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THE EVOLUTION OF INCOME CLASSES IN TERMS OF INEQUALITY OF OPPORTUNITY: A FULL DISTRIBUTIONAL APPROACH

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The evolution of income classes in terms of inequality of opportunity: A full distributional approach

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Abstract

This paper proposes a full distributional approach to measure the probability of belonging to specific economic classes, which are endogenously determined by the individual's position in the income distribution. Using Australian panel data, we identify pre-determined circumstances associated with class membership. Specifically, we use concomitant variable latent class models to quantify the overlap between distributions and to compare distributional differences and segmentation across social classes and link them to inequality of opportunity. Given the renewed interest in social class dynamics and the growing socioeconomic relevance and political salience of class membership, this study provides important insights into the composition of socioeconomic classes and their evolution over time.

Keywords: Inequality of Opportunity, Mixture Models, Class Membership
JEL Classification: D31, D63, J3

1 Introduction

Social and economic classes have resurfaced as a critical topic in public discourse due to the growing polarization of income and wealth, widening inequalities at the top, and declining intergenerational mobility. This renewed focus has sparked vigorous debate over how economic disparities perpetuate class inequalities across generations (Chetty, Hendren, Jones, & Porter, 2019; Chetty, Hendren, Kline, & Saez, 2014; Milanovic, 2019, 2023; Piketty, 2017). Despite growing public interest, academic research has paid relatively limited attention to the interplay between Inequality of Opportunity (IOp) — defined as disparities arising from predetermined circumstances beyond individual control — and class structures, particularly in terms of their political and socioeconomic implications (Cagé, 2022; Ferreira, 2022; Piketty, 2020). This paper attempts to address this gap by using concomitant variable latent class models to empirically identify income classes and estimate the likelihood of individuals belonging to these classes based on predetermined circumstances (Anderson, Farcomeni, Pittau, & Zelli, 2016; Anderson, Linton, Pittau, Whang, & Zelli, 2021). This methodological choice allows for the analysis of inequality of opportunity and polarisation across identified classes without relying on artificial boundary assumptions or rigid theoretical definitions. Instead, class membership emerges directly from the similarity of individuals' circumstances (Anderson et al., 2016).

The basic idea is that income is a good proxy for socioeconomic class and that there are M classes indexed $j = 1, ..., M$. Members of a given class will have some commonality in their circumstances, but there will be some within-class variation due to differences in innate ability, effort, and even approximation error. A direct consequence of the income dispersion within each class is that there will be some overlap between the distributions of the income classes. Therefore, individuals with particular observed income levels cannot be exclusively assigned to a class, but only the probability of class membership can be determined for each individual. As long as each individual's membership in a particular class is driven by circumstances beyond the individual's control, the link between classes and inequality of opportunity is obvious. A bunch of observable and unobservable circumstances may indeed limit or constrain individual income opportunities in different ways. Following this line of reasoning, the entire population is viewed as a collection of a small number of classes $j = 1, 2, \cdots, M$ driven by inherent circumstances, such that an individual in class j faces earnings opportunities described by a distribution f_j that differs from the corresponding distribution f_k for class $k \neq j$. In the limit of no equal opportunity, the income distributions of the classes are perfectly separated and there is no overlap between them. Given that the goal of equality of opportunity is that an individual's achievement should depend on his or her own efforts and choices, rather than on the circumstances for which he or she is not responsible, an increasing overlap in the income distributions of the classes could be regarded as a policy target.

Using Australian panel data, our paper enhances understanding of the complex interrelationship between socioeconomic circumstances, class dynamics, and inequality, contributing to the ongoing scholarly revival and expansion of the literature on inequality and class structures (Gil-Hernández, Salas-Rojo, Vidal-Lorda, & Villani, 2024; Moawad, 2023; Moawad & Oesch, 2024) as well as the growing IOp literature. We begin by identifying the number and size of socioeconomic strata or classes, and we assess the role of observable, predetermined circumstances associated with class membership. Unlike conventional methods that rely on arbitrary class boundaries, we use latent class models that endogenously identify different classes directly from individuals' positions in the income distribution. We then quantify the overlap between the income subdistributions of the classes, compare distributional differences and segmentation across classes, and link these to inequality of opportunity. By using a longstanding household panel survey, we address a critical limitation identified in recent literature: the need for a dynamic rather than a static assessment of income distribution and inequality of opportunity (Bussolo, Checchi, & Peragine, 2023; Checchi & Peragine, 2020). We also use cohort-level measures of income distribution to examine its evolution over time, thus aligning our empirical approach with recent methodological advances (Aaberge, Mogstad, & Peragine, 2011; Andreoli, Fusco, Kyzyma, & Van Kerm, 2021; Bourguignon, Ferreira, & Menéndez, 2007; Moramarco, Palmisano, & Peragine, 2020; Peragine & Serlenga, 2008).

Section 2 describes the dataset we used for the analysis and the selection of the set of predetermined circumstances. Section 3 develops the basic model and the approach to determining outcome classes, as well as the tools for analyzing the extent to which equality of opportunity has progressed. Section 4 reports the main results and section 5 draws some conclusions.

2 Data

The data are drawn from the 2022 release of the Household, Income, and Labour Dynamics in Australia (HILDA) survey (Summerfield et al., 2023). HILDA is a multipurpose panel survey that began in 2001 and so far has 22 waves. It collects information on various aspects of life from more than 17,000 Australians each year. Our samples include individuals aged 20-80 with a positive income. We rely on household income as the outcome variable. Household income is defined after government taxes and transfers, adjusted for inflation and standardised using the square-root adult equivalence scale.

Since the income distribution is viewed as the aggregation of a small number of homogeneous economic classes, each one sharing some commonalities some of which are beyond individual's control, questions on the respondent's parental background are used as proxies for circumstances. All information on parents refers to when the respondent was 14 years old.

Circumstances include: age (and its squared); gender; parents' immigration status; parents' activity status (employed vs unemployed/ deceased/ not living in the household); parents' education level (university degree or not); parents' occupation (ANZSCO, 2006). Other circumstances are whether English is not the first language learnt, whether they grew up with both parents, and whether they had any siblings.

We follow previous studies in defining the circumstances used for our analysis. We acknowledge that this is only a subset of possible variables that can be considered 'factors beyond individual control'. A sensitivity analysis, however, revealed that additional circumstances (such as wether individuals grew up with their biological parents) did not significantly alter the results of the analysis.

To dynamically assess how IOp evolves over time, we adopt a "within-cohort" approach following recent developments by Bussolo et al. (2023) and Andreoli et al. (2021). Specifically, individuals are grouped by birth year into cohorts, estimating distributions within similar age cohorts. We construct birth cohorts using 10-year intervals, as recommended in the social science and demographic literature (Brooks and Bolzendahl, 2004). Given the time span of the HILDA survey data, survey respondents are separated into the following birth cohorts depending on their date of birth: cohort 1 (<1945; n=2,520 unique observations), cohort 2 (1945-1954; n=2,286), cohort 3 (1955-1964; n=3,024), cohort 4 (1965-1974; n=2,993), cohort 5 (1975-1984; n=2,885), and cohort 6 (1985-1994; n=4,139).

Leveraging the length of HILDA survey, our methodology provides critical insights into class membership dynamics, socioeconomic polarization, and inequalities of opportunity within contemporary Australian society. The methodology is briefly sketched in the following section.

3 Empirical strategy

We assume that in a society there is a small number of socioeconomic classes $j = 1, 2, \cdots, M$ driven by inherent circumstances, such that an individual belonging to class j faces income opportunities described by a distribution f_j, which is distinguishable from the distribution f_h for class $h \neq j$. Therefore, the overall income distribution will be a mixture of income classes with mixing weights equal to the proportions of society that are members of the respective classes.

Formally, achievement of individual i, represented by her income x_i, is modeled as a finite mixture of M latent distributions:

$$f(x_i) = \sum_{j=1}^{M} p_{ij} f_j(x_i), \quad \text{with} \quad \sum_{j=1}^{M} p_{ij} = 1. \tag{1}$$

Here p_{ij} denotes the a priori probability that individual i belongs to class

j. These probabilities are explicitly linked to a set of predetermined circumstances, $\boldsymbol{z}_i$, beyond individual control, via a multinomial logistic-type equation:

$$\log\left(\frac{p_{ij}}{p_{i1}}\right) = \boldsymbol{z}_i'\boldsymbol{\beta}_j, \quad \text{for} \quad j = 2, \ldots, M. \tag{2}$$

The component-specific coefficients $\boldsymbol{\beta}_j$ represent the relative impact of the so-called concomitant variables (Dayton & MacReady, 1988) on class membership probabilities, thus quantifying the influence of circumstances on the socioeconomic classes. With the normalization constraint $\boldsymbol{\beta}_1 = \mathbf{0}$, the class membership probabilities can be expressed as:

$$p_{ij} = \text{prob}\{C_i = j|\boldsymbol{z}_i\} = p_j(\boldsymbol{z}_i) = \frac{e^{\boldsymbol{z}_i\boldsymbol{\beta}_j}}{\sum_{h=1}^{M} e^{\boldsymbol{z}_i\boldsymbol{\beta}_h}}. \tag{3}$$

Some assumptions regarding the nature of the f_j's are necessary in order to estimate the model. Normality is a popular specification that can be theoretically rationalized (Anderson, 2019, p. 140). As a matter of fact, a mixture of normals seems to capture better than other functional forms the idea of a stratified economy where relatively homogeneous classes of individuals are concentrated around a pole (the expected mean income) with some dispersion. The deviation of each individual income from the expected mean of the class she belongs is essentially due to her lifetime choice, luck, and especially effort. Nonetheless there are also good statistical rationales (essentially central limit theorems, see for example Gibrat's law of additional effects) for believing that these deviations are normally distributed so that income x_i may be written as $x_i = \mu_j + \sigma_j \cdot e_i$ where $e_i \sim N(0;1)$, so that $\sigma_j \cdot e_i$ can be interpreted as a measure of i's accumulated measure of lifetime effort.

Parameters of each component along with the circumstances effects are estimated simultaneously through maximum likelihood, employing the Expectation-Maximization (EM) algorithm as in Anderson et al. (2016). To choose the number of components M, the mixture model is fitted starting from one component to five components and the best fitting model is selected by the

Bayesian Information Criterion (BIC).[1] In many practical situations, there may be a trade-off between the goodness of fit of the models and the interpretability of the fitted components. For example, very flat components with large dispersion and very small size could play a role in improving the fit of the overall distribution, but may be unacceptable in terms of (economic) interpretability. A reasonable compromise between fit criteria and meaningful explanation of the components has driven the choice.

Once parameters estimates are obtained, the posterior probability that individual i comes from class j can be calculated using Bayes rule:

$$\tau_{ij} = \text{prob}\{C_i = j | \boldsymbol{z}_i, x_i\} = \frac{p_j(\boldsymbol{z}_i) f_j(x_i)}{\sum_{h=1}^{M} p_h(\boldsymbol{z}_i) f_h(x_i)}. \tag{4}$$

These probabilities offer insight into potential disparities in outcomes (income) among individuals in the same classes who face comparable circumstances, facilitating an understanding of income achievements that extends beyond inherent circumstances.

Knowledge of f_j and τ_{ij} also enables to measure the extent of between-class segmentation and polarization. These measures can be attributable to the concept of overlapping. Overlapping can be defined as the area intersected by two or more probability density functions and offers a simple way to quantify the similarity (or difference) among sub-populations which are described in terms of distributions. Intuitively, two groups are similar when their distribution functions overlap. More formally, a measure of overlap between distribution f_k and distribution f_h is:

$$OV_{jh} = \min \int [f_j(x), f_h(x)] dx. \tag{5}$$

A measure of distributional differences based on the totality of bilateral similarities or differences in a collection of M distributions, named DisGini,

[1]See Keribin (2000) for a discussion of the preference for BIC over other information criteria.

has been introduced by Anderson et al. (2021). It can be written as:

$$\text{DisGini} = \frac{1}{(1 - \sum_{h=1}^{M} \pi_h^2)} \sum_{j=1}^{M} \sum_{h=1}^{M} \pi_j \pi_h (1 - \text{OV}_{jh}). \tag{6}$$

where π_j represents the size of the component j, obtained averaging the membership probabilities. DisGini falls in the interval [0,1] and is equal to 1 when there is no overlapping or perfect segmentation (Yitzhaki, 1994) of the constituency distributions and is equal to 0 in case of perfect overlapping. While the Gini coefficient between-group component captures between group inequalities in terms of differences between sub-group means, DisGini captures between-group dissimilarities in terms of the totality of sub-group distributional differences. In this context the M components f_j can be explained in terms of facing different circumstances, and therefore the DisGini measure of distributional segmentation can be interpreted as a measure of inequality of opportunities in a society (TOO STRONG?).

4 Empirical results

4.1 Time evolution of segmentation of income classes and inequality of opportunity

For each year of available data (2001-2022), the unknown mixture parameters were estimated by the EM algorithm as described in section 3. Each model was fitted repeatedly with different starting values in the sense that the same maximum for the likelihood or a value very close to it was invariably obtained. The optimal number of latent classes for the set of circumstances was assessed using BIC. The selected number of classes equal to $M = 3$ was very stable with respect to the different years of analysis, along with the sign, size, and significance of the circumstances associated with the class memberships. Table 1 describes the variables $\boldsymbol{z}$ included in the model.

As expected, what varied were the individual specific class memberships depending on the set of circumstances we included in the model. Table 2

Table 1: Circumstances included in the model

Name	Description	Type
Father Univ.	Set to 1 if the father had a university degree	Binary
Mother Univ.	Set to 1 if the mother had a university degree	Binary
Mother Emp.	Set to 1 if the mother had a full time job	Binary
Father Immigrant	Set to 1 if the father was immigrant	Binary
English	Set to 1 if English was not the first language	Binary
Female	Set to 1 if the respondent was female	Binary
Living parents	Set to 1 if the resp. was living with both parents at age 14	Binary
Siblings	Set to 1 if the respondent ever had siblings	Binary
Father Prof.	Set to 1 if the father had a professional or managerial job	Binary
Age	Age of respondent	Numerical
Age squared	Square of age of respondent	Numerical

shows the sign of the at least 90 percent significant effects of the circumstances on income class membership for selected years. Notably, parents' education, father profession, wether the mother was employed, language spoken at home, gender and age are persistently significant and consistent in size over the whole period.[2]

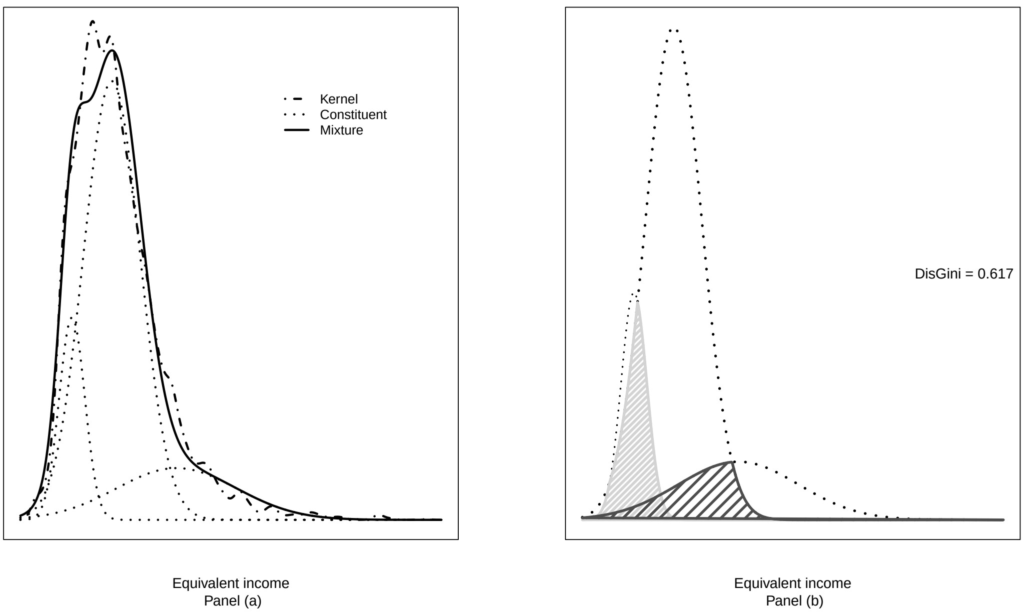
Table 2: The sign of the effects of circumstances on class membership, for selected years 2005, 2014 and 2022. Empty cells represent statistically non significant effect.

Circumstances	Year 2005		Year 2014		Year 2022	
	Low/ Middle	Low/ High	Low/ Middle	Low/ High	Low/ Middle	Low/ High
Father Univ.	+	+		+	+	+
Mother Univ.	+	+		+		+
Mother Emp.	+	+	+	+	+	+
Father Immigrant		+		+		+
English	-	-	-	-		-
Female	-	-	-	-	-	-
Living parents	+	+	+	+	+	+
Siblings		-				
Father Prof.	+	+	+	+	+	+
Age	-	-	-		-	+
Age squared	-	-	-	-	-	-

[2]Model estimates are reported in Appendix.

Panel (a) of Figures 1, 2, and 3 visually compares the fitted three component mixture with a non-parametric estimate of the income distribution for three selected years.[3] The components of the mixture can be interpreted as sub-populations corresponding to 'low', 'middle', and 'upper' latent socioeconomic classes. Panel (b) of the Figures highlights the overlapping between subdistributions, indicating moderate overlap between the poorest and the middle and between the middle and the upper classes, and negligible between the poor and the rich strata. The DisGini estimates are 0.617, 0.581 and 0.615 respectively for years 2005, 2014 and 2022.

Figure 1: Estimation of mixture components in 2005 and relative overlapping.



The Distributional Gini Inequalities, as presented in equation (6), are illustrated in Figure 4. The figure also shows a canonical measure of relative inequality of opportunity, defined as the proportion of unfair inequality to the actual income inequality. In this case, the index of inequality is the Gini index, and the ex-ante counterfactual distribution is the distribution of

[3]Specifically a kernel density estimate with fixed Sheather and Jones bandwidth. For sake of comparison, the variance of each component population has been inflated by a factor of $1+h^2/\sigma_i^2$ to match that of the kernel density, where h is the estimated bandwidth of the kernel.

Figure 2: Estimation of mixture components in 2014 and relative overlapping.

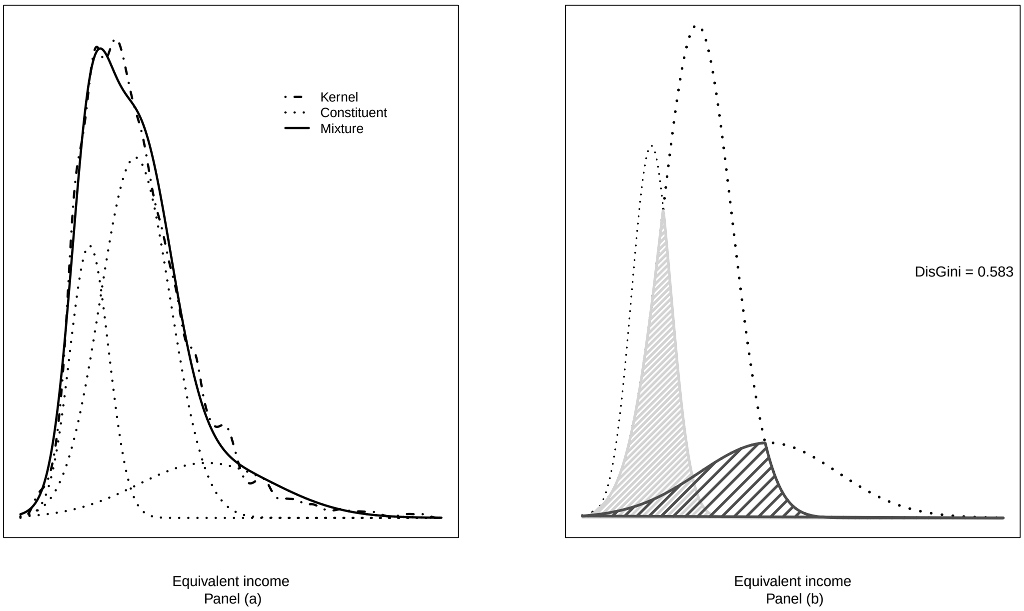


Figure 3: Estimation of mixture components in 2022 and relative overlapping.

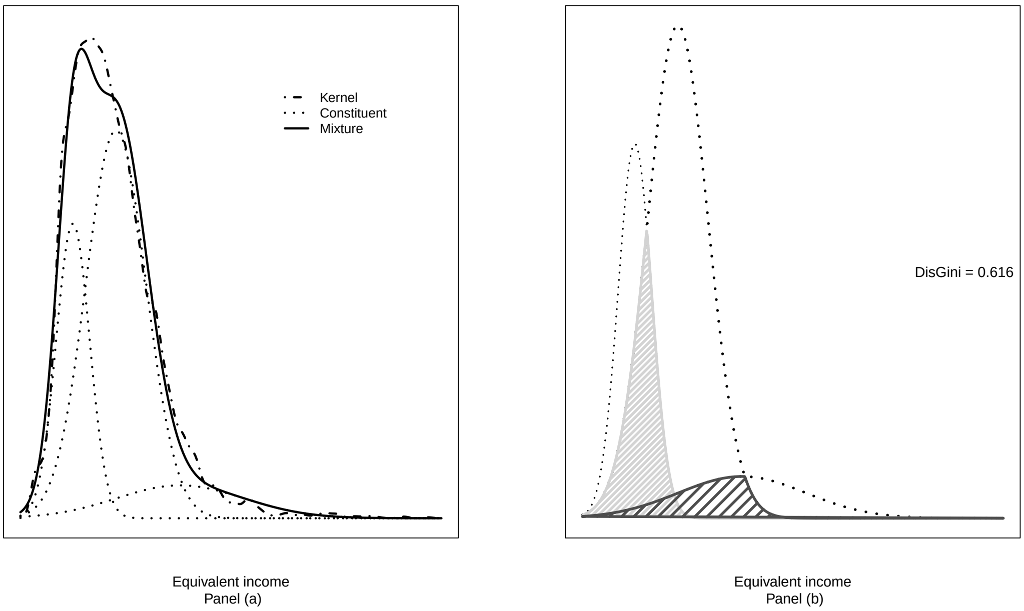
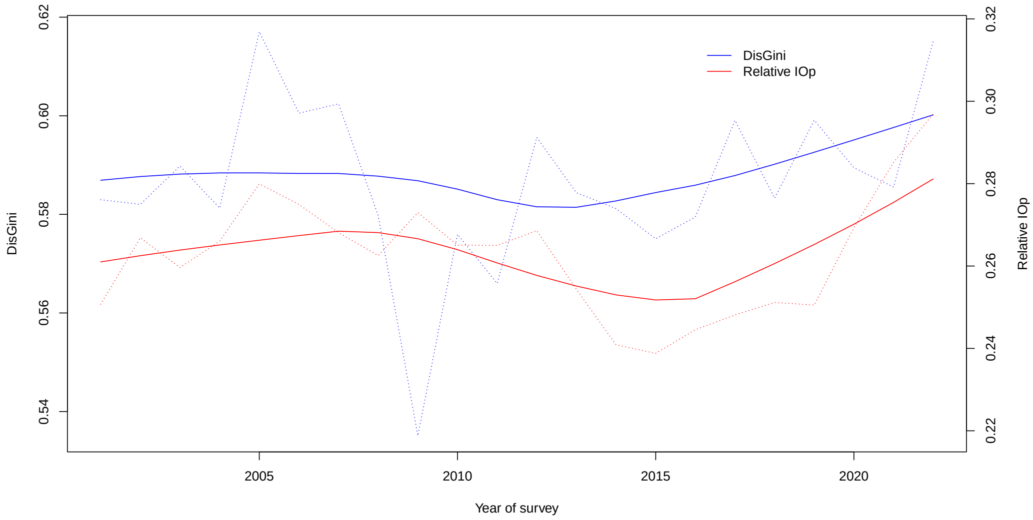


Figure 4: Distributional Gini and Relative Inequality of Opportunity by year. A lowess function is used to smooth data



the predicted values, denoted by $\widehat{x}_i$, obtained by regressing each individual's income to the set of circumstances described in Table 1.

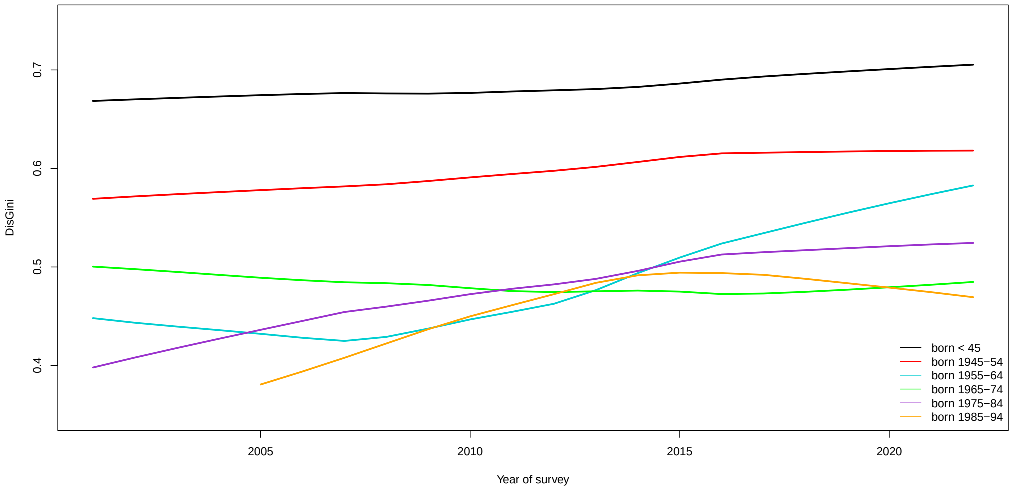
A comprehensive analysis reveals that the segmentation of the classes does not appear to diminish over time. Indeed, the pattern of the DisGini tends to increase after 2011. A similar yet not coincident pattern is evident in the relative IOp. The proportion of inequality in income attributable to the specified circumstances is estimated to be approximately 26 percent at the beginning of the century. This figure is projected to decline to 24 percent between 2024 and 2016, subsequently increasing to a maximum of 30 percent in 2022.

4.2 A cohort evolution

The estimated values of the DisGini for each cohort and survey year are shown in Figure 5. The number of components is chosen according to the value of the BIC. As evident from the figure, the distributions of the oldest cohorts show higher persistent segmentation over time, suggesting a more binding individual lifetime income opportunity. At the same time, the pattern -

smoothed by a lowess function - of the DisGini does not seem to reduce over time for any cohort, with the exception of the last cohort born at the turn of the nineties. On the contrary, the segmentation of the classes tends to increase over time for the birth cohort 1955-1964.

Figure 5: Distributional Gini by year and birth cohorts. A lowess function is used to smooth data

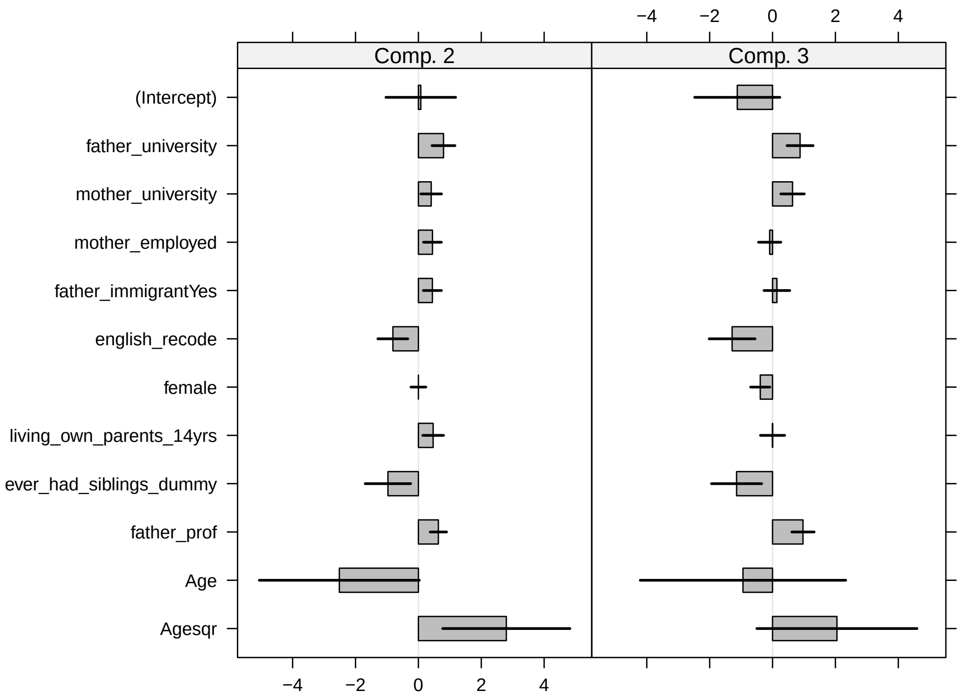


Inherited circumstances can be used to explain the classification of individuals into the different classes. For the cohort born between 1975 and 1984 relative to the years[4] 2020-2022, taken as an illustrative example, Figure 6 contains estimates of the correlated effect parameters $\boldsymbol{\beta}_k$ from the model (2), along with their standard error, with low class as the base category. The coefficients have the expected signs with reasonably small standard errors. In particular, having a university education for both father and mother and having a professional father (manager or professional) significantly increase the probability of belonging to the richest class, while having siblings and not having English as a first language have a significant negative effect on the probability of belonging to the richest groups.

A comprehensive picture of the signs of the significant coefficients associated to the circumstances in the multinomial logistic regressions are reported in Table 3. The estimated coefficients refer to the effects on the probabilities

[4]To increase the sample size we pooled from three years.

Figure 6: Effects of circumstances on the probability of belonging to middle and upper classes with respect to the lower class. Birth cohort 1975-1984, years 2020-2022.



of belonging to the middle class and to the upper class with respect to the lower class.

Table 3: The sign of the effects of circumstances on class membership by cohort for selected years (2005-07, 2014-16, 2020-22). Empty cells represent statistically non significant effect.

Circumstances	**Cohort 1940**		**Cohort 1950**		**Cohort 1960**		**Cohort 1970**		**Cohort 1980**		**Cohort 1990**	
	2005-2007		2005-2007		2005-2007		2005-2007		2005-2007		2005-2007	
	Low/ Middle	Low/ High	Low/ Middle	Low/ High	Low/ Middle	Low/ High	Low/ Middle	Low/ High	Low/ Middle	Low/ High	Low/ Middle	Low/ High
Father Univ.	+	+		+			+	+		+		
Mother Univ.		+						+	+	+		+
Mother Emp.		+							+	+		
Father Immigrant					+	+		+		+		
English	-	-	-	-			-	-				-
Female	-	-	-	-	+		-	-	-			
Living parents			+	+					+	+	+	+
Siblings		-				-	-					-
Father Prof.		+	+	+	+	+	+	+	+	+		
Age	-	-		-					-	-		
Agesq				-					-	-		
	2013–2015		2013–2015		2013–2015		2013–2015		2013–2015		2013–2015	
	Low/ Middle	Low/ High	Low/ Middle	Low/ High	Low/ Middle	Low/ High	Low/ Middle	Low/ High	Low/ Middle	Low/ High	Low/ Middle	Low/ High
Father Univ.		+		+		+	+	+	+	+		
Mother Univ.		+							+	+		+
Mother Emp.							+		+		+	+
Father Immigrant								+	+	+	+	
English		-	-	-	-	-	-	-	-	-		-
Female	-	-	-	-			-	-	-	-		-
Living parents				+					+		+	+
Siblings		-	+						-			
Father Prof.	+	+	+	+	+	+	+	+	+	+		+
Age			-	-		+	+	+			+	+
Agesq						-		-				
	2020-2022		2020-2022		2020-2022		2020-2022		2020-2022		2020-2022	
	Low/ Middle	Low/ High	Low/ Middle	Low/ High	Low/ Middle	Low/ High	Low/ Middle	Low/ High	Low/ Middle	Low/ High	Low/ Middle	Low/ High
Father Univ.		+	+	+	+	+	+	+	+	+		+
Mother Univ.								+	+	+		+
Mother Emp.				-	+		+		+		+	+
Father Immigrant				-			+	+	+			+
English				-	-	-			-	-		
Female	-	-	-	-	-	-	-			-	-	
Living parents					+				+		+	+
Siblings		-	+						-	-		
Father Prof.		+		+	+	+	-	+	+	+	+	+
Age							+	+	-			
Agesq					-	-	-	-	+			

Some results:

- The association between membership and inherited circumstances is always present.

- The profession of the father when the child was 14 is a very strong factor in determining the probability of belonging to higher classes for almost any cohort and period.
- Being a woman is a disadvantage when it comes to belonging to higher classes, even for the latest cohorts.
- If English was not the first language at home, it negatively affects belonging to higher classes for any cohort and period.
- The education of the mother seems to be a more relevant factor for the latest cohorts.
- .....

5 Conclusions

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