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Using the decomposition of the mutual information index as an alternative approach to the study of educational inequality trends in Spain☆

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ABSTRACT

In this study, we investigate the relationship between social origin and educational attainment in Spain from 1946 to 1989, testing the theory of persistent inequalities and using two different methodological approaches: the margin-free versus the margin-dependent traditions. More specifically, we will compare the results of the traditional log-linear measures used most frequently in this field with those of the mutual information index, a measure that considers the marginal change in both educational expansion and occupational upgrading. Moreover, we apply the decomposition of this index, as proposed by Jann & Seiler, which allows us to simultaneously observe and distinguish between the internal component (margin-free: not accounting for changes in marginal distributions such as odds ratios) and the marginal component (non-margin free: including and measuring marginal effect). Previous research using margin-free models reveals educational inequalities in Spain to be constant, whereas our results show a marked decline in educational inequalities when the weights obtained by the marginal distribution are taken into account. We argue that this decomposition may enrich our view of educational inequalities without disregarding traditional margin-free measures.

1. Introduction

There is no doubt that, throughout the 20th century, the expansion of education has been one of the greatest historical improvements experienced by advanced societies. Although the majority of the world's population was illiterate at the beginning of the century, this figure has now been reduced to approximately one in ten (Roser & Ortiz-Ospina, 2016). The cost of covering the basic necessities of existence has fallen, and inclusive education policies have been implemented, both of which have reduced the economic burden on families; thus, we would expect the expansion of education to also translate into a reduction of inequalities between classes. However, it has been widely reported that in many societies, there has not been a significant reduction in educational inequalities (Shavit & Blossfeld, 1993; Whelan et al., 2001; *Author*). The reason for this is that, as the totality of social classes increase their educational level, the differentials between them do not decrease substantially. In other words, educational inequalities between social classes are maintained because the more advantaged social class increases its educational attainment rates as the less advantaged social classes improve, thereby retaining existing gaps between classes (Ayalon & Shavit, 2004). This process, in which the social class distances are-replicated over time, was called the 'translation of structure' by Bourdieu and Passeron (1970).

Some scholars consider that the invariance in educational inequality rates is in part an artefact of a property called 'margin insensitivity' of measures such as the unidiff coefficient in multiplicative log-linear models (Combessie, 1984; Marks, 2004; Hellevik, 2007). This traditional perspective of margin-free measures used in studies of social

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mobility can be complemented by a method that takes into account the margins of the contingency table and, therefore, the importance of the categories of the variables analysed and their variation over time (or across societies). In this study, we will focus on this alternative interpretation.

According to the margin-insensitivity property, by calculating odds ratios with the cells of the joint distribution of a contingency table, we can free ourselves from the influence of marginal distributions and thus construct a net measure. By seeking a genuinely abstract measure that reflects equal opportunities, free-margin models assign equal importance to all barriers between classes, without regard to the different compositions of the groups involved. In studying the relationship between social origin and education, we assume that odds ratios are calculated independently of the distribution of marginals, so that any changes over time are weighted equally, i.e. barriers to access to education do not take into account the changes in the prevalence of social classes or educational levels. In some cases, these changes involve a reduction in certain occupations or educational levels such as agriculture or illiteracy or an increase in the service class in a significant way.

It should be highlighted that margin-free measures were an unprecedented step forward in the studies of social stratification in general and educational inequalities in particular. With the development of the log-linear and log-multiplicative models (Goodman, 1978; Hauser, 1978; Goldthorpe, 1980), a new methodology was instituted, making it possible to address important theoretical questions. To find an ideal measure of equality of opportunity, the log-multiplicative layer effect or unidiff model (Xie, 1992; Erikson & Goldthorpe, 1993) created an aggregation technique that takes an unweighted average across all barriers. Because of its parsimony and predictive ability, this model was set up as a reference model. Being more precise, "the overall size of the log odds ratios shifts as we move from table to table means that each log odds ratio in the same table is scaled up or down by the same factor" (Breen, 2020: 23).[1]

This article aims to test the theory of persistent inequalities using a new methodological strategy that highlights the importance of marginal changes in social background and educational level, without dispensing with the usual procedures used in studies of educational inequality. We propose to study the role played by social origin in educational expansion using the mutual information index (Theil, 1967, 1972; Seiler & Jann, 2019a, 2019b), which is traditionally used in studies regarding school segregation. This index allows us to observe changes over time in the relationship between social origin (O) and educational attainment (E). However, to do this, inequalities of educational opportunity (IEO) are divided into two components: (1) the effects arising from marginal changes, which are expressed in the marginal distributions and (2) effects arising from internal changes, which are expressed in the joint distribution. Since a society can be better defined by some barriers rather than others, in some cases, treating each barrier according to its relevance may be informative.

We will use this decomposition approach with data from Spain, a case of special interest because of two phenomena. First, Spain is one of the countries where educational expansion has been the most intense (Barro & Lee, 2013), and second, many of the studies that have been carried out found evidence of persistent educational inequalities.

This article is organised as follows. In Section 2, we present the main theories on educational inequalities and comment on the empirical studies. In Section 3, we present some of the advantages introduced in the calculations, encompassing both internal and marginal changes. In Section 4, we present and justify the hypotheses of our work. In Section 5, we present the methodology of analysis of the mutual information index. In Section 6, we present the data sources and variables used. In Section 7, we present the results obtained. Finally, in Section 8, we present the conclusions.

2. Theoretical and empirical review

In this section, we discuss the main theoretical approaches in which the analyses of educational inequalities are framed. Additionally, we present some of the main empirical evidence supporting each theory, especially for the Spanish case.

During the second half of the 20th century, two opposing theories of inequality of educational opportunities were proposed: social reproduction theory and modernisation theory. Social reproduction theory is based on the differential forms of socialisation of the social classes. According to this approach, families socialise their children into different subcultures by promoting different values towards school (Bourdieu & Passeron, 1970). Families who come from the middle classes promote socially legitimised knowledge that is highly valued in the school environment. Their education follows what has been called 'a concerted cultivation' (Lareau, 2000) consisting of a virtuous learning circle operating between families and schools.

The first international study to report persistent rates of educational inequality was initiated by Shavit and Blossfeld (1993). Of the 13 countries analysed in their study, only two, the Netherlands and Sweden, showed a decrease in class differentials in terms of education.

A detailed explanation of the evolution of educational inequalities was made by Raftery and Hout (1993) in a study performed some years earlier. On the one hand, the theory of maximally maintained inequality postulates that class differentials remain unchanged over time because, as the working classes saturate the basic educational levels, the middle classes occupy the next-highest level. On the other hand, the theory effectively maintained inequality (Lucas, 2001) highlights that these changes are not only quantitative but also qualitative in nature. Differences in education do not follow a vertical, but rather, a horizontal, pattern of inequality that is manifested in the type and not simply in the amount of education received.

The research by Shavit and Blossfeld (1993) was refuted by Breen et al. (2009), who found evidence of decreasing educational inequalities in eight European countries due to improvements in nutrition and health, as well as educational reforms that reduced the effort required by parents to send their children to school.

The modernisation theory or the liberal theory of industrialism predicts that industrialisation affects the structure and process of stratification (Treiman, 1970). In this sense, the theory holds in which all industrialised societies substitute ascription by achievement, as technological development and modernisation demand the prevalence of merit-based selection and a reduction in the association between origin and education. However, this theory has been challenged over the last 20 years, to the point where some authors have stated that 'modernisation theory it is wrong' (Hout & DiPrete, 2006:8).

Alongside the two main theories, one of which postulates the constancy of educational inequalities and the other that sustains the existence of their reduction, we can also identify a third position that considers that the decline in inequalities is limited to the golden years of capitalism (Barone, 2019; Barone, 2020). These were years of intense industrialisation, full employment, intensification in the urbanisation process and educational expansion at the low educational levels. Barone & Ruggera (2021: 21) report that 'this finding suggests the relevance of structural changes, possibly operating through a cost-equalising mechanism', which led to a reduction of the educational inequalities and stopped since the 1970s. Similarly, Shavit (2014) pointed out that the process of educational equalisation was limited to the low educational levels. Consequently, the association marking the decline in educational inequalities is weakened for the youngest cohorts.

During the last few decades, the Spanish scenario has been characterised by strong economic and occupational modernisation and a major expansion of education. Thus, the case of Spain is a stimulating opportunity to explore these dynamics. The most complete bibliographical

[1] Later, based on the same methodological framework, Cox et al. (2009) developed an average global log–odds ratio that does not assume this property.

review of IEO carried out to date for Spain (Fernández-Mellizo, 2014, 2022) shows a lack of agreement among those researchers dedicated to the study of educational inequalities. Methodological heterogeneity has led to contradictory conclusions, although most studies point towards stability. Among the studies showing persistent inequalities is the work by Calero and Bonal (1999), which analyses the 1981 and 1991 population censuses using descriptive statistics and that of Martínez-García (2002), which uses the 1991 Sociodemographic survey and applies linear regression and conditional logit. Among the studies showing decreases are those of Carabaña (1993) using the 1970 and 1981 censuses and applying descriptive statistics; Ballarino et al. (2009) using the 1991 sociodemographic survey and applying cumulative logit and Di Paolo (2012) using the 2005 Statistics on Income and Living Conditions survey and applying ordinal probit analysis. Finally, studies that show increases and decreases are those of Torres-Mora and Peruga (1997) using the 1991 Sociodemographic survey and applying logit models and Carabaña (1999) using the 1991 Sociodemographic survey and applying linear regression.

The results on IEO have also been investigated within the field of social mobility studies or, more specifically, the analysis of the origin (O)–education (*E*)–destination (D) (OED) social mobility triangle. As Breen and Müller :7) (2020) point out, '(social fluidity between origins and destinations depends on an indirect relationship between O and D via E… and a direct relationship between O and D…)'. From this perspective, most analyses of Spain in this context report constancy in the relationship origin-education (OE) (*Author*; Gil, Bernardi & Luijkx, 2020; and *Author*). Additionally, all of them use the uniform difference model (unidiff), which assumes a common pattern of parent–child log-odds ratios that vary according to a specific scaling factor for each cohort studied.

3. Margin-free and margin-dependent measurement

In the analysis of the relationship between variables in a contingency table, we can apply two types of statistical techniques: those that account for the link by neutralising the effect of the margins of the table (margin-free techniques) or those that take margins into account (margin-dependent techniques). We report on some of the benefits of incorporating variations in the marginal distribution in the calculations along with internal adjustments, in particular, for educational inequalities. We describe how to enrich our view of this phenomenon, usually focused only on internal structures, by incorporating information from the margins. We explain how on some occasions, this may offer us valuable information about educational inequality trends.

In the search for a relative measurement free from the enforced movements in a table, inherent for instance in the calculations of absolute mobility, two types of measurements have been created. On the one hand, the margin-free measurement specifies the net relative change beyond any marginal transformation. To check the probabilities of access to a given social class from different positions, we have no option but to abstract from changes in composition (Vallet, 2007). Thus, the odds ratio statistic is used as a building block. It is understood to be a net measure devoid of any morphological influence. Since it is free from the influence of marginal distribution, it is a net measure of the impact of social origin on the final educational destination, and it can be considered a 'pure' or abstract measure of educational inequality. Thus, two tables that are radically different in their marginal distribution can be identical in their odds ratios (Vallet, 2007). Moreover, if we multiply all cells in a given row or column by a constant, the odds ratios will not be altered. That is, the analyses of the tables will not be affected by different marginal distributions' sample sizes of the different layers (cohort or country) 'since the odds ratios remain the same' (Wong, 2010:6).

On the other hand, the margin-dependent measurement takes into account the changes in margins. For example, the index of dissimilarity is margin-dependent in terms of the units under study (e.g. neighbourhoods or schools) but not in terms of the groups (e.g. racial/income groups). This means that educational inequalities will generally change when the distribution of respondents according to social origin or educational attainment increases. Given educational expansion and the father's occupational upgrading, taking into account marginal distribution may be highly relevant.

Is a measure that considers only internal changes enough in certain circumstances? There is no problem when marginals do not contribute substantially to the results; however, in the case under study, can one abstract from educational expansion and the father's occupational upgrading? And does the size weight of barriers between groups not generate sociologically important effects?

If the aim is to analyse barriers by social class, i.e. to analyse the mobility opportunities of some classes versus others, the margin-free measurement models are certainly fully satisfactory. However, they are not satisfactory if we want to have a global idea of the degree of social openness, combining marginal and internal changes in a society in space (in regions or countries), or over time (across cohorts, ages or periods). Among other things, it is not very realistic to reach a conclusion about the degree of openness or closure of a society without considering the weight of the barriers experienced by each of the groups that form it. According to Seiler and Jann : 7) (2019a), we have gone too far with this type of analysis, as is illustrated by the case of the city-state of Singapore.

> '…when studying industrialization or modernization processes, the diminishing weight of the farming classes is of special importance, as it is a defining (or at least a characteristic) feature of these processes (Treiman, 1970; Kuznets, 1955). Marginalization of agriculture could mean that the size of the farming class approaches zero, for example because of the complete urbanization of an area; Singapore (Fields 1994) could serve as an almost perfect real world example. This extreme case is helpful for illustrating why ignoring changes in class distribution can produce misleading results when analyzing the changing effects of social origin'.

This is a clear example in which the analysis technique based on log-linear models and the calculation of odds ratios such as unidiff can occasionally lead us to incomplete results. Let us take the example of Spanish society, which has undergone rapid major class transformations as an exemplar of late industrialisation. The unidiff coefficients may lead us to partial conclusions if we do not take into account that agricultural workers, landowners and day labourers have declined sharply in number and other classes (professionals and service workers) have increased in number. In other words, since log-linear and log-multiplicative models make their calculations using a sort of aggregation technique for odds ratios, exchanges with different prevalence levels are considered equally important. It is not always the best strategy to give the same weight to cells that contain hardly any units as to cells that are heavily populated. The marginal distribution must be considered because it affects the importance of the dependencies between origin and destination owing to the proportion of society affected by these associations (Seiler & Jann, 2019a).

Taking a different approach, Hellevik (2007) considers that the persistence in educational inequality rates derives from the fact that they are analysed with measures of association rather than with measures of inequality. If income inequality measures were used to analyse educational inequality, a substantial decrease in inequality by social origin would be seen, at least as far as access to university is concerned. Moreover, the same author stresses that the entrenched belief in net changes unaffected by marginal changes has been a major obstacle to reaching an agreement on the relationship between social class and education.

The paradigm based on log-linear models has almost certainly been the most significant advance in the study of social mobility and educational inequalities. However, its use in isolation and societies in transformation generates, in some specific cases, partial visions of reality that should be corrected to reflect the social changes that represent such an outstanding improvement in having increasingly educated societies or higher occupational levels.

4. Hypotheses

To further elucidate the educational inequalities in Spain, we propose two complementary hypotheses that lead us to expect two different results in the relationship between social origin and educational level reached by offspring.

H1. : Following the margin-free tradition, we expect to find educational inequalities unchanged in Spain.

When we consider the relationship between social origin and educational attainment without taking into account the influence of the margins, we can expect educational inequalities to remain constant. This is a consistent finding in previous studies in Spain using this type of methodology. Researchers following the margin-free tradition have found that educational inequality rates remained unchanged and concluded that the improvement of economic conditions and educational opportunities did not have a strong impact on educational inequalities. Indeed, educational improvements of the working classes (both skilled and unskilled) and the agricultural classes (both landowners and day labourers) were not important enough to compensate for the gap in educational inequality in comparison with the upper classes.

H2. : We expect to find a decrease in educational inequalities in Spain when the barriers have been weighted for their relevance.

If we do not supplant the margin-free tradition with the marginal tradition, certain changes that should be considered to be tending towards fluidity under a conception of an open society tend rather towards constancy or rigidity, especially when the tables we are analysing are very different in their composition. However, on some occasions, measures that do not account for proportional differences give us incomplete information. If we rely on margin-free measures, the movement of small farmers and agricultural workers to educational levels beyond primary education will not be calibrated according to the demographic importance that urbanisation and educational expansion had (thus, two cohorts with the same odds ratios will contribute equally to educational inequality, regardless of the numerical magnitude of the two phenomena). When there are major changes in the social structure of origin and the educational pyramid, for example, when farmers and agricultural workers are fewer in number and people with only non-compulsory educational levels decrease in number, it may be beneficial to give different weights and propose a complementary hypothesis, as above.

To specify this hypothesis, we need to think that younger cohorts will have greater fluidity if we take into account the prevalence of barriers and not just how pronounced they are. In other terms, their marginal structure will be more beneficial reducing social origin impact.

5. Methodology of analysis

The methodological strategy we follow to account for our hypotheses establishes a two-pronged approach. Our objective is to determine whether an analysis based on the mutual information index (hereinafter referred to as the M-index) leads to conclusions different from an analysis based on the unidiff model, i.e. whether taking into account marginal distributions matters. Furthermore, using counterfactual decomposition, we will discover the contribution of both internal and marginal changes. We will then present the structure of education by cohort and by social class and gender and changes in the parents' occupational structure.

For relative changes within the margin-free tradition, we apply log-linear and log-multiplicative models to perform a time-varying analysis of the relationship between social origin and education. Thus, we obtain the constant fluidity first and then the unidiff models, which estimate the changes in the strength of association between the social origin (O) and education (E) across cohorts (C) and which are evaluated by the Bayesian information criterion (BIC) statistic. The two models are expressed as follows:

$$logF_{ijkl} = \mu + \lambda_i^O + \lambda_j^E + \lambda_k^C + \lambda_l^S + \lambda_{ikl}^{OCS} + \lambda_{jkl}^{ECS} + \lambda_{ij}^{OE}$$

$$logF_{ijkl} = \mu + \lambda_i^O + \lambda_j^E + \lambda_k^C + \lambda_l^S + \lambda_{ikl}^{OCS} + \lambda_{jkl}^{ECS} + \beta_k \phi_{ij}$$

The first equation assumes a log-linear model formed by the main effects and second-order interactions, which shows the constancy of the relationship between social origin and education over time. The second replaces the term λ_{ij}^{OE} by a constant second-order interaction $\beta_k \Phi_{ij}$, which represents the multiplication of the OE interaction by a scaling factor that expresses, given the same general pattern of behaviour, the level of attenuation or accentuation of inequality of social origin over time.

We use the mutual information index to take into account the internal and marginal effects of educational inequality simultaneously. The logic of the index goes back to the approaches of information theory (Shannon, 1948), introduced in the social sciences by Theil (1967, 1972), in which the concept of entropy indicates the degree of uncertainty of a particular piece of information and responds to the criterion that the more information one has about an event, the less information one gains when observing it. Entropy can be used to measure the amount of information shared; hence, the higher the entropy is, the lower the amount of information is. Thus, we contrast the difference between the information gained a posteriori by introducing a certain measure, X, regarding an a priori unconditional initial situation, Y, which lacks that information. What we gain or learn about the initial situation is a measure of the importance of X in knowing Y that allows us to analyse the relationship between the two variables.

Following the example of Seiler and Jann (2019a; 2019b), this can be achieved by comparing two distributions: the first corresponds to how much information we have about an event Y (for example, the educational level achieved by a group of people), i.e. its unconditional distribution, obtained a priori; the second, obtained a posteriori, corresponds to how much information is obtained if the conditional distribution of Y over another variable X is known. In our case, this would mean comparing the unconditional distribution of education (E) with its distribution conditional on social origin (O) (Fig. 1). If the difference is substantial, it may be observed that the social class of origin exerts a subsequent strong influence on educational attainment.

The entropy of the distribution of variable E (the education achieved) is defined a priori as follows: $E(P_E) = -\sum_{j=1}^{J} p(E_j).\ln(p(E_j))$.

Here, $p(E_j)$ is the unconditional probability of reaching the education

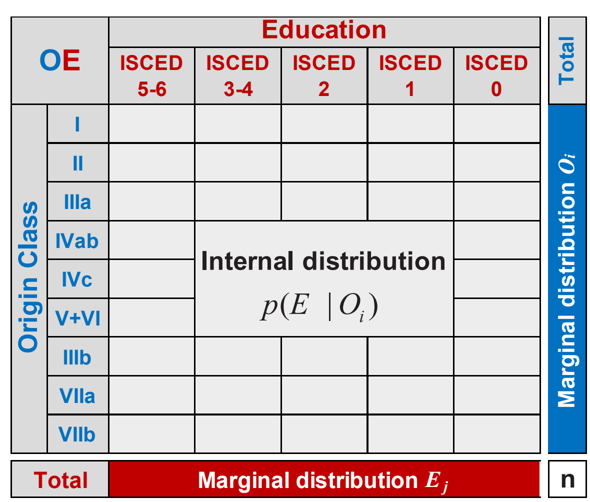

Fig. 1. : Marginal and internal distributions of the contingency table between the origin class (O) and education (E).

level j based on a priori information without considering the social class of origin.

A posteriori, the entropy of the variable E given the information of the variable O (the social class of origin) is defined as follows:

$$E(P_{E|O}) = -\sum_{i=1}^{I} p(O_i)\cdot \sum_{j=1}^{J} p(E_j|O_i)\cdot \ln\left(p(E_j|O_i)\right)$$

Here, $p(E_j|O_i)$ is the probability of reaching the education level j conditioned to a posteriori knowledge of the social class of origin i.

The mutual information index, M, is obtained as the difference between the two above expressions, as follows:

$$M = E(P_E) - E(P_{E|o}) = \sum_{i=1}^{I}\sum_{j=1}^{J} p(O_i, E_j)\ln\left(\frac{p(E_j|O_i)}{p(E_j)}\right)$$

Here, $p(O_i, E_j)$ refers to the joint probability of class origin and educational destination.

The M-index is a measure of association that accounts for both internal association and marginal distribution. Obtaining internal barriers in the OE relationship through 'margin-free' measures (odds ratios) is not the best way, because OE combinations only concern pairs of categories/cells: it is fine for one-to-one comparisons but not for comparisons between countries or cohorts as a whole. Each OE combination, when relative changes are measured excluding marginal changes, is not appropriate for showing existing dependencies between variables, and to generalise relative changes, it is necessary to consider different weights of marginal distribution (how many people the relative change affects: a relative social change, or a barrier in a specific cell, which affects a small proportion of individuals is not the same as a relative change that affects a large part of the population), because changes in marginal distributions impact OE associations (Seiler & Jann, 2019a: 8).

The M-index can be expressed as a simple average of the components specific to each observed case c, considering the following two generic variables x and y:

$$E(M_c) = M = \frac{1}{n}\sum_{c=1}^{n} \ln\left(\frac{p(y_c|x_c)}{p(y_c)}\right)$$

This can be generalised to a multidimensional set of variables X (e.g. for social origin) and another set of additional control variables V as follows:

$$M^* = E(P_{Y|V}) - E(P_{Y|V,X})$$

Thus, the M-index can be compared across categories of third variables such as countries or, in our case, cohorts.

The a priori model would be $p(y_c|v_c)$ and the a posteriori one $p(y_c|v_c, x_c)$. The estimation process involves 1) estimating a multinomial logit of y over v and obtaining the predicted probabilities $p(y_c|v_c)$, 2) estimating a multinomial logit of y over v and x and obtaining the predicted probabilities $p(y_c|v_c,x_c)$ and 3) calculating for each observed case c the estimates.[2].

$$\widehat{m}_c = \ln\left(\frac{\widehat{p}(y_c|v_c, x_c)}{\widehat{p}(y_c|v_c)}\right)$$

An important aspect of this measure is that it can be decomposed into two effects. Comparing cohorts over time, the difference in the mutual information index between two cohorts (c1 and c2) is the result of two contributions.[3].

1) The effect arising from internal changes, which are expressed in the joint or conditional distribution and the OE association intensity and the patterns taken changes over time. That is, how pronounced the class barriers are, as the odds ratio also measured.
2) The effect of marginal changes, which are expressed in marginal distribution: education (E) and class origin (O) over time in our case. That is, how prevalent the barriers are: the effect of educational expansion and changes in class structure.

The M-index between the two cohorts (c1 and c2, or countries, etc.) is the result of these two contributions:

$M_{c1} - M_{c2} = \Delta M$ (Δmarginals, Δ*int*ernal) = Marginal Contribution + Internal Contribution

When we compare the M-index by cohort, the part of the difference that is due to differences in the marginals can be obtained by a counterfactual decomposition that maintains the internal association (a contribution that is margin-free, like unidiff), but the marginal distributions change. From a technical point of view, the separation of the two effects is performed by a counterfactual decomposition, i.e. by calculating the M-index based on simulated data in which the associations are maintained but the marginal distributions are swapped. The method used in this article is based on the composition of Deming and Stephen (1940), which is the one used in Stata (Seiler & Jann, 2019a; Jann & Seiler, 2019). This raking procedure consists of an iterative proportional fitting.

6. Data sources and variables

To test the proposed hypotheses, we pooled cross-sectional data from three nationally representative surveys for Spain: the living conditions survey (EU-SILC/ECV) conducted in 2005 (n = 30,375), 2011 (n = 29,210) and 2019 (n = 30,375) (INE, 2008, 2013 and 2020). These surveys are conducted by the Spanish National Statistics Institute as a joint project designed at the European level for studying income and living conditions and poverty and they add in those years a specific module with the possibility of measuring the intergenerational transmission of poverty, which includes the parents' data.[4]

We chose the sample of the special survey module 'Intergenerational transmission of poverty'. To have a population with complete higher education, we considered people aged 30 years or more. The 2011 survey changed the reference population that was asked about their parents' occupation by lowering the age limit from 65 to 59 years. To homogenise the three samples, we took this age as the top limit. With these filters, the final sample size was 43,669 cases: 14,166 in 2005, 13,701 in 2011 and 15,802 in 2019.

The variables of education and social class were considered following a standard of social stratification studies. Education was coded according to the International Standard Classification of Education (ISCED) 1997 into five categories based on the more detailed original Spanish classifications. Educational level was classified in the following categories: ISCED 0, no education or up to pre-school; ISCED 1, primary; ISCED 2, lower secondary; ISCED 3–4, upper secondary and post-secondary non-tertiary; and ISCED 5 A and 6, tertiary.

The social class of parents was constructed for the respondents following the classification of Erikson et al. (1979) and the operationalisation proposed by Ganzeboom and Treiman (1996). We used the Erikson, Goldthorpe & Portocarero scheme in eight categories: I (service class: higher-grade professionals, administrators and officials; managers in large industrial establishments and large proprietors); II (service class: lower-grade professionals, administrators and officials;

[2] We use the Stata command 'mindex' by Jann and Seiler (2019) for our analyses. In Stata, the command is 'mindex education i.father_class, over (cohort)'.

[3] In Stata, the command is 'mindex education i.father_class, over(cohorteducation) refgroup(1) decompose vce(boostrap, reps(100))'

[4] A sensitivity test was applied to check that the period effect did not alter the results. See Appendix B, Table B1.

higher-grade technicians and managers in small industrial establishments); IIIa (higher-grade routine non-manual workers); IIIb (lower-grade routine non-manual workers); IVab (small employers and self-employed); V + VI (skilled manual workers); VIIa (unskilled manual workers) and VIIb + IVc (semi- and unskilled workers in agriculture and farmers and smallholders).

For the class of origin, we considered the dominance criterion to take into account both parents (Erikson, 1984) by attributing to family origin the highest occupation of the father or mother when the respondent was between 12 and 16 years old. We constructed four birth cohorts distributing the sample between 1946 and 1989, with the following division: 1946–1956, 1957–1967, 1968–1977 and 1978–1989. The range of ages included in each cohort by the survey is presented in Table 1.

7. Results

7.1. Descriptive results: education and social origin over time

There is no doubt that educational expansion in Spain has been one of the most profound in Europe. In a very short period, Spain went from having a large illiterate population to being fully comparable to the most highly educated of societies. Fig. 2 illustrates the comparison of the trends in educational expansion in European countries. We compare Spain with countries that had an earlier and more intense period of industrialisation (the United States, Sweden, the Netherlands, the United Kingdom and Germany). We see that in the early 20th century, Spain began to distance itself from these countries as a result of a convulsive period that involved the loss of the colonies, military coups, the civil war and the post-war period (Martorell & Juliá, 2012). Indeed, while all these industrialised countries had shown a sharp rise in educational attainment by 1950, Spain had barely improved its position in comparison with the beginning of the century. However, since the beginning of the 21st century, this gap is narrowing and Spain is approaching the position of most of the more developed countries.

This trend can be observed in more detail if, instead of looking at average education per year, we analyse educational attainment by the cohorts involved in our study. As can be seen in Fig. 3, the shape of our first cohort (1946–1956) resembles a submarine with a broad base with basic education that progressively narrows over time. In the beginning, 44% of the Spanish population was in ISCED levels 0 and 1. However, for the last of these cohorts (1978–1989), the shape practically reversed, although with a greater proportion of people in the middle levels, reaching almost 85% in levels 3–6 in the youngest cohort.[5]

In Fig. 4, we present the evolution over time in the association between educational attainment and social origin.[6] The lowest educational level is associated with the agricultural and working classes of origin and the highest with the service and non-manual routine classes of origin (Treiman & Yip, 1989; Breen, 2019).

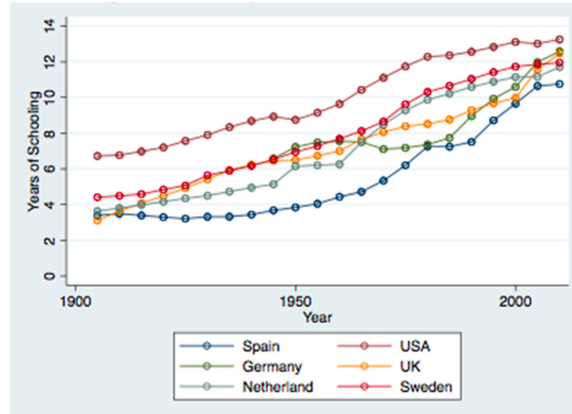

Fig. 2. : Educational attainment in average years of schooling between 1950 and 2010 for Spain, Germany, the Netherlands, United States, the United Kingdom and Sweden.
Source: Based on Barro and Lee (2013) with the average years of schooling of the population aged 16–64. See: http://www.barrolee.com/.

Finally, as we move cohort by cohort, we note a decline in the lowest educational levels in the manual classes and an expansion of the middle levels. Moreover, as this progress is taking place, the service and administrative classes are increasing their presence in university education.

In short, with a greater lag than in other societies, educational expansion has followed the same pattern, in which the lower classes completed basic education and the higher social classes improved their positions in university education.

Table 1
Survey, cohort and age of people of the sample.

Included only people from 30 to 59				
Cohort		Survey		
		2005	2011	2019
1946	1956	49–59	55–59	Empty
1957	1967	38–48	44–54	52–59
1968	1977	30–37	34–43	42–51
1978	1989	Empty	30–33	30–41

Source: The authors based this information on EU-SILC-2005, EU-SILC-2011 and EU-SILC-2019

7.2. The margin-free tradition: what it can tell us

Next, we will present the analysis of relative changes under the margin-free tradition using a margin-insensitive measure through log-linear models. We compare the constant fluidity model, which postulates stability in relative mobility rates, with the uniform difference model, which allows for a cohort variation. Table 2 presents the results obtained for the evolution of inequality of educational opportunities for both sexes in Spain for those born between 1946 and 1989. As can be seen, following the BIC statistic, the unidiff model does not improve the constant model, suggesting that for both sexes, the inequality of educational opportunities remained constant over the years analysed. Although the last cohort showed some increased rigidity, this is not statistically significant. Even if our selection criterion was the chi-square, we would have to accept that the change did not lead to a reduction in educational inequalities but to an increase in rigidity.

The following figure shows the unidiff coefficients in men and women..

7.3. The margin-dependent tradition: What it can tell us

Fig. 6 presents the overall result of the mutual information index.[7] Its interpretation is as follows: given an initial value for the first cohort, a reduction in the value in the next cohort implies a decrease in inequality of educational opportunities, while an increase in the value implies an increase in inequality. As can be seen, the results for men and women do not differ too much. Both experienced a decline in educational inequalities from the first to the fourth cohort. This decrease has halted in the last cohort.

In other words, by weighting the barriers between social origin and

[5] See accurate details in Table A1a and A1b of Appendix A.
[6] See details in Tables A2 and A3 of Appendix A.
[7] See details in Table A4 of Appendix A.

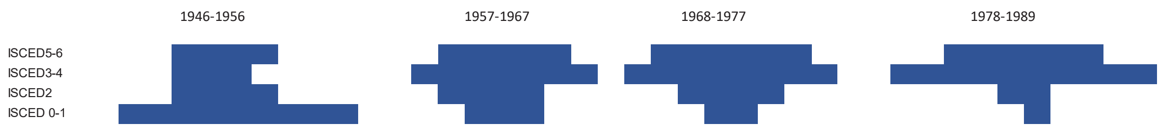

Fig. 3. : Evolution of educational attainment by cohort: Total population.
Source: Based on EU-SILC-2005, EU-SILC-2011 and EU-SILC-2019.

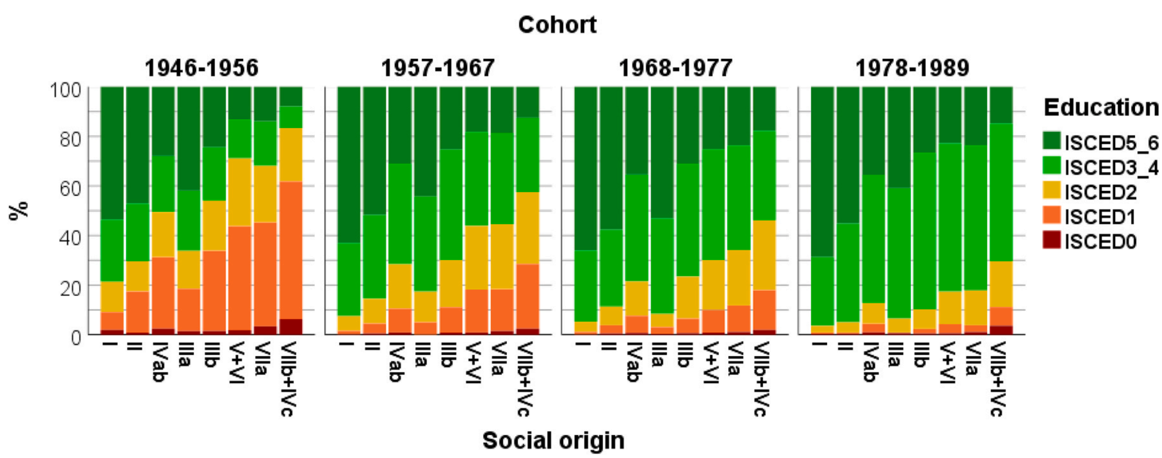

Fig. 4. : Evolution of educational attainment according to social origin by cohort: Total population.
Source: The authors based on EU-SILC-2005 EU-SILC-2011 and EU-SILC-2019.

Table 2
Relative analysis of inequality of educational opportunities: Log-linear models of constancy and uniform variation across cohorts.

Model CSO CSE OE	L^2	BIC	DI	DF
Men (n = 21261)				
Constant	429,55	-2639,55	4,49	308
Unidiff	416,67	-2622,53	4,32	305
Cohort	1946–1956	1957–1967	1968–1977	1978–1989
Coefficient	1,00	0,97	1,03	1,19
Standard error		*0,06*	*0,06*	*0,08*
		(0,85–1,08)	*(0,91–1,14)*	*(1,07–1,30)*
Model CSO CSE OE	L^2	BIC	DI	DF
Women (n = 22485)				
Constant	475,35	-2610,98	4,74	308
Unidiff	467,30	-2588,97	4,72	305
Cohort	1946–1956	1957–1967	1968–1977	1978–1989
Coefficient	1,00	1,13	1,02	1,14
Standard error		*0,06*	*0,06*	*0,08*
		(1,07–1,19)	*(0,96–1,08)*	*(1,06–1,22)*

Source: The authors based on EU-SILC-2005, EU-SILC-2011 and EU-SILC-2019
Note. L^2: Likelihood ratio; BIC: Bayesian information criterion; DI: Dissimilarity index; DF: Degree of Freedom

educational attainment according to their relevance, we obtain a different picture of educational inequality trends. Therefore, taking into account the marginal changes, according to the mutual information index, we can conclude that Spain experienced a substantial reduction in educational inequalities over a long period (1946–1977). In men, the important reduction appears between the first and second cohorts and in women a decrease in all cohorts except the last one is observed. However, the 1980s witnessed the end of this reduction in school inequalities. To interpret these results more accurately, the overall index needs to be decomposed.

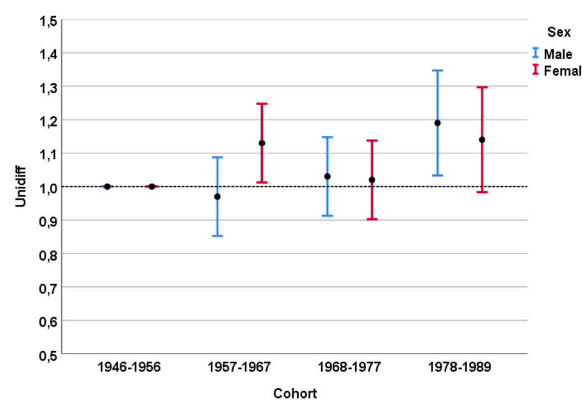

Fig. 5. : Relative analysis of inequality of educational opportunities: Unidiff coefficients.
Source: The authors based on EU-SILC-2005, EU-SILC-2011 and EU-SILC-2019.

7.4. *The decomposition*

An analysis of how far the marginal changes go and how far the internal changes go would help us to resolve important questions in the field of educational inequalities over time. By decomposing the mutual information index, we can determine the contribution of the marginal changes from one cohort to another, distinguishing it from internal changes. In other words, as the mutual information index is based on a weighted average taking into consideration the marginal distribution, we now decompose it to separate marginal from internal changes, so that this internal measure has an unweighted average.

Fig. 7 shows the decomposition of the mutual information index between the marginal and the internal effects, first for men and then for women.[8] We can see that the evolution of the internal component is

[8] See details in Table A5 of Appendix A.

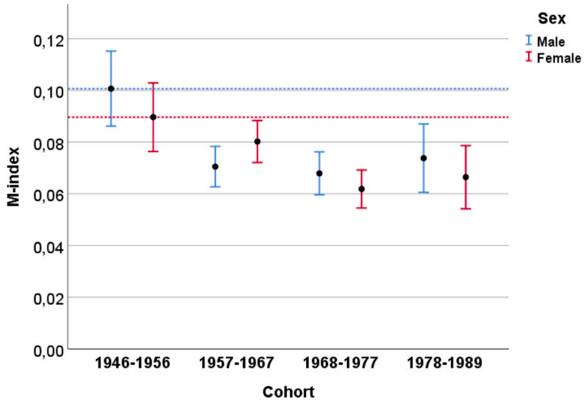

Fig. 6. : The mutual information index by sex and cohort.
Source: The authors based on EU-SILC-2005, EU-SILC-2011 and EU-SILC-2019.

similar to the evolution of the unidiff parameters for both men and women, although for men, in the last cohort, a statistically significant behaviour towards greater rigidity is observed.

Conversely, the marginal component shows a decrease in inequalities for both men and women over time.

In short, the results show that the reduction in educational inequalities has been driven by marginal changes, while internal changes remain more or less constant, except in the last cohort where is increased.

Now, it is much easier to interpret our results. Those who were born between 1946 and 1989 experienced a great transformation in terms of both the educational expansion and the occupational upgrading of their parents. If these changes are taken into account to weigh the average, considering the composition of groups, educational inequalities show a decline. This has been possible even though the internal differences remain constant (or even increase for men in the last cohort). Thus, education inequalities have declined as a consequence of changes in the structure of Spanish society, which have rendered some barriers less important despite their persistence.

8. Conclusions

The results of our study lead to a revision of the usual conclusions shown in the analyses of the inequality of educational opportunities in the case of Spain. Concerning previous theories, it could be noted that, with the application of the mutual information index measure, the evidence collected mainly called into question the theory of persistent inequalities, although this idea would have to be nuanced due to the slowing of this trend in the last cohort. These are the results when we consider the prevalence of educational barriers that different classes have to navigate. If we do not consider this prevalence, which would be another correct way to measure the relative change, the evidence points towards constancy. In our view, this index, therefore, enriches the analysis of the IEO by offering us a new perspective.

In Europe, educational inequalities declined considerably after the post-war period during the *Trente Glorieuses* (Breen et al., 2009), but reached a point at which they stopped weakening (Barone & Ruggera, 2018). The only difference with regard to the trends followed by other European countries is that in Spain, the reduction of educational inequalities occurred later, after the post-war period, at a time when

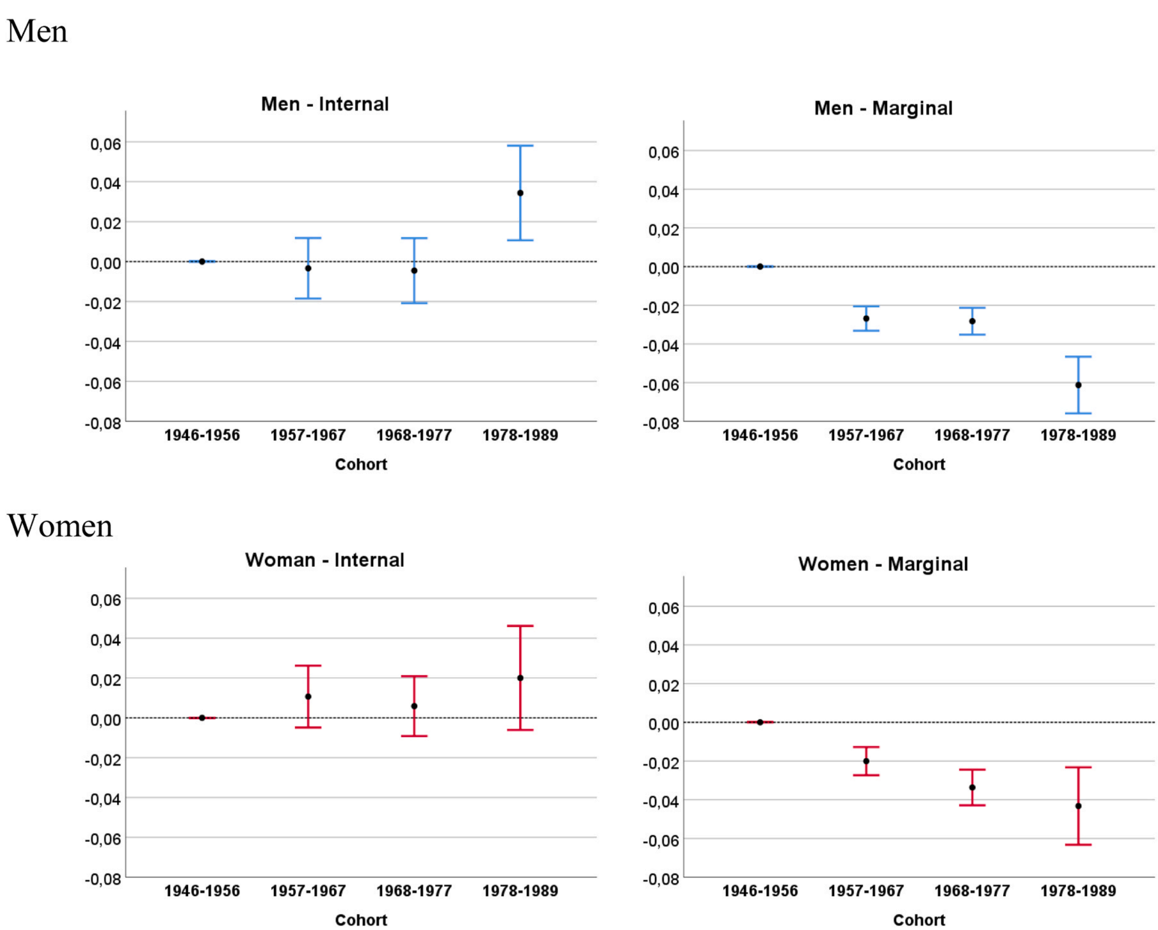

Fig. 7. : Decomposition of the mutual information index separating the effect of the relative changes (Internal) from the marginals (Marginal) by sex and cohort.
Source: The authors based on EU-SILC-2005, EU-SILC-2011 and EU-SILC-2019.

economic improvements and educational reforms were introduced (Breen, 2020; Authors).

In this study, we have tried to go a step further by introducing a single measure that would allow us to account for both internal and marginal changes. This measure is based on information theory and the notion of entropy. Based on the mutual information index to explain educational inequalities over time, we have considered the joint and decomposable measurement of the effects of change over time of internal and marginal relationship patterns. We have done this by applying the most extensive scheme employed to date with data for Spain. Instead of the usual six or seven social classes of the Erikson, Goldthorpe and Portocarero model, we used a scheme of eight social classes.

We think that the decomposition of the mutual information index (Seiler & Jann, 2019a, 2019b) may help us enrich the study of educational inequalities, thus broadening the perspective on this topic. At the theoretical level, we have tried to explain why considering the weight of barriers via marginal changes may offer an alternative interpretation of educational inequality trends. We have, thus, emphasised two processes: (a) occupational upgrading (of parents) and (b) educational expansion (of respondents). The former could have contributed to an overall improvement in economic conditions leading to nutritional improvement and the release of family expenditure; moreover, the latter was fostered by the creation and implementation of a less selective national system (Roser & Ortiz-Ospina, 2016).

Our main results confirm the two hypotheses proposed. Thus, following the margin-free tradition, we find educational inequalities unchanged in Spain, or even more, the last cohort shows in men an increase in rigidity. Regarding the second hypothesis, however, in Spain, it is observed that the cohorts born between 1946 and 1989 experienced significant changes as a consequence of educational expansion and occupational upgrading. When these changes are considered, weighting the average and taking into account the composition of groups, educational inequalities have declined substantially. This has been possible even while the internal differences have remained constant (although in men there was a rise in the last cohort).

The mutual information index moderates its downward trend due to the performance of the last cohort. When we compare tables that differ greatly in their marginal composition, using the mutual information index enriches our methodological perspective and leads us to elaborate alternative theoretical conclusions. In this sense, the index allows us to ask questions that we could not otherwise ask with margin-free table comparisons. Thus, educational inequalities have declined because the structure of Spanish society has changed in such a way that strong barriers have become less important (though they are still strong).

There is an interesting field to explore and assess the potential of this measure. By applying it to other case studies to obtain a general overview comparing different countries, it will be particularly interesting to know how it works in peripheral countries where the processes of industrialisation and structural change have been more delayed than in the central countries. In this sense, we believe that this measure can open up a vast field of analysis and debate that will complement the comparative studies that have traditionally been carried out in this field of international research throughout the different generations of social mobility studies.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Table A1a
Educational level by cohort: Total population.

Four levels of education					
Educational level	Cohort				
	1946–1956	1957–1967	1968–1977	1978–1989	Total
ISCED0_1	43.7%	16.9%	9.6%	4.4%	16.9%
ISCED2	20.5%	22.3%	17.5%	10.6%	18.8%
ISCED3–4	16.5%	36.0%	40.1%	52.6%	36.7%
ISCED5–6	19.3%	24.8%	32.8%	32.4%	27.6%
Total	100.0%	100.0%	100.0%	100.0%	100.0%

Source: The authors based on EU-SILC-2005, EU-SILC-2011 and EU-SILC-2019.

Table A1b
Educational level by cohort: Total population.

Five levels of education					
Educational level	Cohort				Total
	1946–1956	1957–1967	1968–1977	1978–1989	
ISCED0	3.70%	1.40%	1.00%	1.10%	1.60%
ISCED1	40.10%	15.50%	8.60%	3.30%	15.30%
ISCED2	20.50%	22.30%	17.50%	10.60%	18.80%
ISCED3–4	16.50%	36.00%	40.10%	52.60%	36.70%
ISCED5–6	19.30%	24.80%	32.80%	32.40%	27.60%
Total	100.0%	100.0%	100.0%	100.0%	100.0%

Source: The authors based on EU-SILC-2005, EU-SILC-2011 and EU-SILC-2019.

Table A2
Origin by cohort: Total population.

Origin	1946–1956	1957–1967	1968–1977	1978–1989	Total
I	5.3%	6.0%	7.3%	9.4%	6.8%
II	5.6%	6.1%	8.3%	9.2%	7.2%
IVab	13.9%	15.8%	18.1%	18.9%	16.7%
IIIa	3.1%	3.5%	4.7%	5.4%	4.1%
IIIb	5.9%	7.0%	9.2%	12.2%	8.3%
V + VI	17.0%	18.0%	18.9%	17.6%	18.0%
VIIa	19.0%	21.4%	19.6%	17.2%	19.8%
VIIb + IVc	30.3%	22.2%	14.1%	10.2%	19.1%
Total	100.0%	100.0%	100.0%	100.0%	100.0%

Source: The authors based on EU-SILC-2005, EU-SILC-2011 and EU-SILC-2019.

Table A3
Evolution of educational attainment according to social origin by cohort:.

Total population						
Education	ISCED_0	ISCED_1	ISCED2	ISCED3_4	ISCED5_6	Total
Origin	1946–1956					
I	1.9%	7.2%	12.2%	25,00%	53.6%	100.0%
II	0.8%	16.7%	12.2%	23.2%	47.1%	100.0%
IVab	2.4%	28.8%	18.2%	22.5%	28,00%	100.0%
IIIa	1.4%	17.1%	15.2%	24.3%	41.9%	100.0%
IIIb	1.5%	32.3%	20.2%	21.5%	24.4%	100.0%
V + VI	1.8%	41.9%	27.4%	15.7%	13.2%	100.0%
VIIa	3.4%	41.9%	22.9%	17.8%	14,00%	100.0%
VIIb + IVc	6.3%	55.5%	21.6%	8.6%	8,00%	100.0%
Origin	1957–1967					
I	0.1%	1.4%	6,00%	29.4%	63.1%	100.0%
II	0.5%	4,00%	10,00%	33.7%	51.8%	100.0%
IVab	0.9%	9.7%	17.9%	40.5%	31.1%	100.0%
IIIa	0,00%	5,00%	12.3%	38.3%	44.3%	100.0%
IIIb	0.8%	10.4%	18.9%	44.6%	25.4%	100.0%
V + VI	0.9%	17.3%	25.7%	37.9%	18.2%	100.0%
VIIa	1.5%	16.9%	26.3%	36.8%	18.6%	100.0%
VIIb + IVc	2.4%	26.2%	28.9%	30,00%	12.5%	100.0%
Origin	1968–1977					
I	0.1%	1,00%	4.1%	28.7%	66,00%	100.0%
II	0.5%	3.4%	7.5%	30.9%	57.7%	100.0%
IVab	0.7%	6.9%	13.9%	43,00%	35.5%	100.0%
IIIa	0.3%	2.8%	5.4%	38.4%	53.1%	100.0%
IIIb	0.6%	5.9%	16.9%	45.4%	31.1%	100.0%
V + VI	0.8%	9.2%	20.1%	44.8%	25.2%	100.0%
VIIa	1.1%	10.7%	22.3%	42.2%	23.7%	100.0%
VIIb + IVc	1.9%	16,00%	28.2%	36,00%	17.8%	100.0%
Origin	1978–1989					
I	0.3%	0.5%	2.7%	27.7%	68.7%	100.0%
II	0.3%	0.5%	4.2%	39.7%	55.2%	100.0%
IVab	0.9%	3.5%	8.4%	51.6%	35.5%	100.0%
IIIa	0.6%	0.3%	5.6%	52.5%	40.9%	100.0%
IIIb	0.5%	1.8%	7.9%	63.1%	26.6%	100.0%
V + VI	0.5%	3.7%	13.2%	59.7%	22.8%	100.0%
VIIa	1,00%	2.8%	14,00%	58.5%	23.6%	100.0%
VIIb + IVc	3.6%	7.6%	18.5%	55.5%	14.8%	100.0%

Source: The authors based on EU-SILC-2005, EU-SILC-2011 and EU-SILC-2019.

Table A4
The mutual information index by sex and cohort.

Men		
Cohort	**Coef.**	**Std. Err.** (*)
1946–1956	0.1006795	0.0074055
1957–1967	0.0704876	0.0039967
1968–1977	0.0678970	0.0042533
1978–1989	0.0737856	0.0067501
Women		
Cohort	**Coef.**	**Std. Err.** (*)
1946–1956	0.0896361	0.0067642
1957–1967	0.0802154	0.004146
1968–1977	0.0618521	0.0037563
1978–1989	0.0664117	0.0062509

(*) Obtained by bootstrap (100 replications).
Source: The authors based on EU-SILC-2005, EU-SILC-2011 and EU-SILC-2019

Table A5
Decomposition of the mutual information index separating the effect of the relative changes (Internal) from the marginals (Marginal) by sex and cohort.

Men						
Internal						
Cohort	**Coef.**	**Std. Err. (*)**	**z**	**P > z**	**[95% Conf. Interval]**	
1946–1956	0	(omitted)			0	0
1957–1967	-0.0033498	0.0077342	-0.43	0.665	-0.0185086	0.0118090
1968–1977	-0.0045350	0.0082928	-0.55	0.584	-0.0207886	0.0117186
1978–1989	0.0343542	0.0120964	2.84	0.005	0.0106457	0.0580627
Marginal						
Cohort	**Coef.**	**Std. Err. (*)**	**z**	**P > z**	**[95% Conf. Interval]**	
1946–1956	0	(omitted)			0	0
1957–1967	-0.0268422	0.0032122	-8.36	0.000	-0.033138	-0.0205465
1968–1977	-0.0282475	0.0035520	-7.95	0.000	-0.0352093	-0.0212857
1978–1989	-0.0612481	0.0074652	-8.2	0.000	-0.0758796	-0.0466166
Women						
Internal						
Cohort	**Coef.**	**Std. Err. (*)**	**z**	**P > z**	**[95% Conf. Interval]**	
1946–1956	0	(omitted)			0	0
1957–1967	0.0106605	0.0079259	1.35	0.179	-0.0048741	0.0261950
1968–1977	0.0058826	0.0076767	0.77	0.444	-0.0091636	0.0209287
1978–1989	0.0200311	0.0133232	1.50	0.133	-0.0060819	0.0461441
Marginal						
Cohort	**Coef.**	**Std. Err. (*)**	**z**	**P > z**	**[95% Conf. Interval]**	
1946–1956	0	(omitted)			0	0
1957–1967	-0.0200811	0.0037185	-5.40	0.000	-0.0273693	-0.0127929
1968–1977	-0.0336666	0.0047081	-7.15	0.000	-0.0428943	-0.0244388
1978–1989	-0.0432554	0.0102121	-4.24	0.000	-0.0632708	-0.0232401

(*) Obtained by bootstrap (100 replications).
Source: The authors based on EU-SILC-2005, EU-SILC-2011 and EU-SILC-2019

Appendix B

The homogeneity test in Table B1 analyses how the surveys employed have affected the different cohorts for men and women. We present a double log-multiplicative model made up of the following terms *CSO CSE, βcOE* and *βsOE*. The last interaction (*βsOE*) has been modelled according to the linear constraints that permit us to evaluate the survey changes on cohorts. With linear restrictions, we intend to force the coefficients of the models to comply with a specific relationship, in this case, an equality restriction. We want to unify those periods that do not introduce a change in the cohorts. In this way, we obtain a parsimonious model that helps us to detect which period may have a different effect per cohort. The first model allows only cohort variations. Conversely, the latter allows both cohort and linear variations for all surveys. The intermediate models allow variation by cohort but constrain some surveys over others; they are reflected within each parenthesis. Therefore, we chose in each case the models with the most negative BIC.

Table B1
Homogeneity test models.

Men				
Models	**L^2**	**BIC**	**DI**	**DF**
1. ***CSO CSO OExC OExS (No Survey Variation)***	371.79	-2378.44	4.03	276
2. ***CSO CSO OExC OExS (Variation 1 vs. 2 3)***	372.18	-2378.05	3.98	276
3. ***CSO CSO OExC OExS (Variation 1 2 vs. 3)***	271.79	-2478.48	3.09	276
Unidiff parameters (Cohort)	1.00	1.19 (0.06)	1.15 (0.06)	1.10 (0.94)
Standard errors	1.00	0.63 (0.33)		
Unidiff parameters (Survey)				
Standard errors				
4. ***CSO CSO OExC OExS (Variation 2 vs. 1 3)***	353.02	-2397.21	3.87	276
5. ***CSO CSO OExC OExS (Complete Variation)***	309.04	-2440.19	3.50	276
Women				
Models	**L^2**	**BIC**	**DI**	**DF**
1. ***CSO CSO OExC OExS (No Survey Variation)***	404.14	-2361.06	4.36	276
2. ***CSO CSO OExC OExS (Variation 1 vs. 2 3)***	368.12	-2397.62	3.99	276
3. ***CSO CSE OExC OExS (Variation 1 2 vs. 3)***	307.60	-2458.08	3.57	276
Unidiff parameters (Cohort)	1.00	1.02 (0.07)	0.95 (0.07)	0.92 (0.14)
Standard errors	1.00	1.28 (0.12)		
Unidiff parameters (Survey)				
Standard errors				

(continued on next page)

Table B1 (*continued*)

Women				
Models	**L^2**	**BIC**	**DI**	**DF**
4. ***CSO CSO OExC OExS (Variation 2* vs. *1 3)***	389.58	-2376.10	4.12	276
5. ***CSO CSO OExC OExS (Complete Variation)***	328.66	-2437.01	3.75	276

Source: The authors based on EU-SILC-2005, EU-SILC-2011 and EU-SILC-2019
Note. L^2: Likelihood ratio (or deviance); BIC: Bayesian information criterion; DI: Dissimilarity index; DF: Degree of Freedom. C: Cohort, S: Survey, O: Origin, E: Education

In regard to men and women, the best fit corresponds to model 3, which allows only for the temporal change in the last of the survey. In men, unidiff parameters increased, while in women, these parameters decreased slightly. This means that if there is a survey effect, it only affects the last survey. Taking into account the unidiff parameters of the surveys, we do not see a change in the cohort's parameters, which continue to show invariance.

Given the size of errors in the partitioning of cohorts and surveys, we should be cautious about these differences. However, it is reasonable to posit that changes could occur after Spain's 2008 financial crisis. We know that in terms of survey enrolment rates, the crisis brought a marked increase (Martínez-García & Molina, 2019). Future research may explore this area in further detail.

Unsurprisingly, model 3 fits better by adding such a survey change, given the wide range that we cover in terms of cohorts (from 1946 to 1989) since we are comparing individuals who were born in extremely different periods. It would then be necessary to check whether, after the crisis, a growing number of people of service class origins, aged 30 or more, enrolled in higher education.

However, considering this change, in any case, we do not detect a variation that implies a substantial reduction in educational inequalities. Assuming a hypothetical survey effect (and we should be cautious about such an assumption), the analysis reveals a high level of invariance or constancy in the effect of social origin on education.

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