary	0.28	0.26
Ireland	0.26	0.22
Italy	0.21	0.15
Latvia	0.23	0.19
Lithuania	0.09	0.06
Luxembourg	0.31	0.34
Macedonia	0.21	0.22
Malta	0.32	0.31
Montenegro	0.15	0.13
Netherlands	0.27	0.22
Norway	0.27	0.21
Poland	0.18	0.15
Portugal	0.29	0.28
Romania	0.29	0.27
Slovakia	0.23	0.20
Slovenia	0.25	0.27
Spain	0.30	0.27
Sweden	0.25	0.18
Switzerland	0.14	0.13
Turkey	0.25	0.27
UK	0.29	0.25

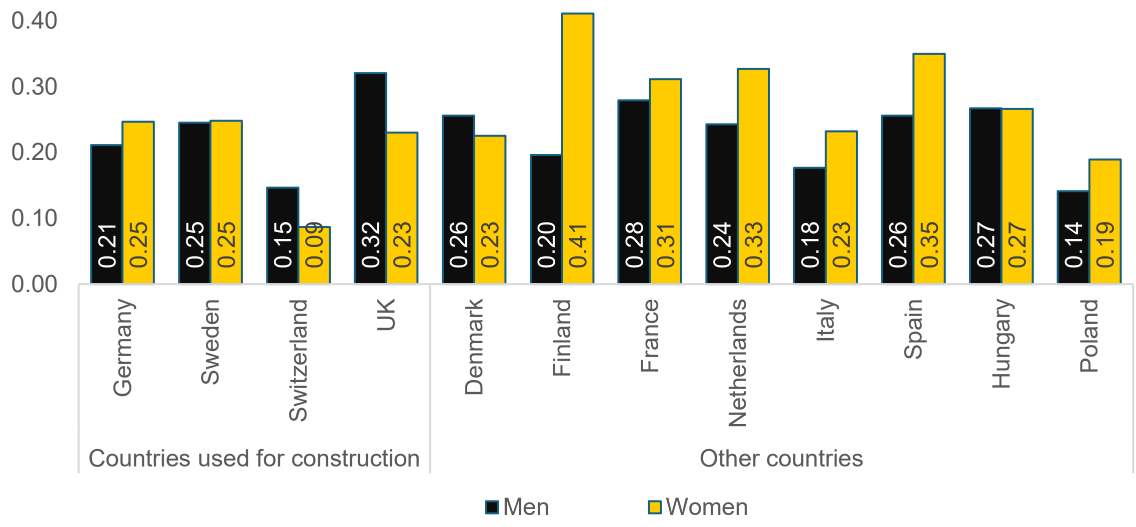
Data: EWCS 2010, 2015 (only 2015 for Switzerland); Albania, Kosovo and Serbia excluded because of small samples.
Note: OEP and ISEI-08 are measured at ISCO-08 4-digit level.

Figure A.1: Variance in earnings (r2) explained by OEP and ISEI (both measured at ISCO-88 4-digit)



Data: EWCS 2010, 2015 (only 2015 for Switzerland). Both OEP and ISEI are based on ISCO-88 at the 4-digit level.

Figure A.2: Variance in earnings explained by OEP for men and women separately (r2)



Data: EWCS 2010, 2015 (only 2015 for Switzerland). OEP is based on ISCO-08 at the 4-digit level.