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UPPER AND LOWER BOUND ESTIMATES OF INEQUALITY OF OPPORTUNITY: A CROSS-NATIONAL COMPARISON FOR EUROPE

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I provide lower and upper bound estimates of inequality of opportunity (IOp) for 32 European countries, between 2005 and 2019. Lower bound estimates use machine learning methods to address sampling variability. Upper bound estimates use longitudinal data to capture all-time invariant factors. Across all years and countries, lower bound estimates of IOp account from 6 percent to 60 percent of total income inequality, while upper bound estimates account from 20 percent to almost all income inequality. On average, upper bound IOp saw a slight decrease in the aftermath of the Great Recession, recovering and stabilizing at around 80 percent of total inequality in the second half of the 2010s. Lower bound estimates for 2005, 2011, and 2019 show a similar pattern. My findings suggest that lower and upper bound estimates complement each other, corroborating information and compensating each other's weaknesses, highlighting the relevance of a bounded estimate of IOp.

JEL Codes: D31, D63, J62

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1. Introduction

Promoting equal opportunities lies at the core of several national and cross-national policy agendas. Many governments and international institutions have incorporated the challenge of achieving equal opportunities in their long-term strategies. Indeed, the first of the three European Pillars of Social Rights of 2017 is to promote equal opportunities (European Comission, 2021). The same holds for other institutions as well as many national governments. To be able to pursue the goal of equal opportunity, we first need to know the potential extent of inequality of opportunity (IOp), both across countries and over time. With that in mind and using the EU-SILC, I provide "upper bound" estimates of IOp for 32 European countries between 2005 and 2019 and "lower bound" estimates for 2005, 2011, and 2019.

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The key precept behind IOp is that the source of inequality matters from an ethical point of view. In particular, what matters is the distinction between morally legitimate sources, commonly called "effort," "preferences," or "responsibility," and morally illegitimate sources, called "circumstances" (Roemer, 1998), with IOp quantifying the importance of the latter. The growing interest in measuring IOp can be seen in varied theoretical developments, applications for several countries, and multiple review articles on the subject (Bourguignon, 2018; Ferreira and Peragine, 2016; Ramos and Van de gaer, 2016; Roemer and Trannoy, 2015).

Most approaches to measuring IOp follow what is typically called the "lower bound" approach to estimating IOp (Ferreira and Gignoux, 2011; Luongo, 2011). This approach relies on a vector of circumstances, typically obtained from retrospective modules in socioeconomic surveys and aims to quantify the extent to which these variables can explain total income inequality. Many methods are available to do so, such as cell-based or regression-based analysis, or focusing on before or after effort has been exerted (referred to as "ex-ante" and "ex-post" approaches, respectively) as well as using different measures of inequality (see Ramos and Van de gaer, 2021, for an overview of the different methods). Among the multiple methods, a common characteristic of this approach is that the set of available circumstances is never exhaustive, and thus these methods are grouped under the general term "lower bound" approach.

Recent literature has pointed out that these estimates also suffer from upwards bias, due to sampling variance (Brunori *et al.*, 2019b). This is especially true when the sample size is small and there are a large number of potential circumstances. To avoid such an issue, a number of articles have suggested the use of machine learning methods when estimating IOp (Brunori *et al.*, 2021). These methods treat the estimation of IOp as a prediction problem and are aimed at improving both in-sample and out-of-sample predictions, thus providing a good benchmark to choose an "optimal" set of circumstances. In this article I use conditional inference random forests to estimate the lower bounds of IOp. While I acknowledge and address this upwards bias, for consistency with the existing literature I still refer to this approach as the "lower bound" approach.

Niehues and Peichl (2014) proposed an alternative to the lower bound approach, providing upper bound estimates of IOp through the use of longitudinal data. The intuition behind this approach is that most circumstances are already given when one reaches adulthood and are therefore fixed at the point of observation. Using longitudinal data, they predict a fixed effect for each individual in a given sample, which they then use as their measure of circumstances. This is a "black box" approach as it does not tell us what those circumstances are, only that they are accounted for. Because the fixed effect is assumed to capture all (or at least, most) circumstances but also time invariant efforts, this approach results in "upper bound" estimates of IOp. While not as widespread as the lower bound approach, a few articles have provided upper bound estimates for the UK and some middle-income countries (Flatscher, 2020; Hufe *et al.*, 2022).

Because lower and upper bound estimates differ from the "real" level of IOp, reporting them on their own can create some issues. First, from a measurement point of view, we do not know how far these estimates depart from the actual level of IOp, a point discussed in Ferreira and Peragine (2016) for the lower bound estimate.

Second, from a policy point of view, these estimates can be misinterpreted as the real level of IOp, muddling redistributive efforts for policy makers, a concern raised by Kanbur and Wagstaff (2016). Third, from a normative point of view, misinterpreting estimates of IOp can shift the perceived importance of structural causes of inequality, which shape concerns about inequality, as Mijs (2019) shows. Together, on the contrary, lower and upper bound estimates of IOp provide a range rather than a single point estimate, better informing comparisons both across countries and over time.

Furthermore, the two approaches can complement each other. They can corroborate information, for example cross-country rankings or the evolution of IOp over time. Similarly, departures between them can help us understand some of the driving forces behind the changes in IOp. They can also compensate for the problems of the other approach: concretely, the fact that lower bound estimates omit certain circumstances, while the upper bound approach has nothing to say on the relative importance of each circumstance. Together, they can help us understand patterns that neither approach could on its own.

Lower bound estimates of IOp account for anywhere between 6 percent and 60 percent of total income inequality, measured using the mean log deviation (MLD) index, while upper bound estimates, based on fixed effect regressions, account for from around 20 percent to just below 100 percent of income inequality. IOp is higher in the Baltic countries, followed by Southern Europe, and is lowest among the Nordics. Over time and on average, I find that IOp—estimated using the upper bound approach—decreased in the aftermath of the Great Recession and increased until 2014, stabilizing at around 80 percent of income inequality. This trend is particularly clear in Western Europe, to a lesser extent in Southern Europe and the Baltic countries, and even less so in East and Central Europe, where IOp levels were already high before 2012.

The upper and lower bound estimates of IOp are strongly correlated (0.58), but the gap between the two is quite heterogeneous. Across the five regions studied here, the smallest gaps represent around half of the lower bound, while the largest ones go up to three times the lower bound. Overall, the gap has decreased over time due to an increase in the lower bound, particularly between 2005 and 2011, possibly explained by the larger set of circumstances that has become available. Across regions, the gap is larger for countries in Eastern and Central Europe as well as Southern Europe. The gap is smaller in Baltic countries and in Western Europe. A smaller gap between the upper and lower bound estimates of IOp can be interpreted as an improvement in the precision of our knowledge about the "real" level of IOp, reinforcing the idea that these estimates complement each other.

The rest of this article is organized as follows. Section 2 introduces a model to explain what is being captured by the lower and upper bound estimates of IOp, as well as the estimation approaches in both cases. Section 3 describes the data. Section 4 reports the estimates and main findings. Section 5 concludes.

2. Estimating Lower and Upper Bounds of IOp

IOp quantifies the extent to which inequality in income (or other outcome) depends on factors over which we have no control, called circumstances

(Roemer, 1998). Faced with the need for a set of circumstances on which to measure IOp, we can run into two main problems. On one hand, we can have a partial set of circumstances. These missing circumstances will result in an underestimated measure of IOp (Ferreira and Gignoux, 2011). On the other hand, too many circumstances can be problematic when our sample size is limited, resulting in overfitting and potential overestimation of the extent of IOp (Brunori *et al.*, 2019b). Using a parametric, ex-ante, and direct measure of income IOp (as shown in Bourguignon *et al.*, 2007, among others) I present two approaches to constructing the circumstance set, each of which addresses one of the previously mentioned issues.

The first approach, proposed by Niehues and Peichl (2014), addresses the "missing circumstance" problem. Common examples of missing circumstances include IQ or measures of innate talent, as well as measures of parental time investments. Using longitudinal data, they predict individual fixed effects that capture circumstances but also time-invariant efforts, personal traits that individuals have chosen to adopt such as being punctual or hard-working. The resulting measure of circumstances cannot be disentangled, so we cannot know the relative importance of time-invariant efforts, nor the basis on which circumstances are included and their relative importance. The upper bound approach thus gives a measure of the maximum possible level of IOp, if we were to treat all time-invariant characteristics as circumstances. This approach seeks to capture all circumstances, in the process capturing additional factors and thus obtaining an "upper bound" estimate of IOp.

The second approach addresses the overfitting problem that arises from the use of too many circumstances when the sample size is limited. Brunori *et al.* (2019b) discuss the existence of an upward bias due to sample variance. Given a small sample and our goal of including as many circumstances as possible, IOp estimates can suffer from overfitting. If interpreted as a prediction problem, this means that our estimate can only predict outcomes in the sample in which it has estimated, upwardly biasing their predictive capacitive in other samples. To address this issue, Brunori *et al.* (2021) propose the use of machine learning methods where the model specification considers both the downward bias due to omitted circumstances and the upward bias from overfitting the data. Even when acknowledging this upward bias, and because this approach relies on a set of observable circumstances, I still call it the "lower bound" approach to contrast it with the previously discussed "upper bound" approach.

2.1. *Decomposing Total Inequality: The Role of Circumstances*

I describe the canonical model of equal opportunity as presented in Ferreira and Peragine (2016) and include a time dimension as shown in Niehues and Peichl (2014).[1] I use this model as a benchmark to represent what is being captured by each of the two approaches.

[1]While several papers have looked at IOp over time, few articles have looked into time as a factor through the use of a dynamic model. Aaberge *et al.* (2011) look at long-term IOp using permanent income, Roemer and Ünveren (2017) study the long-term effect of equal opportunities policies, Bussolo *et al.* (2019) include time-varying circumstances, and Moramarco *et al.* (2020) measure intertemporal IOp.

Take the level of income Y for individual i in year t as a linear function of circumstances C_i, time-varying efforts E_{it}, and time-invariant efforts E_i.[2]

(1) $$Y_{it} = \alpha_0 + \beta_0 C_i + \gamma_0 E_{it} + \eta_0 E_i + \mu_t + \varepsilon_{it},$$

where μ_t represents year fixed-effects and ε_{it} is the error term. In this model, the year fixed effect μ_t is treated as neither effort nor circumstance, but simply a "shifter" of the level of income. Circumstances typically reflect childhood or early adulthood characteristics such as the socioeconomic level of one's parents or household composition when growing up. While time does not fit that definition, it can be interpreted as a measure of what Lefranc *et al.* (2009) call "residual luck," a factor that is neither a circumstance nor an effort.

Circumstances affect income directly and also indirectly through their influence on efforts. Efforts are determined by circumstances and an "autonomous" component (v_{it} and u_i) that represents a source of legitimate inequality. Efforts are modeled as a linear combination of circumstances and the autonomous component.

(2) $$E_{it} = \alpha_1 + \beta_1 C_i + v_{it}.$$

(3) $$E_i = \alpha_2 + \beta_2 C_i + u_i.$$

Treating the influence of circumstance on efforts as a circumstance itself is a common assumption in the IOp literature, but not the only one. Barry (2005) considers the effect of circumstances on efforts to be within the space of personal responsibility. He states that differences due to individual choice should result in legitimate inequality, irrespective of what drives these choices (see Jusot *et al.*, 2013 for an empirical application on this issue). This indirect path can still be an important source of inequalities later in life through shaping educational or labor market choices. As such, I consider the indirect influence of circumstances to be a circumstance too.

By substituting Equations (2) and (3) into Equation (1), we get for a given year t:

(4) $$\begin{aligned} Y_{it} = {} & \overbrace{(\alpha_0 + \gamma_0\alpha_1 + \eta_0\alpha_2 + \mu_t)}^{\tilde{\alpha}_t} + \overbrace{\eta_0 u_i}^{\tilde{u}_i} \\ & + (\underbrace{\beta_0 + \gamma_0\beta_1 + \eta_0\beta_2}_{\tilde{\beta}})C_i + (\underbrace{\varepsilon_{it} + \zeta_0 v_{it}}_{\tilde{\varepsilon}_{it}}). \end{aligned}$$

Reorganizing it we get Equation (5), where $\tilde{\beta}$ reflects all of the paths through which circumstances can influence income.

(5) $$Y_{it} = \tilde{\alpha}_t + \tilde{\beta} C_i + \tilde{u}_i + \tilde{\varepsilon}_{it}.$$

[2]I use the level of income rather than the logarithm of income in all my specifications—both for the lower and upper bound estimates. This to satisfy properties than one could theoretically expect from a measure of IOp (Van de gaer and Ramos, 2020). Such a choice does not affect the IOp estimates in a substantial way, as discussed in Section C of the Appendix.

In the context of IOp, income is determined by a (time-specific) constant, $\tilde{\alpha}_t$ (that includes the time fixed effect for that year), time-invariant circumstances (C_i), an individual time-invariant effect that stems from efforts ($\tilde{u}_i$), and an error term ($\tilde{\varepsilon}_{it}$).

One could estimate the reduced form model (Equation 5) or the complete structural model (Equations 1–3). Such an estimation would provide information on the indirect paths through which circumstances shape efforts. It would also allow for the inclusion of market conditions, or for the influence of circumstances to vary according to demographics that can be interpreted as "preference shifters" (i.e. efforts) or circumstances (Roemer and Trannoy, 2015). My focus is on determining the complete influence of circumstances, whether direct or indirect, and I therefore focus on the estimation of the reduced form equation, which I discuss in the following section.

2.2. *Measuring IOp: Estimation and Prediction of a Counterfactual Distribution*

Typically, Equation (5) would be estimated using a parametric or "regression-based" approach, that is, to estimate the association between circumstances and the outcome using a linear regression model that allows for the inclusion of multiple circumstances without the need to split the data into subgroups as is the case with most nonparametric approaches.

If we had access to the full set of circumstances C_i, we could estimate IOp for a given cross-section straightforwardly using:

$$Y_i = \alpha + \beta C_i + u_i. \tag{6}$$

Absolute IOp would be, for a given inequality measure $\mathtt{I}(\cdot)$, say, the Gini or the MLD index, given by $\mathtt{I}(\hat{\alpha} + \hat{\beta} C_i)$. A relative measure of IOp would be the level of IOp as a share of total income inequality, or $\mathtt{I}(\hat{\alpha} + \hat{\beta} C_i)/\mathtt{I}(Y_i)$. Throughout the article, I use the MLD index to measure inequality, a choice I further discuss in Section A of the Appendix.

From there we can show where the lower and upper bound approaches depart. The lower bound approach uses a subset of all circumstances ($\overline{C}_i \subset C_i$), while the upper bound approach captures all circumstances and the time-invariant measure of effort ($\overline{\overline{C}} = C_i + \tilde{u}_i$). For each of these approaches we estimate Equation (6) using $\overline{C}_i$ or $\overline{\overline{C}}$, respectively, following the same approach discussed before to obtain a measure of absolute and relative IOp.

The Lower and Upper Bound Approaches: Machine Learning and Fixed Effect Models

For the lower bound estimate of IOp, I predict income using conditional inference random forests, as proposed by Brunori *et al.* (2021). This is a supervised learning method aimed at making out-of-sample predictions for a dependent variable based on a series of predictors. This algorithm relies on multiple conditional inference regression trees. These trees divide the population into groups that share the same circumstances, what Roemer (1998) called "types."

The conditional inference tree algorithm is relatively straightforward. It first uses a binary split to divide the full sample into two groups based on a specific binary split of a given predictor, say, dividing the sample between men and women. These groups are then further divided into two groups, each of which is based on another cutoff, for example, men with high and low education. As the goal is to create the best possible prediction, the choice of the variable and binary split is determined by the lowest p-value available. The algorithm continues to split the sample until it is not possible to reject the null hypothesis of independence between the dependent variable and any of the predictors, for a given statistical significance level.

Random forests estimate several conditional inference trees, averaging them when making predictions. This is to address the fact that conditional inference trees are fairly sensitive to changes in the data, particularly when predictors are strongly correlated, as is the case with circumstance variables. This sensitivity means that the sample could be split in many different ways, particularly for the first binary split. Conditional inference trees could also have very long "roots" (sometimes called "unpruned" trees), splitting the sample into too many and small groups, creating issues of overfitting. Random forests consist of a large number of uncorrelated conditional inference trees, thus avoiding the problems with any one individual tree.[3]

Beyond its benefits in addressing the upward bias due to overfitting, there are two additional advantages of relying on random forests. First, trees—and therefore, forests—have a simple visual interpretation. The predictors and their splits can be presented through a series of splitting points and terminal nodes that resemble the roots of a tree. In the case of random forests, where there are multiple trees, one can show a surrogate tree built to approximate the prediction of a conditional inference random forest (Molnar, 2022). The second benefit of random forest models is that they deal with missing values not by eliminating observations but by surrogate splits, which create predicted values based on other variables. This is particularly helpful as it allows for including circumstances that might prove relevant but where few respondents provided answers.

The upper bound approach, on the contrary, uses longitudinal data to create its measure of circumstances. For each individual we predict a fixed effect, which is then used as our measure. This approach was proposed by Niehues and Peichl (2014) and has been used for the UK (Flatscher, 2020) as well as for a number of middle-income countries (Hufe *et al.*, 2022). The main benefit of this approach is that it does not require data on circumstances, only repeated waves for each individual. The problem is that this approach cannot help if our interest lies in determining the main circumstances that are at play and their relative importance. As such, this approach is a good complement to the lower bound approach, particularly when we suspect the existence of important but unobserved circumstances. While the former is potentially able to capture all circumstances, the latter is able to give us plenty of information about which circumstances matter the most (i.e. that make the best predictors) and their interactions.[4]

[3]I estimated a random forest model using the `fastcforest` command in R with 500 random forests. For further details on the method, see Breiman (2001) and Brunori *et al.* (2021).

[4]For a detailed overview of the upper bound approach, as well as the empirical implications of using short panels, see Appendix B.

3. European Data: The Cross-Sectional and Longitudinal EU-SILC

This article uses data from the European Union Statistics on Income and Living Conditions (EU-SILC). The EU-SILC collects cross-sectional and longitudinal data on poverty and income dynamics for Europe, with some countries conducting surveys and others using a combination of surveys and administrative registries (see Carranza *et al.*, 2022 for an updated list of the use of register data and its implications). The cross-sectional sample gathers information for respondents each year, while the longitudinal sample follows each respondent for four consecutive years, before renewing the sample in a rotating panel structure.

In total, I include estimates for 32 countries over the 2005–2019 period. When studying trends, I group these countries into the five European regions as defined by EuroVoc. With this data set I provide lower bound estimates of IOp 2005, 2011, and 2019 and estimates of upper bound IOp for the full period. Countries include from 4 to 15 years of data, 13.4 years on average, with 20 countries reporting data for the full period. Table 1 includes the list of countries by region and the number of years per country. In addition, to address the fact that inequality estimates might be influenced by outliers (Cowell and Flachaire, 2007), I winsorize the income distribution, scaling back all incomes below the 1st percentile and above the 99.5th percentile for every year-country pair.

My outcome of interest is an individual's yearly household equivalized disposable income. That is, the total income of a household that is available to spend or save in a year, divided by the number of "equivalized" adults, using the modified OECD equivalence scale. Equivalized income provides a measure of disposable income, and therefore of overall welfare. It is also the most common outcome when measuring IOp, as shown, for example, in Ferreira and Gignoux (2011); Ramos and Van de gaer (2016). Contrary to earnings, it avoids issues with cross-country differences in labor market participation, particularly among women. The final sample includes all individuals aged 25–55 with positive income.

I use the cross-sectional sample to obtain the lower bound estimates of IOp and the longitudinal sample for the upper bound estimates. Unfortunately, it is not possible to use a common sample for both approaches, nor to merge them to use the

TABLE 1
European Regions and Number of Years of Data

Baltic	East and Central	Nordic	South	West
Estonia (15)	Bulgaria (13)	Denmark (15)	Cyprus (15)	Austria (15)
Latvia (15)	Croatia (8)	Finland (15)	Greece (15)	Belgium (15)
Lithuania (15)	Czechia (15)	Iceland (14)	Italy (15)	France (15)
	Hungary (15)	Norway (15)	Malta (12)	Germany (4)
	Poland (15)	Sweden (15)	Portugal (14)	Ireland (13)
	Romania (11)		Spain (15)	Luxembourg (15)
	Serbia (4)			The Netherlands (15)
	Slovakia (14)			Switzerland (7)
	Slovenia (15)			UK (14)

Notes: EuroVoc classification of European regions. Number of years of available data in parenthesis.

same group of respondents. The longitudinal sample does not include retrospective information on the respondents, and the cross-sectional sample does not allow for the estimation of fixed effect regressions. All data are weighted by the longitudinal weight or by each year's personal cross-sectional weight for the upper and lower bound approach, respectively.

I estimate the lower bound estimates of IOp using the cross-sectional sample. Estimates are available for 2005, 2011, and 2019, as these waves include ad-hoc modules with retrospective information on their parents. The choice of circumstance variables is detailed in Table 3. The final set of circumstances differs between 2005, on one hand, and 2011 and 2019 on the other hand, as the questionnaire was extended between 2005 and 2011. These circumstances capture individual characteristics such as gender, but also socioeconomic information regarding the parents as well as information on household composition at age 15.

The original approach detailed in Niehues and Peichl (2014) uses the preceding years to estimate the fixed effects, but this is not always possible for the EU-SILC. As the EU-SILC panel began in 2005, the first three IOp estimates (2005, 2006, and 2007) use the following years rather than the preceding ones to estimate the fixed effects. This is done by using the 2008, 2009, and 2010 samples, respectively. For example, the upper bound estimate of IOp for 2005 uses the 2008 wave, estimating the fixed effects for the years 2006–2008, and measuring IOp in the year 2005. Table 2 describes the range used to estimate the fixed effects for every year, and Section B in the Appendix provides further details.

I include all available circumstances for each specific year, limiting the number of categories by grouping them as shown in Table 3, irrespective of their response

TABLE 2
Fixed Effect (FE) Estimation Window

IOp Year	Estimation of FE	Sample
2005	2006 to 2008	2008
2006	2007 to 2009	2009
2007	2008 to 2010	2010
2008	2005 to 2007	2008
2009	2006 to 2008	2009
2010	2007 to 2009	2010
2011	2008 to 2010	2011
2012	2009 to 2011	2012
2013	2010 to 2012	2013
2014	2011 to 2013	2014
2015	2012 to 2014	2015
2016	2013 to 2015	2016
2017	2014 to 2016	2017
2018	2015 to 2017	2018
2019	2016 to 2018	2019

Notes: Table shows the 3-year range used to estimate the FE, for all upper bound estimates of IOp. Because the EU-SILC panel started in 2005, the first 3 years use the following rather than the previous years. For the first 3 years, I used the next 3 years. Starting on 2008, I use the previous 3 years. The reference year is excluded from all estimations of the FE to avoid artificially augmenting the upper bound estimate of IOp. The last column specifies the sample year used to measure that specific estimate.

TABLE 3
CIRCUMSTANCE VARIABLES

2005		
Gender of Respondent	Education (Both Parents)	Family Composition
a. Woman	a. Lower secondary or less	a. Both parents
b. Man	b. Upper/postsecondary	b. Single mother
Activity (both parents)	c. Tertiary	c. Other
a. Employee	Occupation (both parents)	Number of siblings
b. Self-employed	a. High-grade services	a. None
c. Unemployed	b. Lower-grade services	b. 1 or 2
d. Retired	c. Small-business owners	c. 3 or 4
e. Housework	d. Skilled workers	d. 5 to 9
f. Other	e. Unskilled workers	e. 10 or more
2011 and 2019		
Activity (both parents)	Family composition	Gender of respondent
a. Employee	a. Both parents	a. Woman
b. Self-employed	b. Single mother	b. Man
c. Unemployed	c. Other	Education (both parents)
d. Retired	Number of adults in household	a. Illiterate
e. Housework	a. None	b. Lower secondary or less
f. Other	b. One	c. Upper/postsecondary
Occupation (both parents)	c. Two	d. Tertiary
a. High-grade services	d. 3 or 4	Country of birth (both parents)
b. Lower-grade services	e. 5 or more	a. Present country
c. Small-business owners	Number of children in household	b. Other EU27
d. Skilled workers	a. None	c. Other Europe
e. Unskilled workers	b. One	d. Outside Europe
Number of working people	c. Two	Citizenship (both parents)
a. None	d. 3 or 4	a. Present country
b. One	e. 5 or more	b. Other EU27
c. Two	Tenancy status of parents	c. Other Europe
d. 3 or more	a. Owner	d. Outside Europe
Managerial status (both parents)	b. Tenant	
a. Supervisor	c. Rent-free living	
b. Non-supervisor		

Notes: List of all circumstance variables and their categories, by year. The years 2011 and 2019 include the same set of circumstances. Questions on family composition (e.g. number of siblings, adults, or working people) all refer to household composition at age 15. ISCO codes from occupations were grouped using the categorization from Oesch (2006).

rate.[5] The set of circumstances described in Table 3 is similar to previous studies that used the same data set, although not directly comparable. For example,

[5]I only exclude circumstances based on perceptions. These circumstances include the financial situation of the household and whether families were able to make ends meet. I omit these circumstances because how we interpret these perceptions might change across countries and over time, capturing different indirect factors. Brunori *et al.* (2021) also exclude these two circumstances from their analysis.

Ramos and Van de gaer (2021) include place of birth and mother's occupation. While not exhaustive, these variables ensure comparability across countries and provide an overall characterization of childhood circumstances. While I include a priori all circumstances, each country-year pair will use a different set based on its out-of-sample prediction.

Table 4 shows the unweighted number of observations for the cross-sectional and longitudinal sample. Sample sizes vary greatly across countries, going from just over 3,600 to almost 25,000 observations for the lower bound sample and from 306 to over 5,000 observations for the upper bound sample. The latter is much smaller because it only includes individuals who have four waves of data. In other words, the upper bound sample is restricted to the first rotational group in every given year.[6]

From Table 4, we can see that a few countries have information in the cross-sectional sample but not in the longitudinal sample. For example, Croatia, Germany, and Ireland had cross-sectional surveys in 2011 but no longitudinal survey in 2011. The same thing happened for Malta, Switzerland, and Slovakia in 2019. This was due to multiple reasons. For example, Germany started including longitudinal data in 2018, while Ireland did not report information for 2010 and 2011 due to errors being found in the data (O'Donoghue *et al.*, 2013). For that reason, those years will have lower bound estimates of IOp but not upper bound estimates.

4. Upper and Lower Bound IOp Estimates

My main findings are reported as two sets of figures. First, I report lower and upper bound estimates of IOp together with total inequality for the 3 years for which all estimates are available, 2005, 2011, and 2019 (Figures 1–3). The second set of figures shows the evolution of IOp over time, grouping countries into regions as defined by the geographical classification in EuroVoc (Figures 4 and 5). Tables I.E.1 and I.E.2 in Appendix E include the full set of IOp estimates.

I also explore the relationship between the lower and upper bound estimates of IOp. First, I report the association between them using absolute and relative measures in Figure 6. Second, I look into the gap between them and how it has evolved over time, which I interpret as a measure of precision in the estimation of IOp, in Figure 7. The final subsection discusses some of the assumptions behind the upper bound estimate of IOp.

4.1. *IOp by Country: 2005, 2011, and 2019*

Figures 1–3 show the lower and upper bounds of IOp together with the level of total inequality for all countries in 2005, 2011, and 2019, respectively. All the inequality estimates are based on the MLD index and countries are ranked based on their upper bound estimate of IOp, except for those without an upper bound estimate, which are reported at the top of the list.

[6] Lower bound estimates do not vary substantially when using the first rotational group. Preliminary analysis based on a limited set of circumstances and an OLS regression for 2011 (not reported) shows a median difference of 0.002 points of the MLD.

TABLE 4
Total Observations in Each Sample/Year

	Lower Bound			Upper Bound											
Country	2005	2011	2019	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Austria	5,724	6,112	5,057	1,041	999	1,105	1,052	1,203	1,187	1,047	1,027	964	1,056	922	1,068
Belgium	5,416	5,982	6,010	1,110	1,050	1,074	850	932	997	922	927	1,088	934	968	1,595
Bulgaria	-	6,747	6,141	-	764	842	1,369	1,441	1,142	1,108	1,014	2,793	2,582	2,484	2,602
Cyprus	4,801	4,644	4,207	875	846	829	687	675	1,346	942	1,294	774	987	930	938
Czechia	4,391	8,253	7,038	3,174	2,797	2,089	1,460	1,927	1,954	1,801	1,413	1,490	1,463	1,511	1,606
Germany	13,083	11,634	8,387	-	-	-	-	-	-	-	-	-	-	1,793	1,534
Denmark	6,759	5,224	4,014	910	855	866	828	760	671	575	816	779	698	517	545
Estonia	4,620	5,251	5,779	452	1,241	1,121	1,093	899	1,066	1,045	1,205	1,180	1,167	990	1,150
Spain	15,983	15,161	16,017	2,741	2,804	2,945	3,000	2,866	2,556	2,195	2,396	2,437	2,376	2,264	2,026
Finland	12,344	9,093	8,735	1,491	1,350	1,245	1,191	1,096	1,997	2,169	2,006	1,928	1,768	1,846	1,683
France	10,078	10,659	9,593	4,425	4,424	4,678	4,852	5,153	4,690	4,536	4,503	4,392	4,088	3,807	3,705
UK	10,502	7,053	-	1,423	1,156	1,136	1,055	919	929	1,010	1,482	1,008	1,590	1,945	-
Greece	6,183	5,962	13,296	1,064	1,255	1,079	1,337	1,197	1,052	938	1,012	1,834	2,007	4,742	3,571
Croatia	-	6,476	6,806	-	-	-	-	-	977	934	903	788	1,003	1,625	1,507
Hungary	7,685	12,559	5,060	1,606	1,782	1,882	1,696	2,130	1,727	2,999	1,328	1,390	1,262	1,133	966
Ireland	5,798	4,272	3,946	394	339	-	-	347	365	353	306	600	1,136	579	435
Iceland	3,695	3,648	-	565	503	534	578	555	524	540	490	490	481	443	-
Italy	24,822	20,378	16,281	4,114	3,924	4,049	3,674	2,979	2,616	3,338	3,314	3,230	3,082	2,311	3,734

(continued)

TABLE 4
(Continued)

Country	Lower Bound 2005	Lower Bound 2011	Lower Bound 2019	Upper Bound 2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Lithuania	4,980	4,906	4,181	724	1,033	1,125	1,001	1,044	1,151	925	943	769	998	689	805
Luxembourg	4,445	6,651	4,579	500	553	428	2,804	3,123	806	747	716	748	646	473	898
Latvia	3,823	6,257	4,082	711	771	969	1,136	1,090	1,184	1,087	1,018	953	917	966	938
Malta	-	5,076	4,093	-	865	808	791	1,111	1,073	1,163	1,026	1,112	984	-	-
The Netherlands	10,783	10,662	10,397	2,579	1,323	2,099	1,902	1,707	1,874	1,962	1,719	1,667	1,563	1,379	1,864
Norway	6,916	4,864	6,010	2,655	2,372	2,253	2,008	1,871	1,400	1,329	874	880	787	770	811
Poland	20,260	15,208	18,771	3,533	3,775	3,513	3,130	3,062	3,086	2,963	3,105	2,842	2,708	2,223	2,272
Portugal	5,277	5,676	12,650	-	882	961	888	1,186	1,165	1,329	1,372	1,479	1,452	3,057	2,827
Romania	-	7,319	6,848	-	-	1,841	1,728	1,680	1,819	1,650	1,613	1,624	1,613	1,829	1,577
Serbia	-	-	6,223	-	-	-	-	-	-	-	-	1,369	1,393	1,394	1,266
Sweden	6,230	6,376	5,061	1,190	1,148	1,386	1,018	1,036	920	740	592	676	686	786	712
Switzerland	-	7,261	6,649	-	-	-	-	-	-	1,238	1,158	1,138	1,170	1,206	-
Slovenia	13,121	13,109	10,368	2,155	2,123	2,186	2,509	2,269	2,128	2,072	2,105	1,801	1,740	1,616	1,785
Slovakia	6,998	6,867	5,851	1,356	1,408	1,592	1,628	1,596	1,508	1,580	1,581	1,621	-	1,533	-

Notes: The first 3 years for the upper bound estimates are not reported because the 2005–2007 period uses data for 2008, 2009, and 2010, respectively (see Section 3). The longitudinal sample includes individuals with four waves of data only.

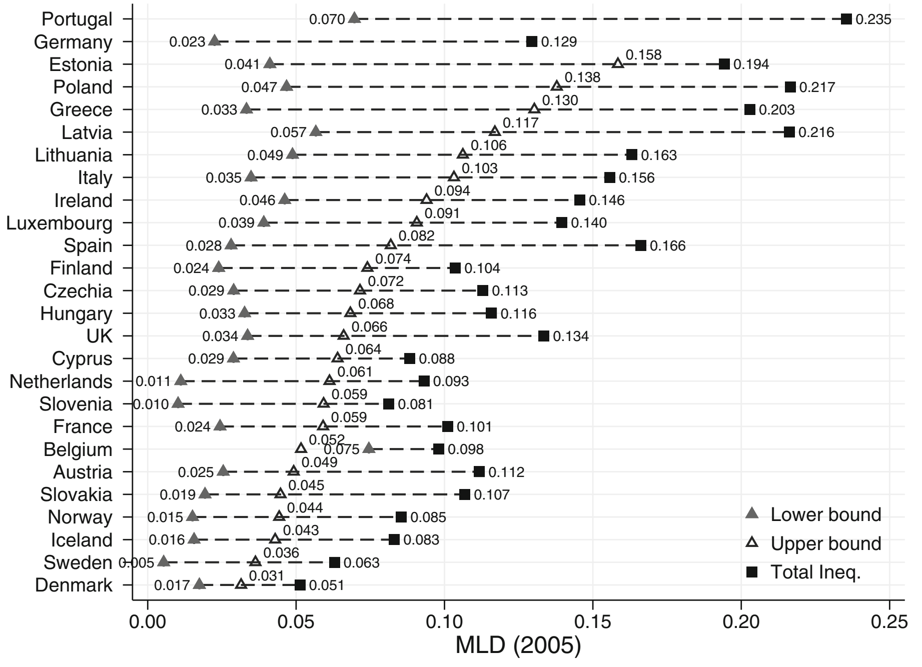

Figure 1. Inequality of Opportunity by Country (2005).
Notes: Lower and upper bound estimates of IOp, together with total income inequality. Countries are sorted by their upper bound estimate of inequality of opportunity. Countries with no upper bound estimate are shown on top. All inequality estimates use the MLD index

Figure 1 shows that the lower bound estimate of IOp in 2005 ranges from 0.005 points of the MLD index for Sweden to 0.08 for Belgium. Among the countries with low levels of lower bound IOp, I find the Nordics as well as the Netherlands and Slovenia. Countries on the other side of the ranking include Latvia, Lithuania, Poland, and Portugal. The upper bound estimates range from 0.05 for Denmark up to 0.22 for Poland. The lower and upper bound estimates show similar country rankings with three exceptions: Cyprus and Belgium with high lower bound estimates relative to their upper bound estimates, and Denmark, with a relatively high upper bound estimate. In relative terms, the lower bound estimates account for between 6 percent and 47 percent of total inequality, while the upper bound estimates account for between 42 percent and 82 percent.

The country rankings are fairly similar when we look at 2011, but the lower bound estimates of IOp are now higher. The lower bound IOp goes from 0.01 to 0.08 (12–58 percent of total inequality), while the upper bound estimates go from 0.03 to 0.14 (38–80 percent of total inequality). The low IOp countries include the Nordics, Czechia, Belgium, and Slovakia. The high IOp countries include Portugal, Romania, and Latvia and Spain. We find a similar country ranking when looking at 2019, with roughly the same countries among those with low and high IOp.

The lower bound estimate of IOp accounts for the largest share of total inequality in countries like Belgium and Luxembourg, where it explains around half of all income inequality for 2011 and 2019. At the other extreme, lower bound IOp

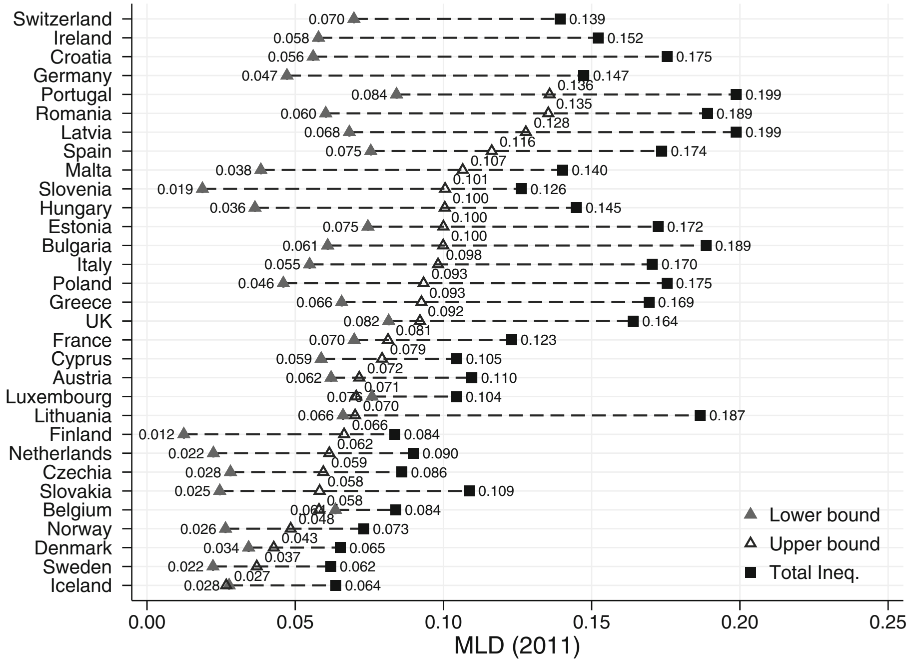

Figure 2. Inequality of Opportunity by Country (2011).
Note: See Note in Figure 1

accounts for the smallest share of total inequality in Slovenia, Slovakia, the Netherlands, and the Nordics, accounting for less than one-fifth of total inequality on average across all three available years.

The upper bound estimates of IOp follow the total level of inequality more closely than the lower bound estimates, as one would expect given the way they are estimated. The correlation between total inequality and the upper bound estimate is 0.88, compared to 0.69 for the lower bound. In relative terms, the upper bound estimate of IOp accounts for the largest share of total inequality in Finland, Switzerland, Slovenia, Cyprus, and the Netherlands (around 75 percent on average across all years), while in Hungary, Bulgaria, Serbia, and Slovakia it accounts for the lowest share (around half).

Through this analysis we begin to see some of the differences between the two approaches. Finland, Slovenia, and the Netherlands are among the lowest countries when looking at the relative lower bound of IOp, but among the highest for the upper bound. The opposite is true for Austria, Serbia, and Bulgaria. These large discrepancies can be explained in part by the role played by time-invariant factors that the upper bound manages to capture and the vector of circumstances from the lower bound misses. These could be either missing circumstances or time-invariant efforts. We explore the gap between the bounds in detail in Section 4.3.

4.2. *IOp Trends Over Time*

Figures 4 and 5 show the evolution of IOp over time. Figure 4 includes the level of income inequality and the upper bound estimate of IOp for the 2005–2019

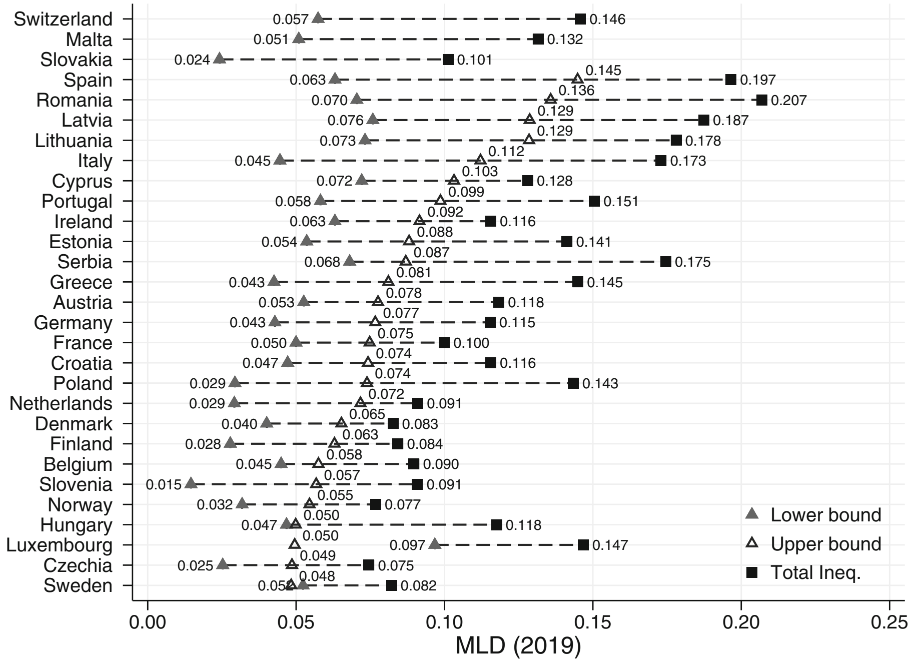

Figure 3. Inequality of Opportunity by Country (2019).
Notes: See Note in Figure 1. Bulgaria is excluded as it significantly distorts the *x*-axis, with upper bound IOp and total inequality estimates of almost 0.3 (lower bound estimate of 0.118)

together with lower bound estimates of IOp for 2005, 2011, and 2019. Figure 5 shows the relative IOp, the share of total income inequality accounted for by the lower and upper bound estimates of IOp. To simplify the analysis, the countries are grouped into five European regions as defined by EuroVoc (see Table 1 for the list of countries) as well as a sixth category that includes all countries. Both figures show the population-weighted average for each region. The upper bound estimate of IOp and the total level of income inequality report a bootstrapped 95% confidence interval with 1,000 repetitions.

The upper bound estimate of IOp shows the trend for the whole period. If we look at the population-weighted average among all of the available countries (top-left panel in Figure 4), we can see that the upper bound estimate of IOp and income inequality—relative to 2005—saw a decline in 2008, in the immediate aftermath of the Great Recession. This decline was followed by an increase in inequality, peaking around 2014 and stabilizing around that level. By 2019, total income inequality had reached its 2005 level while upper bound IOp was still 10 percent above it. The lower bound estimates of IOp show a similar trend, capturing the pre–Great Recession level of IOp, the increase in 2011, and the stable trend that followed.[7] Following the peak in inequality in the first half of the 2010s, income

[7]Note that the lower bound trend is partly influenced by the increase in available circumstances, particularly from 2005 to 2011, increasing their predictive power—this is partly mediated by the random forest algorithm, as it limits the number of circumstances based on sample size.

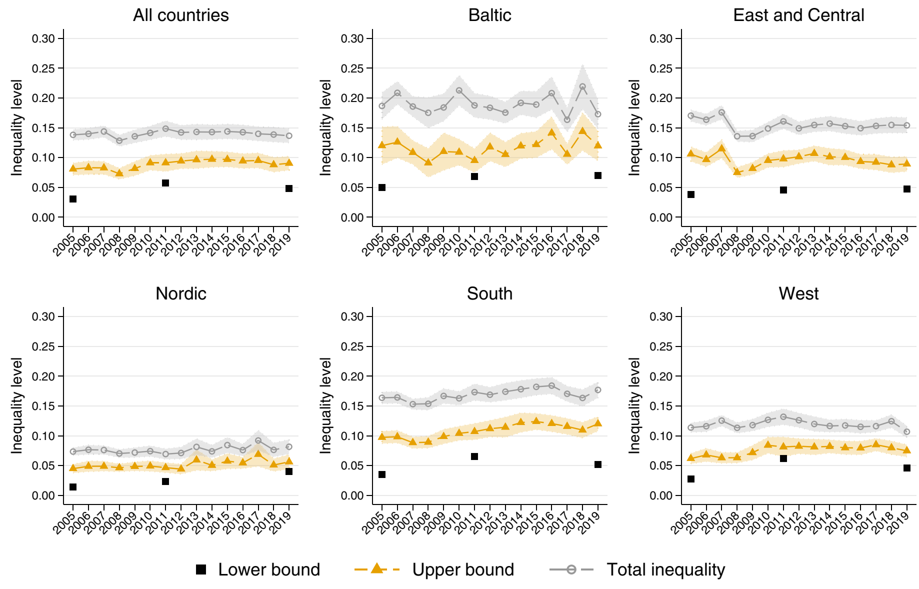

Figure 4. Inequality of Opportunity Level (IOL) by Region (Population-Weighted).

Notes: Population-weighted lower and upper bound estimates of IOp, together with total income inequality for the five regions based on the EuroVoc categories, and a sixth category including all countries. All inequality estimates use the MLD index. Upper bound estimates report their 95% confidence interval from a 1,000 iteration bootstrap of the whole estimation process, with replacement [Colour figure can be viewed at wileyonlinelibrary.com].

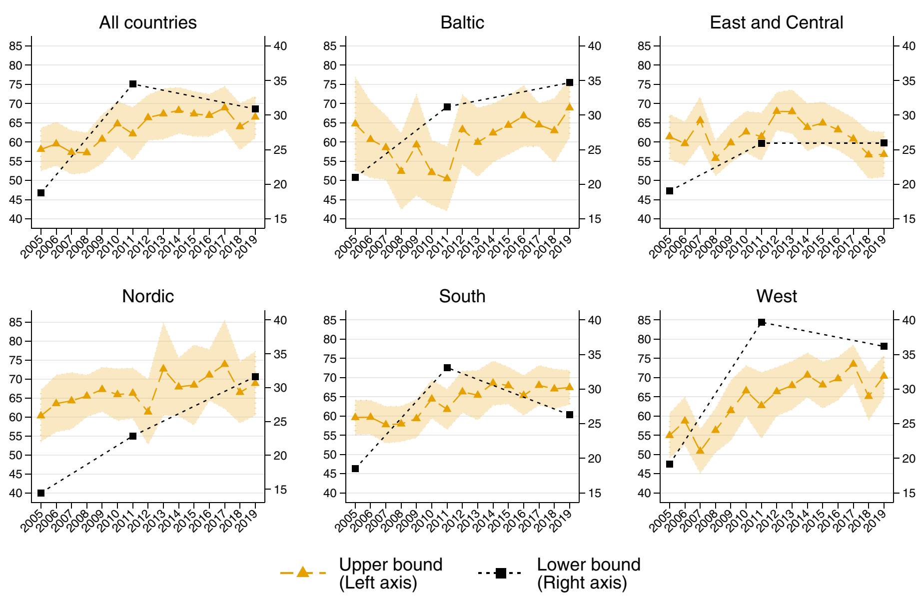

Figure 5. Inequality of Opportunity Ratio (IOR) by Region (Population-Weighted).

Notes: See Note in Figure 4 [Colour figure can be viewed at wileyonlinelibrary.com].

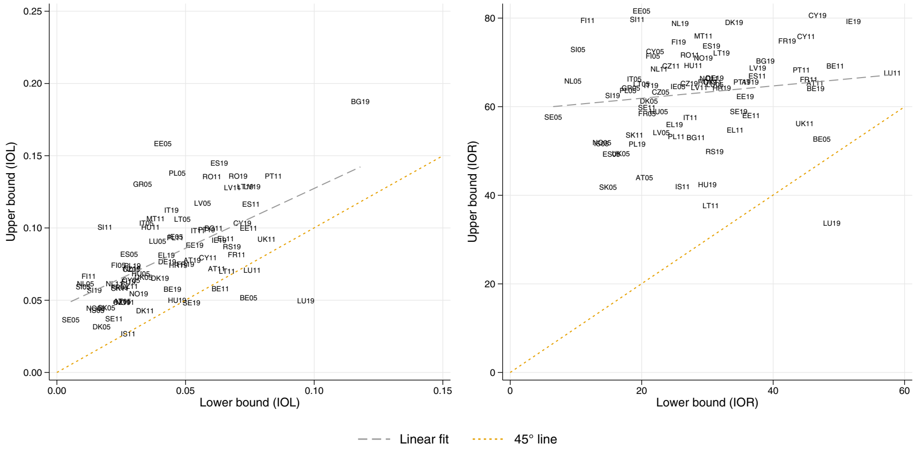

Figure 6. Association Between Lower and Upper Bound Estimates of IOp.
Notes: Correlation between lower and upper bound estimates of IOp. IOp level (left panel) and IOp ratio (right panel), together with the linear fit and the 45° line. All inequality estimates use the MLD index [Colour figure can be viewed at wileyonlinelibrary.com].

inequality dropped faster than IOp on average, resulting in a steady increase in the share of total inequality accounted for by circumstances, as shown in Figure 5.

The post–Great Recession fall in upper bound IOp followed by the subsequent increase is particularly noticeable in Southern and Western Europe, which closely follow the average trend. In both cases inequality decreased faster than IOp, assigning a larger relative importance to the role of circumstances in determining differences in income (see Figure 5). The Nordic countries suffered no decrease in IOp but rather a steady (yet not statistically significant) rise in IOp. The Baltic countries show an erratic trend, with higher overall levels of upper bound IOp than other regions. Finally, Eastern and Central Europe also saw a decrease in inequality in 2008, which stabilized at lower levels of IOp after that. Across all regions but Eastern and Central Europe, we can see that IOp rose faster and decreased slower than income inequality. These findings suggest that IOp can rapidly increase when income inequality goes up, but IOp decreases at a much slower rate than income inequality.

Regions can be ranked based on their lower and upper bound estimates of IOp. On average, Baltic countries have the highest levels of inequality, upper bound IOp and lower bound IOp, followed by Southern Europe. Eastern and Central Europe show much higher levels of income inequality and upper bound IOp than Western Europe but somewhat similar levels of lower bound IOp. Finally, the Nordic countries have the lowest levels of all three indicators.

This is not the case when looking at relative measures of IOp. Because the upper bound estimate of IOp moves very closely to total inequality, we can see a relatively homogenous picture across all regions, showing, on average, that upper bound IOp accounts for 60–67 percent of total inequality. Relative upper bound IOp is higher among the Nordics—due to them having a particularly low level of income inequality—followed by Western Europe, where upper bound IOp is higher.

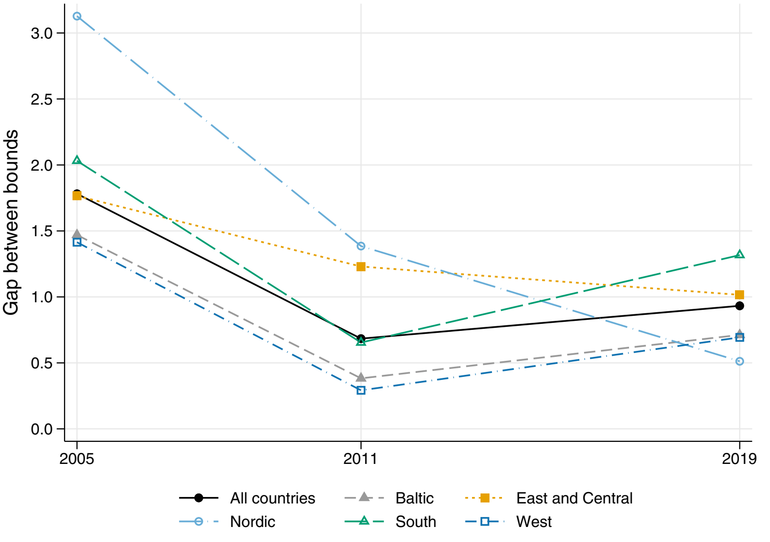

Figure 7. Difference Between Bounds Relative to the Lower Bound.

Notes: Difference between the upper and lower bound estimates of IOp divided by the lower bound estimate, for the 3 years for which there are data. Population-weighted average for the European five regions based on the EuroVoc categories, and a sixth category including all countries. All inequality estimates use the MLD index [Colour figure can be viewed at wileyonlinelibrary.com].

Under the lower bound estimate Western Europe and the Baltic countries have higher relative IOp, with lower bound IOp accounting for around 30 percent of total inequality while Southern Europe and Eastern and Central Europe have somewhat lower levels, around 25 percent, with lower bound IOp accounting for 23 percent of total inequality among Nordic countries.

4.3. *The Correlation and Gap Between Bounds*

Figure 6 shows the association between the lower and upper bound estimates of IOp. The panel on the left shows the levels of IOp, while the panel on the right shows the relative measure of IOp, both using the MLD index. All country-year pairs for which there are data on both estimates are reported. Figure 7 includes the change in the gap between the upper and lower bound estimates of IOp, measured as a share of the lower bound estimate, grouped into population-weighted regions.

Almost all the estimates in Figure 6 are above the 45° diagonal line, meaning that the upper bound estimate is higher than the lower bound. There are two cases for which this is not the case, 2005 Belgium and 2019 Luxembourg, where the lower bound estimate is slightly higher than the upper bound estimate. The two estimates are strongly correlated when measured in levels, but much less so when measured in relative terms with correlations of 0.58 and 0.15, respectively. The lower correlation under relative IOp is explained by the fact that the upper bound is closely correlated with total income inequality, resulting in limited variability for the relative upper bound estimate. Contrary to the relative lower bound estimate of IOp, the relative upper bound estimate is not very informative in terms of cross-country comparisons.

We can also discuss the gap between bounds, measured as the difference between the level of IOp under the upper bound and lower bound estimates, presented as a share of the lower bound estimate. From Figure 7 we can see that the gap between bounds can be large. Even in the region with the lowest gap, it still accounts for half of the lower bound estimate of IOp. Throughout the 3 years of data, the gap is consistently larger for Eastern and Central Europe and, to a lesser extent, for Southern Europe. Across all regions, the Nordic countries saw the largest reduction of the gap, going from three times the lower bound in 2005 to half of it in 2019.

The gap between the two estimates saw an important decrease between 2005 and 2011 across all regions. Given that most of the upper bound estimates did not change or increased between 2005 and 2011, this is due to the additional circumstance variables that became available in the 2011 survey, as noted in Table 3.[8] Contrasting the 2005 estimates with those in 2011 we can see the importance of including new circumstances, as long as these new variables contribute additional information and do not correlate with already available circumstances.

5. Discussion

IOp has gained national and global recognition as an issue that needs to be addressed, and a big challenge is to provide appropriate estimates. Most articles that measure IOp rely on a single point estimate to quantify it. Depending on the approach, these point estimates can suffer from downward or upward bias. Downward bias can happen under partial observability of circumstances, while upward bias can happen due to overfitting or because our measure of circumstances captures additional factors. On their own, these estimates of IOp provide a partial view of IOp, its evolution over time, as well as cross-country comparisons. In this article I report two estimates of IOp, one that addresses the partial observability of circumstances and another that addresses overfitting and provides further information on the relative importance of each circumstance.

These estimates complement each other in understanding the extent of IOp and its evolution over time. The first approach has typically been called a “lower bound” approach, and its most common application relies on linear regressions and a set of circumstance variables, where IOp is determined by the relative importance of these circumstances. Combined with machine learning methods, this approach addresses the issue of overfitting in the presence of a large number of circumstances. The second approach addresses the partial observability of circumstances using longitudinal data to predict an individual fixed effect. That predicted fixed effect captures all circumstances (to the extent that they are time-invariant, at least) together with other time-invariant factors, thus resulting

[8] Another potential explanation could be larger sample sizes, which would allow the random forest algorithm to make better use of the available predictors. However, we can see in Table 4 that this is not necessarily the case. The regions with the largest drops, the Nordics and Southern Europe, saw decreases in sample size for over 75 percent of their countries.

in an "upper bound." The upper bound approach can go beyond observable circumstances, but it cannot tell us anything about their relative importance, something that the machine learning-adjusted lower bound estimate is very good at. Together, these estimates offer a more detailed overview of the level and changes in IOp.

I find that upper bound IOp fell in the immediate aftermath of the Great Recession, just like income inequality fell. Following the Great Recession, most European regions experienced a U-shaped pattern of inequality. Both IOp and income inequality saw an increase in all regions except for Eastern and Central Europe, with IOp increasing faster than income inequality. The rise in inequality slowed down around the first half of the 2010s; this was followed by a decrease in both metrics where income inequality decreased faster than IOp. As a result, the share of income inequality accounted for by IOp increased throughout the 2005–2019 period, particularly in Western Europe, settling at around 80 percent. The lower bound estimates of IOp, available for 2005, 2011, and 2019, show the same picture, one where IOp increased between 2005 and 2011, followed by a slight decrease in 2019. The two estimates complement each other by reinforcing these findings.

There are large benefits of reporting both bounds together. The upper bound estimates, as they do not require data on circumstances, allowed us to observe the complete 2005–2019 period, including the fall in inequality immediately after the Great Recession and the large increase in the following years. The lower bound estimates of IOp confirmed that trend, but also provided some insight into how regions differ in terms of the relative importance of IOp, something the upper bound estimate cannot do due to the strong correlation between it and total income inequality. Each estimate provides useful and different information, and the two together give a detailed picture of the importance of circumstances in shaping economic inequality.

One of the main challenges ahead is to acquire better data to estimate both bounds over time. Reporting both estimates is extremely demanding in terms of data. We need information on circumstance variables and longitudinal data for the same (or at least similar) years. As it stands, this article relies on a fairly limited set of circumstances for the lower bound estimate and a short panel for the upper bound estimate. This means that the lower bound estimates are lower than they could be, while the upper bound estimates are higher than if we were to use a longer panel. This becomes even more of a challenge if our goal is to provide comparisons both across countries and over time.

One way to address the strong data requirements would be to rely on administrative data, for example, data on standardized tests—which usually include socioeconomic questionnaires—income and earnings data from tax returns or social registries, health records, together with intergenerational identification systems to link parents and their children. Administrative data sets can provide a set of circumstances and are likely to be measured yearly, thus providing a great input for the estimation of joint lower and upper bound estimates of IOp over time. The use of administrative data has great potential for the study of associations across generations, as has been shown by Chetty and Hendren (2018a, 2018b) for the US and Adermon *et al.* (2021) for Sweden.

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Appendix S1 Supporting Information