ECOBAS Working Papers
2019 - 01

Title:

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ESTIMATING INEQUALITY OF OPPORTUNITY IN MANY NEW PERIODS: THE CAPITAL INCOME APPROACH

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This version: February 2020

The measurement of opportunity inequality has attracted increasing attention in recent years, despite the fact that its empirical application suffers from many data limitations. In this paper we address one of these restrictions: the scarcity of data on family background. We propose to use a widely available variable as alternative proxy of family background, instead of the traditional and sparse proxies commonly employed. This alternative proxy is capital income. Using data of 31 European countries we first successfully test the accuracy of our approach, and then we apply it to obtain many new inequality of opportunity estimates. These results are useful for the measurement of inequality of opportunity, but also in any other area of research where we want to account for family background. (123 words)

JEL Codes: D63, D31

Keywords: inequality of opportunity, family background, capital income

1. Introduction

Throughout all her life Sophie Germain had to face opposition to study mathematics simply because she was born a woman. Germain was forced to study in secret during her youth, and to hide her gender with a pseudonym—Monsieur Le Blanc—once she grew up. Yet, in spite of the hurdles, she eventually became a great mathematician who impressed prominent figures of her time like Joseph-Louis Lagrange and Carl Friedrich Gauss. Now we know that we owe her a number of contributions, specially in number and elasticity theory, but we do not know what else she could have achieved, had she enjoyed the *opportunity* to receive early formal education and social support. Nonetheless, even though Germain suffered utter discrimination because of her gender, she had something most people did not: a rich family. She never had to work for money, nor had she to fulfill domestic tasks; she had the time, which she used to study.

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We believe that the life of Sophie Germain is interesting in its own right, but we resort to it now to illustrate what (in)equality of opportunity, IOP henceforth, is. This field follows the work of a group of political philosophers and an economist who tried to define what makes a distribution *fair*. Sen (1980), Dworkin (1981a, 1981b), Arneson (1989) and Cohen (1989), building upon the work of Rawls (1971), sought to define a concept of equity that would accommodate concerns regarding advantages acquired through birth and results obtained by means of personal effort. The result of their work is a theory to systematically classify differences as just or unjust.

In short, inequalities with respect to any outcome—be it income, wealth, health status and such—are deemed "fair" or "unfair" depending on where they stem from. Inequality caused by factors individuals can choose—like the degree of effort exerted—are considered fair, while unfair inequality arise from sources individuals cannot control—like gender or race. For instance, Germain suffered discrimination due to her gender, something she cannot be held responsible for. This is, being a woman complicated her path to become a mathematician only because her society had established a role for her gender that did not match such prestige. In the same way, Germain enjoyed time to devote to her passions because she did not have to work, thanks to the economically comfortable position of her family. Of course, she had no merit or responsibility on that either. Consequently, the IOP approach would consider the inequalities steaming from her gender and privileged socioeconomic origin as unfair; the former playing a negative influence and the latter furnishing a head start. However, Germain attained greater levels of knowledge and (postmortem) prestige than most people, and some of that inequality is surely due to the greater amount of effort she must had exerted. Such inequalities, stemming from variables individuals can choose, are deemed fair.[1]

The measurement of "fair" and "unfair" inequality is an appealing field that has been growing notably in recent years, despite the fact that it suffers from many shortcomings, which include a lack of correspondence with IOP theory, stringent data limitations and the absence of an established methodology. This article presents a strategy aiming to ease the data requirements to measure IOP. We propose a method to circumvent the restriction imposed by the scarce availability of a key piece of information routinely employed for estimating IOP: family background of individuals.[2] The standard approach for estimating IOP uses data on parental education and/or occupation to proxy socioeconomic origin. Although these are, naturally, not perfect proxies, it is generally assumed that they serve the purpose well—the problem we address here is related to their availability only. The methodology presented in this article consists of using capital income as alternative proxy, because it also approximates family background *and* it is widely available.

In order to grasp the magnitude of the constrain imposed by relying on parental education

[1]For a recent survey on the philosophical grounds of the IOP approach, see Ferreira and Peragine (2016) or Roemer and Trannoy (2016).

[2]The importance of socioeconomic origin in determining economic and social outcomes has been explored extensively by the literature on intergenerational mobility. See for example Corak (2013).

and/or occupation data availability, consider the following two well-known databases for the study of poverty and inequality. The Luxembourg Income Study (LIS), the largest available income database of harmonized microdata collected from about 50 developed and developing countries, has information on parental education (parental occupation is not available) in only 63 of its 364 datasets (about the 18 per cent)[3]. Likewise, the European Union Statistics on Income and Living Conditions (EU-SILC), another extensively researched database on comparable income, poverty and living conditions—although referred to European countries only—has information on parental education and occupation in 2 of its 14 waves (around the 14 per cent). Of course these are just two examples, but the pattern is general: data on parental features is scarce. The bottom line is that following a standard methodology for estimating IOP we can only obtain a small number of data points.[4] On the other hand, data on household capital income is available in around the 99 per cent of LIS' datasets, and in all waves of the EU-SILC. Therefore, using capital income to proxy socioeconomic origin we could obtain many new IOP estimates.

Yet, why would capital income constitute an appropriate proxy? The relationship between capital income and family background appears in a large body of literature studying wealth inequality, intergenerational transmission of advantages, and financial returns determinants. We review it in the next paragraphs.

In his famous book "Capital in the Twenty-First Century", Piketty (2014) wrote about the return of what he dubbed patrimonial capitalism, referring to the importance of bequests and inter vivos gifts in the determination of the wealth distribution. In fact, Piketty had already described in a previous article the contemporaneous rising relevance of intergenerational wealth transmission in France, measured as a fraction of either aggregate private wealth or national income (Piketty 2011). He finds the annual inheritance flow to be about 20% of disposable income, a figure much larger than the typical annual flow of new savings, and almost as big as the annual flow of capital income. Later, Alvaredo et al. (2017) extended the same analysis to include also the UK, Germany, Sweden and the USA, reaching similar conclusions. They estimate that in these countries the stock of inherited wealth as a share of total private wealth was about 50–60% (and rising) in 2000–2010. As a matter of fact, the work by Piketty and coauthors revisit a question that in the 1980s fired up a famous debate, which is commonly known as the Modigliani vs. Kotlikoff-Summers controversy. The discussion started in Kotlikoff and Summers (1981), who argued that "intergenerational transfers account for the vast majority of aggregate U.S. capital formation [and] only a negligible fraction of actual capital accumulation can be traced to life-cycle savings". Specifically, they estimated that the inheritance share in

[3]As of the time of writing this article.

[4]A practical consequence of this restriction are a number of studies attempting to assess the evolution of IOP in Europe considering only two points in time, like Suárez Álvarez and López Menéndez (2017) or Andreoli and Fusco (2017). Other studies have explored the relationship of IOP with a number of economic and social phenomena by performing regressions with around 50 observations, such as Checchi, Peragine, and Serlenga (2016) and Marrero and Rodríguez (2012). Albeit these are relevant pieces of research that pursued interesting matters, they faced severe constrains due to the small amount of data points they could rely on.

total US' private wealth is up to the 80%. Modigliani (1986) replied by pointing out a number of methodological errors and insisted the share is actually much lower, at around 20% (see also Kotlikoff 1988 and Modigliani 1988). Subsequent studies found support for either one or the other side, or argued for a sort of a point in between. For a summary of the early literature on the role of bequests in the determination of aggregate private wealth go to Davies and Shorrocks (2000). More recently, Piketty, Postel-Vinay, et al. (2014) dismissed all Kotlikoff and Summers (1981), Kotlikoff (1988), and Modigliani (1986, 1988), pinning down the source of their dissent to the choice of the capitalization rate of past inheritance. Nevertheless, Piketty (2011), Piketty, Postel-Vinay, et al. (2014), and Alvaredo et al. (2017)'s results are more in line with the conclusions of Kotlikoff and Summers. An overall look at this literature can be found in Piketty and Zucman (2015).

In any case, bequests are only one of the channels driving the transmission of wealth from parents to children. Indeed, the intergenerational mobility literature has identified multiple mechanisms through which wealth persists across generations.[5] An early paper studying the correlation of wealth across generations found that in the US, the age-adjusted elasticity of child wealth with respect to parental wealth is 0.37 *before* the transfer of bequests (Charles and Hurst 2003). The authors argue that the main drivers of this correlation are earnings persistence within families, and that parents and children tend to allocate their portfolios quite similarly (either because children mimic or learn from their parents or because they share preferences such as risk tolerance). In contrast with posterior research, Charles and Hurst (2003) find that education plays a minor role. With a quasi-experimental design based on adoptees data, Fagereng, Mogstad, et al. (2018) conclude that "family background matters significantly for children's accumulation of wealth and investor behavior as adults, even when removing the genetic connection". The mechanisms they identify are children's education, income, financial literacy, and inter vivos transfers of wealth from parents. In a series of companion papers, Boserup et al. (2016) study Danish wealth records and find that bequests increase wealth of recipients by a 36%, on average. Yet, Boserup et al. (2018), using the same data, find that wealth holdings during childhood, of which the main source are (inter vivos) transfers from parents, have a stronger predictive power of future holdings than parental wealth itself. They justify this relationship on the basis that wealth ownership during childhood is a marker for characteristics that are not captured by parental wealth alone, pointing at intergenerational correlation in savings and/or investment behavior. Finally, Boserup et al. (2017), also using the same Danish data, find a U-shaped pattern when looking at the wealth rank correlation as a function of child age. It is very high when children are entering adulthood—confirming the importance of inter vivos transfers—, it then declines until children reach the age of 30, when it starts to rise again, and finally increases even further upon the receipt of bequests. They find a correlation of 0.27 before bequests, and explain the pre-bequest wealth correlation on the basis

[5] Although the transmission of other advantages has been studied as well, such as ability, goals, or family reputation and connections; see Becker and Tomes (1979, 1986) for classical references.

of early inter vivos transfers and human capital accumulation. It is worth noting that since Denmark is a (relatively) egalitarian country, it is reasonable to expect wealth correlation across generations to be higher in other economies. Consistent with Boserup et al. (2017), Mudrazija (2014) finds a non-linear pattern of parent-child net transfers across the adult life-cycle in 11 European countries, with positive transfers from parents to adult children decreasing modestly until advanced old age, when the decrease intensifies—hence remarking the importance of inter vivos transfers. Although the pattern is general its intensity differs across countries, what Mudrazija explains on the basis of different welfare regimes. However, this heterogeneity could also respond to different fiscal treatment across countries of inter vivos transfers with respect to bequests (Kopczuk 2007).

Parallelly, the portfolio literature has related returns on investments to education and financial literacy (Von Gaudecker 2015; Bucher-Koenen and Ziegelmeyer 2011), what also suggests the possibility of an indirect link between parental education and children's capital income identified by Fagereng, Mogstad, et al. (2018). Moreover, research in sociology has found as well that savings and wealth ownership are largely determined by the intergenerational transmission of human capital (Hansen 2014; Hällsten and Pfeffer 2017).

So far we have treated wealth and capital income almost interchangeably, although they are not the same thing. Regrettably, wealth databases are scant and we are forced to consider capital income only. Nevertheless, although capital income does not perfectly follow total wealth holdings, they are closely related. For instance, Saez and Zucman (2016) estimate the long-run evolution of US' wealth inequality using capitalized income tax data. Fagereng et al. (2016) contested Saez and Zucman (2016)'s method and, using Norwegian data, showed that heterogeneity in returns to wealth and potential correlation of returns with wealth (i.e., that richer individuals tend to enjoy disproportionately higher returns) may introduce an upward bias in the estimated inequality. Nevertheless, this critique is not about the existence of a connection of wealth holdings with returns. In fact, Fagereng et al. (2020) show again that capital income is indeed positively correlated with wealth.

In conclusion, the literature reviewed in the last paragraphs suggests that capital income may indeed serve as proxy of family background. However, in the context of IOP we must be aware of an important caveat. In Roemer (1998)'s sense, only exogenous variables (exogenous meaning being beyond individual control) may qualify as circumstances. Since capital income is not outside the influence of personal choice, or at least not completely, our proposal of including it in the circumstances' set violates this theoretical principle. We defend our strategy on three grounds: a) capital income should be understood not as an income variable, but as a variable correlated to socioeconomic origin—to the extent that strong intergenerational persistence exists, the concern of it being within individuals' control is lessened; b) to tackle this concern further we follow a procedure to isolate the exogenous component of capital income, which we detail in subsection 3.2; and most importantly, c) we perform extensive accuracy and robustness tests of the IOP estimates produced, with satisfactory results.

The possibility of overcoming the limitation imposed by the scarcity of data on family background has been explored before. Marrero, Rodríguez, and Weide (2016) simply opt to omit any information about individuals' background in their circumstances' set, using US' data. Ferreira, Gignoux, and Aran (2011) estimate IOP in Turkey using demographic and health surveys data instead of standard household surveys. Teyssier (2017) employs a multiple imputation technique to attribute fatherly education and occupation to individuals in the sample for whom this data is missing, using Brazilian data. We add to these contributions by proposing a method that we apply and of which accuracy test more broadly, considering a group of countries instead of solely one. Note that although our sample is constituted by developed economies, there is considerable heterogeneity in their characteristics and income. In addition, our methodology can be implemented more generally.

The rest of the paper is organized as follows: in the next section we briefly review the literature on IOP measurement; in section 3 we outline the details of the approach to measure IOP we propose, and the methodology of the test we perform to assess its reliability; in section 4 we show the results of the accuracy and robustness tests and in section 5 we take advantage of our method to estimate IOP in a number of countries and periods in which, to the best of our knowledge, it has never been measured before. Section 6 concludes.

2. The measurement of inequality of opportunity

The IOP approach can be seen as a reduced-form model in which any outcome is a function of a set of circumstances C and a variable of effort e:

$$I = \Phi(C, e)$$

- Circumstances are factors that might influence a given outcome but cannot be chosen, and therefore individuals cannot be held responsible for them. These include gender, race, geographical origin, family background and the sort. In the formulation we just presented, effort implicitly captures different forms of luck[6] and the effect of circumstances on effort is not addressed.[7]

- Effort is the intensity with which individuals devote themselves to work, and can, conversely, be decided. We have described it as a scalar, what is common in the literature, but it can be thought of as a vector.

Thus, the IOP approach distinguishes between inequalities that arise from differences in personal responsibility, which may be considered ethically acceptable, and those that do not, which may therefore be classified as unjust. Following the groundbreaking contributions of

[6]The evaluation of luck is controversial. See Dworkin (1981a, 1981b), Fleurbaey (2008) and Lefranc et al. (2009).

[7]For the constrain of circumstances on effort, see Roemer (1998).

Table 1: Distribution of an outcome that depends on circumstances and effort.

	e_1	e_2	e_3	$\dots$	e_m
C_1	y_{11}	y_{12}	y_{13}	$\dots$	y_{1m}
C_2	y_{21}	y_{22}	y_{23}	$\dots$	y_{2m}
C_3	y_{31}	y_{32}	y_{33}	$\dots$	y_{3m}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
C_n	y_{n1}	y_{n2}	y_{n3}	$\dots$	y_{nm}

Roemer (1993, 1998), Van de gaer (1993), Van de gaer et al. (2003) and Fleurbaey (1995), many authors have proposed different methods to empirically assess the extent of unfair inequality. For surveys of the existing approaches to measure IOP, see Ramos and Van de gaer (2016) or the already mentioned Roemer and Trannoy (2016) and Ferreira and Peragine (2016). In this article we use one of the most popular procedures: the non-parametric *ex-ante between-types inequality* approach, variously proposed by Van de gaer (1993), Peragine (2002), Checchi and Peragine (2010), and Ferreira and Gignoux (2011). As the name suggests, this method allows to obtain *ex-ante* IOP estimates.[8] Also, these IOP estimates are generally interpreted as lower bound estimates,[9] although recent research has pointed out that they may also suffer from upward bias due to sampling variance (Brunori et al. 2019). Nevertheless, we will not explore these issues here and we will limit ourselves to the topic at hand, which is testing the use of capital income as an alternative proxy of family background. We will now proceed to briefly describe the IOP measurement approach we will use.

The non-parametric procedure know as ex-ante between-types inequality consists of replacing the outcome of each individual by a feature of the outcome distribution of individuals sharing the same circumstances, generally the mean value. Suppose we have a population of individuals, each of whom is fully characterized by the elements (y, C, e), where y is an outcome, C a vector of circumstances, and e an effort scalar. Then, this population can be partitioned in two ways: into *types* T_i, within which all individuals share the same circumstances, and into *tranches* T_j, in which everyone exerts the same degree of effort. Denote y_{ij} the outcome generated by circumstances C_i and effort e_j, and suppose there are n types and m tranches. Now we can represent the population with a matrix $[Y_{ij}]$ of n rows and m columns, as displayed in table 1.

Now, to "remove" the effect of effort e_j on outcome y_{ij}, we replace y_{ij} by some feature of the outcome distribution in each type T_i, like the mean value μ_i. This is shown in table 2. By doing so any inequality within types is eliminated, remaining only inequality between types, i.e., inequality due to circumstances.[10] Finally, we can apply an inequality measure to μ_i in

[8] We will not consider any *ex-post* approach throughout this article. On the differences (and clash) between the ex-ante and ex-post approaches see Fleurbaey and Peragine (2013).

[9] For the proof, see Ferreira and Gignoux (2011); for further discussion see Niehues and Peichl (2014) and Hufe et al. (2017).

[10] Note that assuming all inequality between types is inequality of opportunity implies regarding as normatively

Table 2: Removing withing types inequality.

	e_1	e_2	e_3	$\dots$	e_m
C_1	μ_1	μ_1	μ_1	$\dots$	μ_1
C_2	μ_2	μ_2	μ_2	$\dots$	μ_2
C_3	μ_3	μ_3	μ_3	$\dots$	μ_3
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
C_n	μ_n	μ_n	μ_n	$\dots$	μ_n

order to obtain an absolute

$$\text{IOP}_{abs} = I(\mu_i)$$

and a relative measure of IOP

$$\text{IOP}_{rel} = \frac{I(\mu_i)}{I(y)}.$$

3. The capital income approach

This article presents a strategy that aims to ease the data requirements to measure IOP. This strategy, which we call the capital income approach, involves the selection of circumstances: instead of proxying family background with information on parental education and/or occupation—which is scarce—, we propose to employ a measure of capital income—which is widely available. Simply put, we suggest that capital income can also be used to proxy socioeconomic origin.

Our project consists of two parts:

- Validating the approach: we first consider datasets in which data on parental features and capital income are available, in order to obtain IOP estimates using a "standard" set of circumstances (including parental education and occupation) and the set we propose (which excludes parental features but includes a measure of capital income). In order to keep the use of capital income as the only relevant difference with respect to other studies, we try to maintain every other methodological aspect as standard as possible. Finally we compare the two kinds of estimates obtained, with the objective of assessing the accuracy of our method. We conclude that the results of the capital income approach are accurate to the extent they are similar to those of a standard methodology, which we take as our baseline.

- Benefiting from the approach: once the reliability of our method has been assessed, we

irrelevant possible differences in (absolute) effort distributions across types. See Roemer (1998).

show an application to estimate IOP in datasets that do not have information on parental features.

3.1. Data

We make use of the European Survey of Income and Living Conditions, which is a well-known and researched database for the study of inequality, poverty, and social exclusion that offers harmonized data on income and circumstances at the individual and household level. It has been conducted yearly since 2003 for up to 31 European countries in its most recent waves. The EU-SILC has information about parental features in two waves only—2004 and 2010—, but capital income of households is available in all waves and countries. Hence, we will consider the two waves of 2004 and 2010 for the validation purpose, and all of them to take advantage of the capital income approach. We include in our analysis all countries available, but the number of them participating in the survey has been increasing since it started being conducted.[11]

We restrict our sample to people aged 30 to 59 in account for life-cycle effects, what is common in the literature. We also remove from our sample all observations with missing values in any circumstance. In addition, we cap very high values in each country's income distribution, in particular by replacing all incomes above the 99th percentile with the value at that percentile.

As the outcome variable we consider annual gross wage.[12] We prefer to consider gross values because it allows to have an account of how the market rewards each type without the effect of state intervention. Also, we focus on the personal instead of the household level because we want to include gender in the circumstances' set.[13] We can speak of a trade-off in relation to the choice of an outcome at the individual level: on the one hand, it overlooks household bargain issues that influence labor market participation, but on the other hand, part of the effect of circumstances on personal achievement works precisely through labor supply decisions, specially that of gender (Goldin 2014; Bursztyn et al. 2017; Kleven, Landais, et al. 2019). To account for the problem of different patterns of labor market participation we estimate a Heckman two-step selection model into employment (Heckman 1979). The kind of employment modeled includes employees or self-employed who worked full- or part-time during at least 7 months during

[11] In the first wave, referred to 2003, 15 countries took part: Austria, Belgium, Denmark, Estonia, Finland, France, Greece, Iceland, Ireland, Italy, Luxembourg, Norway, Portugal, Spain and Sweden. In 2004, 11 more were added: Cyprus, Czech Republic, Germany, Hungary, Latvia, Lithuania, Netherlands, Poland, Slovakia, Slovenia and the United Kingdom. In 2006, 4 more were included: Bulgaria, Malta, Romania and Switzerland. Finally, in 2009 Croatia joined.

[12] Defined as "Employee cash or near cash income (Gross)" (variable PY010G) plus "Non-Cash employee income (Gross)" (PY020G), setting all non-positive values to one. We exclude "Value of goods produced by own-consumption (Gross)" (PY070G) because it is not available in all countries. Gross means that neither taxes nor social contributions have been deducted at source. From 2006 to 2008, both included, the variable "Non-Cash employee income (Gross)" is not available in the Netherlands' datasets, so we compute wage without it in those years. Also, in the data of France, Greece, Italy, Latvia, Spain and Portugal prior to 2006 the gross value of these variables is not available, so for all waves of these countries we consider the net values (variables PY010N and PY020N).

[13] In another article we have discussed the sensitivity of IOP estimates to the income aggregate considered and how taking income at the household level may implicitly nullify the contribution of gender to total IOP (Valle-Inclán 2020).

the reference period.[14] We believe that explicitly modeling the selection into remunerated occupations entails an improvement with respect to limiting our sample to individuals at work only (see for example Andreoli and Fusco 2017). However, since this choice is non-standard we also conduct our analyses without a selection model, what we report in subsection 4.1.

Regarding circumstances, for the "standard" set, which we take as our baseline, we consider gender, immigrant status, parental education and parental occupation. These are circumstances that have been frequently used—see (Ferreira and Peragine 2016) for a list of circumstances employed in eight studies. We use the IOP estimates obtained with the baseline set of circumstances to compare them with those obtained with our proposed set, which we call *capital set*. The capital set differs from the baseline in the last two circumstances only, which are substituted by a measure of capital income. Hence, the capital set of circumstances includes gender, immigrant status and a measure of capital income.

As gender we consider binary gender, since it is the information available in the database.

Regarding immigrant status, we differentiate between individuals born in the country of residence and those born outside. In spite of being frequently used, immigrant status is not considered a circumstance by some researchers. For that reason we would like to justify this choice. Although emigration clearly falls within the control of individuals (except in extreme situations such as famines, wars, political prosecution or natural disasters), we believe it can be considered a circumstance on the basis that the country where we live largely determines our income (Milanovic 2015), and unless we emigrate, the country where we live is the country where we were born, what is outside our control. Moving to a country with a more favorable income distribution may return a gain, but at a cost in terms of effort that those already born in such country do not have to assume. Furthermore, natives do not face possible discrimination due to their national origin.

With respect to paternal education, we group individuals according to the highest educational level attained by any of their parents: pre-primary, primary or lower secondary education (levels 0, 1, and 2 of ISCED-97), upper secondary and post-secondary non-tertiary education (levels 3 and 4 of ISCED-97), and first and second stage of tertiary education (levels 5 and 6 of ISCED-97). This is, we distinguish three levels of parental education.

Finally, regarding parental occupation, we also create three groups of individuals according to the highest job category of their parents, which correspond to elementary occupations (group 9 of ISCO-88), plant and machine operators and assemblers, craft and related trades workers, skilled agricultural and fishery workers, service workers and shop and market sales workers, clerks (groups 8, 7, 6, 5 and 4 of ISCO-88), and technicians and associate professionals, profes-

[14] We used the variables "Number of months spent at full-time work" (PL070) and "Number of months spent at part-time work" (PL072) in waves prior to 2008. In waves from 2008 on these variables were updated in the survey design to "Number of months spent at full-time work as employee" (PL073), "Number of months spent at part-time work as employee" (PL074), "Number of months spent at full-time work as self-employed (including family worker)" (PL075), and "Number of months spent at part-time work as self-employed (including family worker)" (PL076).

sionals, and legislators, senior officials and managers (groups 3, 2 and 1 of ISCO-88).[15]

In the next subsection we detail the construction of the measures of capital income that we will include in the capital set, which have also three levels.

Therefore, with the baseline set of circumstances we have up to 36 types, product of 2 genders $\times$ 2 geographical origins $\times$ 3 levels of parental education $\times$ 3 levels of parental occupation. On the other hand, with the capital set we have up to 12 types, product of 2 genders $\times$ 2 geographical origins $\times$ 3 levels of capital income. However, the number of types falls shorter than 36 or 12 in some datasets, because some combinations of circumstances are infrequent and do not appear in the data. To prevent the possible bias produced by types with very few observations that may contain extreme values (see for example Brunori et al. 2019), we retain only those types with at least a minimum number of observations, which we set to 10.

Only 36 types, let aside 12, is clearly less than the *true* number of types. This is a problem when our objective is to measure IOP as truthfully as possible, but it is not a concern here. On the contrary, a small set of circumstances constitutes a tougher test for the capital income approach, provided that, generally, the bigger the number of circumstances, the smaller their relative role will be. Hence, differences between the two kinds of estimates should be easier to spot with small sets of circumstances.

With respect to the choice of circumstances, a non-subjective process of cross validation has been proposed by Brunori et al. (2019). We do not apply their cross validation approach here because we attempt to keep our methodology as standard as possible. However, note that their proposal concerns the selection of circumstances alone, and hence it is perfectly compatible with the capital income approach. In fact, in subsection 4.1 we manually modify the sets of circumstances, employing both bigger and smaller sets, and find that the accuracy of our approach holds, or even improves as we add more types to the analysis.

Finally, regarding the empirical methods to estimate IOP, as we have previously mentioned we apply the non-parametric ex-ante between-types inequality approach. In addition, we take mean values of each type in logarithms, a choice with an almost negligible effect on the results. As inequality measure, we employ the Theil 0, also known as mean log deviation. The Gini index is probably the most widely used inequality measure in the scientific literature, but in the IOP field the mean log deviation is generally preferred due to its unique property of path-independent decomposability (Foster and Shneyerov 2000). While we do not discuss the convenience of choosing one class of measures over another,[16] we acknowledge that this choice is not neutral and implies a normative choice (Atkinson 1970). In consequence, for comprehensiveness we have also conducted our analyses employing the Gini index, and we discuss those results in subsection 4.1.

[15] In the case of Sweden we are forced to exclude the circumstance parental occupation due to the very small number of respondents, what would drive the number of observations per type unacceptably low.

[16] For a discussion of the axiomatic properties one might wish to require see for example Ferreira and Gignoux (2011).

3.2. Construction of the capital income variables

In this subsection is detailed how we construct the measures of capital income to be included in the capital set of circumstances. Looking at the research presented in the introduction, using capital income to proxy socioeconomic origin might seem adequate. However, in the IOP setting an important concern arises: the amount of capital income can be, at least to some extent, decided by individuals. Only characteristics over which individuals cannot exert any control are included in the circumstances' set, and that is precisely what justifies the qualification of any inequality stemming from these factors as unfair.

Kotlikoff and Summers (1981) model wealth as:

$$W = L + T, \tag{1}$$

where W is the stock of wealth, and L and T are life-cycle and transfer components, respectively. Adapting their model to the IOP nomenclature and our case, we can think of capital income as determined by two elements:

$$K = M + D, \tag{2}$$

where K is capital income, and M and D are *meritocratic* and *dynastic* components. The dynastic component is product of advantages acquired through birth such as bequests and access to good education. The meritocratic component comes from effort exerted during our lifetime.

The evidence reviewed in the introduction portraits the dynastic component as larger than the meritocratic, but even if we trust this literature we would be concerned by the influence of the latter if we were to introduce a simple measure of capital income in our circumstances' set. Hence, we would like to consider the dynastic component only. For this purpose we endeavor to isolate D from (2), which we will then include as a measure of dynastic capital income in our circumstances' set. However, for comparison purposes we will also use K, a simple measure of capital income containing both its meritocratic and dynastic components, to proxy family background. We proceed now to detail how these two measures of capital income are constructed.

The procedure to isolate the dynastic component of capital income consists of running an OLS regression of household per capita gross capital income[17] against a number of effort

[17]Gross household capital income is defined as "the income received less expenses occurring during the income reference period by the owner of a financial asset or a tangible non-produced asset (land) in return for providing funds to, or putting the tangible non-produced asset at the disposal of, another institutional unit". This is, income coming from rental of a property or land (variable HY040G) + interests, dividends and profits from capital investment in an unincorporated business (variable HY090G). Gross means that neither taxes nor social contributions have been deducted at source. This sum is then divided by the number of adults in the household. We use information of capital income at the household level because at personal level it is not widely available. In the data of France, Greece, Italy, Latvia, Spain and Portugal prior to 2006 the gross value of these variables is not available, so for all waves of these countries we use the net values (variables HY090N and HY040N).

variables—namely personal education, personal occupation, and a dummy on mating—and a variable on the position in the life cycle—namely age. Then, we take the residuals of this regression, which can be seen as the value of capital income once its meritocratic component has been removed, and use them as input to construct a variable to be used as proxy of family background.

This procedure to "remove" the meritocratic component follows the logic behind Ferreira and Gignoux (2011)'s parametric approach to measure IOP, which "removes" the effect of effort on a given outcome by means of an OLS regression. Of course, we acknowledge that this procedure to isolate the dynastic component of capital income is far from ideal, but we believe it entails a step in the right direction in light of the accuracy and robustness tests performed in section 4.

We will now briefly discuss the variables of effort considered. We include personal education in the regression because it is a popular effort variable in empirical studies (see for example Almås et al. 2011). Yet, it is not free of controversy. On the one hand, since primary and secondary school take place before the age of consent, some believe that performance at this stage of life cannot be deemed responsibility of individuals. Success at tertiary schooling, which takes place after the age of consent has been reached, suffers nonetheless from hysteresis—so it bears a problem too. However, on the other hand, if one does not think that everything before the age of consent should be considered a circumstance, or that hysteresis leaves some room for personal responsibility, it is clear that own effort influences educational attainment. In sum, it is possible that personal education is a bad variable of effort, which in spite of that has been used frequently as such—the reason is probably the lack of many alternatives.

Personal occupation is commonly employed as effort variable too. Undoubtedly, personal effort plays a role in determining our job. However, past opportunities to receive high-quality education and network effects play a role too. Therefore, personal occupation is not a perfect variable of effort either, but it is however used with less caution than personal education.

Marital status is not frequently employed as effort variable, although this is not the first time (Ramos and Van de gaer 2020). Nevertheless, we include it here not only for it can be understood as such, but because we want to use it in relation to *household* capital income. Consider the situation in which a person with no capital income mates with someone who receives large amounts of it. In such case we would not be able to distinguish who is the owner of the capital, since we can only look at household capital income. By adding a dummy on mating we are able to account for this possibility.[18]

We include age too, despite the fact that it is exogenous, because the position in the life-cycle may influence the process of wealth accumulation. The use of age to account for life cycle effects is common at least since Modigliani (1966).

Personal education and occupation are defined in exactly the same way as the variables parental education and occupation (coded in three levels following ISCED-97 and ISCO-88

[18]For more on the importance of accounting for spouses see Peichl and Ungerer 2016.

classifications, respectively). Mating is defined as couples living in the same household, either with legal or informal bindings. Age is considered at the end of the reference period.

The OLS regression is as follows:

$$pckinc_i = \beta_0 + \beta_1 education_i + \beta_2 occupation_i + \beta_3 couple_i + \beta_4 age_i + \beta_5 age_i^2 + \varepsilon_i \qquad (3)$$

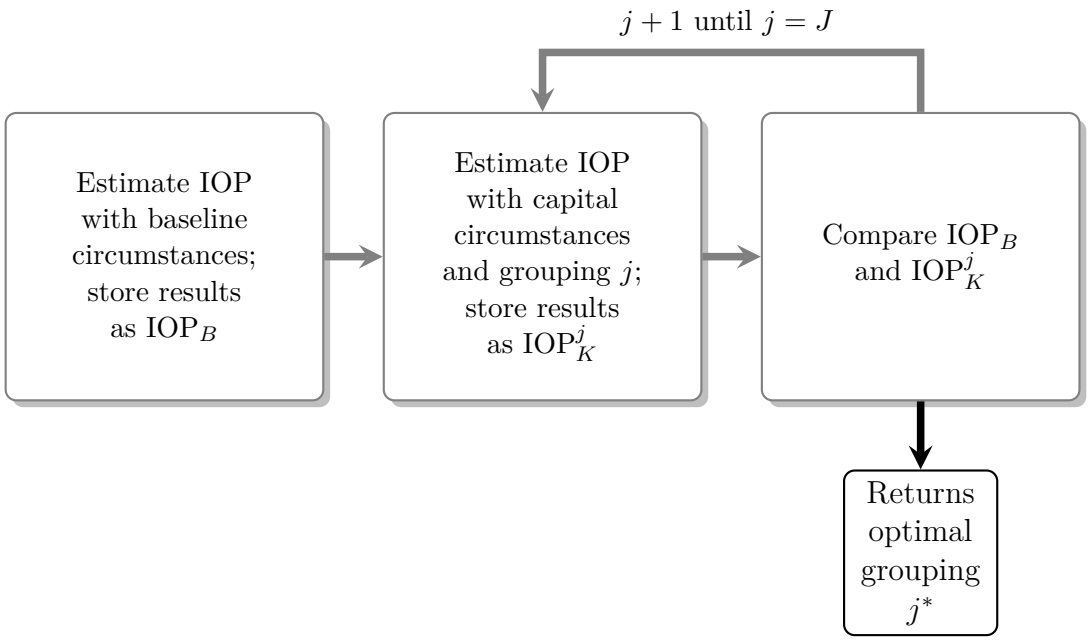
where *pckinc* is the amount of household per capita gross capital income, *education* is the highest educational level attained, *occupation* is the occupational status, *couple* is a dummy on mating, and *age* is self-explanatory.

Now that we have obtained the residuals ε from (3), which can be seen as the dynastic component of capital income, we would like to use them to proxy family background. However, in order to include them in our set of circumstances we must first convert this continuous variable into a discrete one. Generally, in empirical applications of IOP only discrete variables can be included in the set of circumstances. The reason for this is that a continuous variable would dramatically increase the number of types, leading to very few observations, if any, in each type. In consequence we are forced to group individuals according to ε from (3) (this applies also to K from (2), the simple measure of capital income containing both its dynastic and meritocratic components, which we will employ as well for comparison purposes). The grouping could be done in many ways—for instance, purely arbitrary choices can be made, such as splitting the population into quartiles, quintiles or deciles.

However, we believe that the best solution is to simply test *all* possibilities. To that end we have written an algorithm that finds the optimal grouping (optimal according to an accuracy test) by dividing the population into percentiles and testing all possible combinations of groups, up to 100 groups. What this means is the following. The algorithm starts by estimating IOP using the baseline set of circumstances, in which all variables are already discrete. It then stores the results, which we call IOP_B. Next, it makes two groups of individuals according to the residuals ε from (3) (or the variable K from (2)), the first group composed by those in the first percentile, and the second formed by individuals in the top 99 percentiles. Let us call this grouping $j = 1$. It then estimates IOP with a set of circumstances that includes a capital income measure discretized according to grouping $j = 1$, and stores the results. Let us call this results $\text{IOP}_K^{j=1}$. The algorithm finishes this iteration by comparing IOP_B to $\text{IOP}_K^{j=1}$ and assessing their similarity. It repeats this process several times, testing grouping $j + 1$ until $j = J$, and exits by returning the optimal grouping j^* that produces the most similar "capital" estimates IOP_K^{j*} to their baseline IOP_B. The functioning of the algorithm is represented in fig. 1.

However, due to computational capacity restrictions we cannot divide the sample into pieces as small as percentiles nor can we test combinations of up to 100 groups. The number of permutations that amounts to is on the order of billions, and such a program would take a reasonably powerful computer years to complete. Hence, we are forced to limit the analytic

Figure 1: How the grouping algorithm works



capacity of our algorithm. We divide the population into ventiles and test combinations of up to 4 groups only, what implies 1159 permutations. Bear in mind that since we are interested in standard errors we must employ the bootstrap, what means that with for instance 1000 replications the algorithm will be estimating IOP for the whole sample of countries over a million times, what is already computationally challenging.

Nevertheless, it is remarkable how effective the algorithm is, even a capped version of it. In section 4 we show the satisfactory results of the accuracy test with the grouping determined as optimal by the algorithm, and in section 4.1 we show the results using arbitrary groupings.

The rule used by the algorithm to assess the similarity between IOP_B and IOP_K^j consists of an analysis of moments, regression coefficients and correlations of the IOP estimates' distributions at the country level. Specifically, the algorithm minimizes the sum of a) the deviation from 1 of the ratio of the average value of the estimates IOP_B to the average value of the estimates IOP_K^j, b) the deviation from 1 of the ratio of the average standard error of IOP_B to the average standard error of IOP_K^j, c) the deviation from 1 of the regression coefficient of the IOP_B against IOP_K^j, d) the deviation from 1 of the pairwise correlation coefficient between IOP_B and IOP_K^j, and lastly e) the deviation from 1 of the Spearman rank correlation coefficient between IOP_B and IOP_K^j.

The optimal grouping j^* determined by the algorithm consists of the cumulative distribution function [65, 85, 95, 100] in the case of ε from (3), the dynastic measure of capital income, and [85, 90, 95, 100] in the case of K from (2), the simple measure containing both the dynastic and the meritocratic components. What these numbers mean is, for example in the former case, that the first group is composed by the bottom 65 percentiles, the second group by the following

20, the third are the percentiles 86 to 95, and the fourth group are the top 5 percentiles.

Summing up, in this subsection we have detailed the construction of two measures of capital income: one based on K from (2), which encompasses both the dynastic and meritocratic components of capital income, and another based on ε from (3), which represents the dynastic component only. In the next subsection we estimate IOP using these two measures to subsequently test the accuracy of the results by comparing them to their baseline.

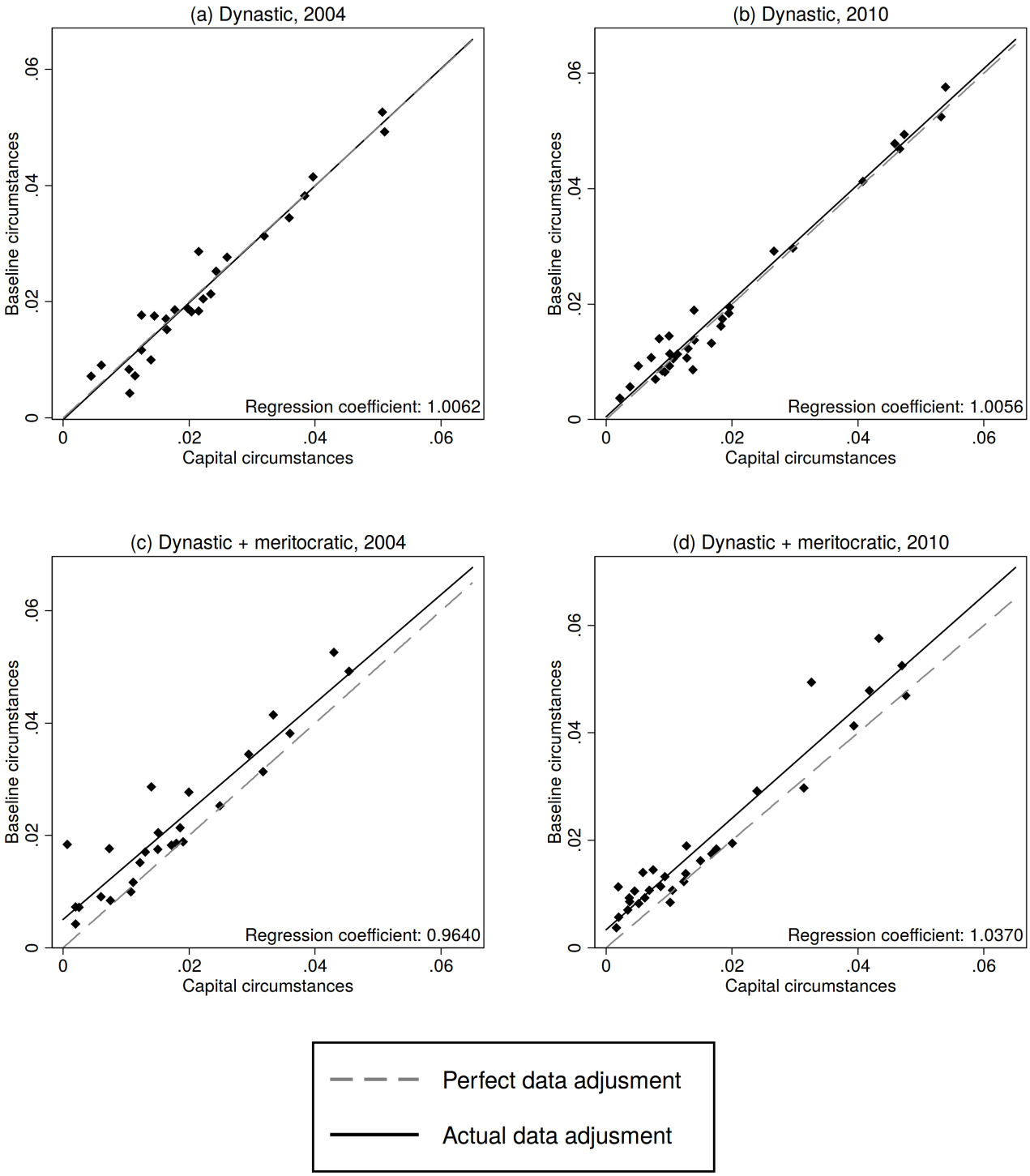
4. Accuracy test

In this section we compare IOP estimates obtained with our baseline set of circumstances, which includes parental education and occupation, to the estimates obtained with the capital set we propose. We will compare these estimates in a number of ways, in order to assess the reliability of the capital income approach. Following Teyssier (2017), the reliability test will consist of a visual inspection of the fit of the capital IOP estimates against their baseline, a comparison of the IOP estimates distributions' moments, and a correlation analysis. We report results of the accuracy test with each one of the two measures of capital income that we have constructed: the dynastic component and the simple measure containing both the dynastic and the meritocratic elements.

Estimates of absolute IOP are plotted in fig. 2. On the vertical axes is displayed IOP measured using our baseline set of circumstances, and on the horizontal ones are shown the estimates obtained with the capital circumstances. Panels (a) and (b) show the results of employing the dynastic component of capital income, and panels (c) and (d) show results obtained with the simple measure of both dynastic and meritocratic capital income. Parallelly, panels (a) and (c) present results in 2004's wave, which includes 26 countries, and panels (b) and (d) display the estimates of 2010, including 31 countries. Each black diamond represents a country in the sample, the solid black lines are linear fits of the capital estimates against their baseline, and the dashed gray 45º lines represent the hypothetical ideal data adjustment. In panels (a) and (b) we can see that the linear fits of the IOP estimates obtained with the dynastic measure overlap the ideal 45º line almost completely, with beta coefficients very close to 1 in both years. This suggests that with our method we can obtain IOP estimates that are, on average, very similar to those obtained with a standard methodology, but suffering from a substantially less stringent data limitation. In panels (c) and (d) we observe that the adjustment of the IOP estimates obtained with the simple capital income measure is not as good, although still fairly close to the 45º line. Indeed, the regression coefficients are also close to 1, albeit slightly further from it. We see this as evidence in favor of the procedure to isolate the dynastic component that we followed in subsection 3.2; although at the same time, these results suggest that using a simple measure of capital income containing both its dynastic and meritocratic components may be accurate enough to constitute an informative approximation.

In addition to the visual analysis with fig. 2, we test the accuracy of the capital income approach by comparing moments of the distributions of the IOP estimates at the country level,

Figure 2: Comparison of absolute inequality of opportunity estimates obtained with baseline and capital circumstances' sets, 2004 and 2010.



Note: 'Baseline circumstances' refers to the set including parental education and occupation; 'capital circumstances' to the set that includes either one of our two measures of capital income. 'Dynastic' refers to the capital set of circumstances including the dynastic capital income measure, 'dynastic + meritocratic' to the capital set containing the measure of both dynastic and meritocratic capital income. EU-SILC database.

Table 3: Comparison of baseline and capital IOP estimates.

	Dynastic		Dynastic + meritocratic	
	2004	2010	2004	2010
Average baseline IOP	0.02192	0.02024	0.02192	0.02024
Average capital IOP	0.02206	0.01965	0.01753	0.01630
Ratio of averages	0.99353	1.02988	1.25082	1.24129
Average baseline SE	0.00035	0.00035	0.00035	0.00035
Average capital SE	0.00035	0.00031	0.00024	0.00024
Ratio of average SEs	0.99437	1.11698	1.44070	1.47874
Pairwise correlation	0.97298	0.98738	0.93455	0.96390
Rank correlation	0.96786	0.90403	0.89333	0.91492

Note: 'Baseline' refers to IOP estimates obtained with a set of circumstances including parental education and occupation; 'capital' to estimates obtained with circumstances' sets including either one of our two measures of capital income. 'Dynastic' refers to the capital set of circumstances including the dynastic measure of capital income only; 'dynastic + meritocratic' to the capital set containing the simple measure of both dynastic and meritocratic capital income. Standard errors obtained via bootstrap stratified by region (1000 replications). EU-SILC database.

as well as assessing pairwise and rank correlations. The results of this comparison are shown in table 3. The moments compared are the average value and the standard error. Standard errors have been computed via bootstrapping stratified by region, following Andreoli and Fusco (2017) (see also Goedemé 2013). The second and third columns refer to the results using the dynastic component of capital income, in the years 2004 and 2010 respectively. The fourth and fifth columns show results obtained with the simple measure of capital income, which includes both its dynastic and meritocratic components, also in the two years studied. The distributions in 2004 have 26 observations, in 2010 they have 31. We will start by discussing the second and third columns. As we can see, the dynastic measure performs satisfactorily. Its average values are similar to those of the baseline, being less than 1% bigger and 3% smaller in 2004 and 2010, respectively. The average standard error is also less than 1% bigger in 2004, although it is a 12% smaller in 2010. Of course, there is no limit to what difference would be acceptable, but a discrepancy of the 12% on such a small standard error (a deviation of 0.0003 from the estimate 0.0197) is hardly a concern. The last two rows of the table refer to correlations between the baseline and capital IOP estimates. The pairwise correlations are over 0.97 in both years, what is remarkably good. This is specially important if we are interested in assessing the evolution of IOP over time. Lastly, the rank correlations are not as high, specially in 2010—but being both over .9, in any case they indicate that a country ranking high in the capital IOP estimates would be likely to rank high with standard estimates too. The rank correlations point at the fact that the capital income approach can generate accurate estimates *on average*, but that some deviations may appear in a few particular cases. Let us now look at the fourth and fifth columns. We can readily see that the simple measure of capital income does not perform as

good in almost all metrics considered. Again, we see this as support for the procedure followed above to isolate the dynastic component.

It is worth noting that the capital income approach appears to perform slightly worse in 2010's wave, when the Great Recession had already started. A possible explanation may be that the financial losses produced by the crisis could have distorted the predictive power of capital income over family background. Nevertheless, this distortion is sufficiently small as to disregard it as a source of concern.

In sum, the results obtained suggest that the capital income approach does perform reliably. The visual test, the moments comparison and the correlation analysis are all satisfactory. In the next subsection we show that these results hold when we vary a number of methodological choices.

4.1. Robustness

To ease the concern that the results of the reliability test might be a product of chance we perform an exhaustive robustness check. If the IOP estimates obtained with our two sets of circumstances are similar by casualty with a particular methodology, it would be unlikely that they remain similar after modifying a number of meaningful methodological features. Table 4 shows the same statistics presented in table 3, but referring to estimates obtained with the following methodological variations:

- Increasing the number of types, by adding "population density of the area of residence" to the sets of circumstances
- Decreasing the number of types, by removing "immigration status" from the sets of circumstances
- Reducing the sample size by excluding individuals who declare to be self-employed
- Reducing the sample size by keeping only individuals who are aged 45 to 59 years old
- Using a selection model into full-time employment
- Avoid using any selection model into employment
- Modifying the definition of capital income to include only property rent
- Using the Gini index as inequality measure, instead of the MLD
- Grouping individuals according to the capital income variables by following the cumulative distribution function of the variable parental education
- Grouping individuals according to the capital income variables by following the cumulative distribution function [30, 60, 90, 100]

- Grouping individuals according to the capital income variables by following the cumulative distribution function [50, 100]
- Lastly, not including a capital income variable at all in the capital circumstances' set

The second and third columns of table 4 display results obtained with the dynastic measure of capital income, while the fourth and fifth correspond to the results using the simple measure that contains both the dynastic and meritocratic components. In the following paragraphs we will only describe the results using the dynastic measure, since it has proven more useful—however, we report all results for comprehensiveness.

The first robustness check, labeled *Five circumstances*, consists of increasing the number of types in our analysis by adding "population density of the area of residence" to the circumstances' sets, distinguishing between rural and non-rural.[19] Whether living in a rural or an urban area can be considered a circumstance is controversial. We argue that living in rural areas may reflect the cost, in terms of effort, that moving to the city represents for individuals born in the countryside.[20] Nonetheless, even upon disagreement over considering population density of the area of residence a circumstance, adding it to the circumstances' sets fulfills the task at hand in any case, which is assessing the sensitivity of the accuracy test to an increase in the number of types. The results obtained seem, if anything, slightly better than those obtained with a smaller sets of circumstances. This goes in line with what we expected in subsection 3.1, namely that the capital income approach is likely to perform better as the dimension of the set of circumstances increases.

In the second robustness test we reduce the number of types by removing the circumstance "immigration status", and it is labeled in table 4 as *Three circumstances*. The metrics obtained do not change substantially, what is satisfactory.

The third test is named *Employees only* and consists of excluding from our sample all individuals who declare to be self-employed.[21] This robustness test responds to possible concerns over the reliability of reported income by self-employed individuals (Kleven, Knudsen, et al.

[19]The EU-SILC database includes a three-level variable on the population density with values "densely populated area", "intermediate area" and "thinly-populated area". We take thinly-populated areas as rural, which are characterized by being a contiguous group of local areas, not belonging to a densely or intermediate-populated area, each of which has a density equal or inferior to 100 inhabitants per square kilometer, with a total population for the group of less than 50,000 inhabitants, and not adjacent to a densely or intermediate-populated area. The definition of area follows the Labour Force Survey recommendations.

[20]Living in a rural or urban area can be chosen by individuals. Nevertheless, individuals tend to develop ties to the place where they were born, in the form of emotional attachment or social networks, meaning that the necessary effort to move to an urban area—where chances of economic success are higher—is positive for those born in the countryside. On the contrary, for those born in the city the required effort is zero. Also, those already born in the city may enjoy more time to develop their social capital in the area. Note that instead of a variable on where individuals *currently* live, ideally we would include a circumstance on whether individuals were *born* in the city or the country side, what is clearly outside personal choice; however, such variable is not available in the EU-SILC.

[21]To do this we first drop individuals who declare their "status in employment" to be 'self-employed' (variable PL040), and then we apply a selection model into employment.

2011). We observe again that the results of the accuracy test do not change meaningfully with respect to those shown in table 3.

In the following check we reduce the sample size by keeping only individuals who are aged 45 to 59 years old, to assess the sensibility of the results to life-cycle effects. We name this test *Older cohorts*, and the results show some sensibility to it in the year 2004, specially the standard error. However, in the year 2010 the accuracy holds. It is interesting to note that if bequests were the main driver of the predictive capacity that capital income has of family background, with this test we should see and increase in accuracy. However, this is not the case, pointing at the importance of other mechanisms.

For the fifth test, labeled *Full-time workers only*, we use a selection model into full-time employment during at least 7 months in the reference period. This may be preferred by some researchers since accepting that, once we have accounted for circumstances, all differences in incomes between people who are employed full-time respond to IOP may be easier than accepting the same thing among people who work both full- and part-time. On the other hand, part of the effect of circumstances works through labor market participation, and hence modeling full-time employment might "leave out" some IOP, especially that related to gender (we have discussed this trade-off in subsection 3.1). In any case, the level of IOP estimates are very sensible to this sample variations, since in our analysis we consider wages. In fact, observe that the average level of IOP has halved. Table 4 shows that the capital income approach performs slightly worse with this methodological variation. Yet, with average moments reasonably similar and correlations around .9 or higher we argue that our method responds with satisfactory robustness to such a substantial change in the sample composition.

The sixth variation consists of not using any selection model at all. The way in which we proceed consists simply of using a sample composed only by individuals who declared to have been at work at least 7 months in the reference period, either full- or part-time, employed or self-employed. Results following this methodology suffer, naturally, from a self-selection bias. The average level of IOP increases, and the accuracy of the capital income approach diminishes slightly.

For the seventh test we defined capital income in a different, more restrictive way. In table 4 this check is referred to as *Property rent only*. Gross household capital income is now defined as gross income coming from rental of a property or land (variable HY040G) (we therefore avoid including interests, dividends and profits from capital investment in an unincorporated business—variable HY090G). Checking results using this even more limited definition of capital income can be fruitful since we can expect the reliability of variable HY090 to be much lower than that of HY040. One reason for this is that it is much easier for individuals to keep track of rental income (which generally comes from a small number of sources) than it is to keep it of interests, dividends and profits (that usually requires to follow closely one's banks accounts and investments). This test suggests the capital income approach is satisfactorily robust to an alternative definition of capital income.

Table 4: Robustness analysis.

	Dynastic		Dynastic + meritocratic	
	2004	2010	2004	2010
Five circumstances				
Average baseline IOP	0.02488	0.02187	0.02488	0.02187
Average capital IOP	0.02516	0.02167	0.02080	0.01870
Ratio of averages	0.98878	1.00908	1.19602	1.16936
Average baseline SE	0.00046	0.00040	0.00046	0.00040
Average capital SE	0.00044	0.00038	0.00035	0.00035
Ratio of average SEs	1.04621	1.04953	1.31559	1.13308
Pairwise correlation	0.97211	0.99009	0.94984	0.96256
Rank correlation	0.94957	0.94433	0.88000	0.91527
Three circumstances				
Average baseline IOP	0.02025	0.01788	0.02025	0.01788
Average capital IOP	0.02101	0.01789	0.01644	0.01464
Ratio of averages	0.96353	0.99942	1.23160	1.22166
Average baseline SE	0.00029	0.00024	0.00029	0.00024
Average capital SE	0.00030	0.00024	0.00020	0.00019
Ratio of average SEs	0.95938	1.00517	1.40930	1.31030
Pairwise correlation	0.97190	0.97777	0.92707	0.95991
Rank correlation	0.96239	0.87702	0.86051	0.83790
Employees only				
Average baseline IOP	0.02391	0.02250	0.02391	0.02250
Average capital IOP	0.02344	0.02216	0.01918	0.01865
Ratio of averages	1.02041	1.01510	1.24656	1.20647
Average baseline SE	0.00042	0.00041	0.00042	0.00041
Average capital SE	0.00039	0.00038	0.00031	0.00033
Ratio of average SEs	1.07014	1.05880	1.37012	1.24083
Pairwise correlation	0.93948	0.97976	0.92130	0.96011
Rank correlation	0.91385	0.87258	0.90838	0.88669
Older cohorts				
Average baseline IOP	0.02551	0.02424	0.02551	0.02424
Average capital IOP	0.02281	0.02285	0.01937	0.01881
Ratio of averages	1.11796	1.06079	1.31641	1.28864
Average baseline SE	0.00067	0.00067	0.00067	0.00067
Average capital SE	0.00048	0.00059	0.00035	0.00044
Ratio of average SEs	1.39678	1.13377	1.90446	1.52011
Pairwise correlation	0.89762	0.98340	0.90608	0.96523
Rank correlation	0.90222	0.93831	0.87145	0.91532

Note: 'Baseline' refers to IOP estimates obtained with a set of circumstances including parental education and occupation; 'capital' to estimates obtained with circumstances' sets including either one of our two measures of capital income. 'Dynastic' refers to the capital set of circumstances including the dynastic measure of capital income only; 'dynastic + meritocratic' to the capital set containing the simple measure of both dynastic and meritocratic capital income. Standard errors obtained via bootstrap stratified by region (1000 replications). EU-SILC database.

Continuation of Table 4: Robustness analysis.

	Dynastic		Dynastic + meritocratic	
	2004	2010	2004	2010
Full-time workers only				
Average baseline IOP	0.01230	0.01149	0.01230	0.01149
Average capital IOP	0.01179	0.01067	0.00812	0.00788
Ratio of averages	1.04324	1.07701	1.51506	1.45773
Average baseline SE	0.00026	0.00026	0.00026	0.00026
Average capital SE	0.00022	0.00023	0.00016	0.00018
Ratio of average SEs	1.19686	1.11124	1.62259	1.47304
Pairwise correlation	0.97136	0.97863	0.93443	0.95802
Rank correlation	0.88444	0.88710	0.70872	0.72661
No selection model				
Average baseline IOP	0.03050	0.02766	0.03050	0.02766
Average capital IOP	0.02883	0.02507	0.02280	0.02099
Ratio of averages	1.05795	1.10316	1.33780	1.31764
Average baseline SE	0.00058	0.00058	0.00058	0.00058
Average capital SE	0.00055	0.00051	0.00038	0.00040
Ratio of average SEs	1.07200	1.13047	1.53479	1.43420
Pairwise correlation	0.93681	0.96917	0.92014	0.94704
Rank correlation	0.86188	0.87782	0.83453	0.85847
Property rent only				
Average baseline IOP	0.02200	0.02030	0.02200	0.02030
Average capital IOP	0.02357	0.02276	0.01588	0.01458
Ratio of averages	0.93335	0.89174	1.38558	1.39204
Average baseline SE	0.00036	0.00035	0.00036	0.00035
Average capital SE	0.00037	0.00037	0.00014	0.00015
Ratio of average SEs	0.96817	0.92501	2.57034	2.25593
Pairwise correlation	0.96076	0.97364	0.92874	0.96904
Rank correlation	0.94803	0.89516	0.85709	0.92137
Gini				
Average baseline IOP	0.11039	0.10311	0.11039	0.10311
Average capital IOP	0.10805	0.09889	0.09149	0.08649
Ratio of averages	1.02169	1.04271	1.20661	1.19212
Average baseline SE	0.00095	0.00095	0.00095	0.00095
Average capital SE	0.00094	0.00088	0.00075	0.00078
Ratio of average SEs	1.01140	1.07479	1.26777	1.21088
Pairwise correlation	0.95186	0.98237	0.88743	0.95675
Rank correlation	0.95556	0.93952	0.89675	0.92016

Note: 'Baseline' refers to IOP estimates obtained with a set of circumstances including parental education and occupation; 'capital' to estimates obtained with circumstances' sets including either one of our two measures of capital income. 'Dynastic' refers to the capital set of circumstances including the dynastic measure of capital income only; 'dynastic + meritocratic' to the capital set containing the simple measure of both dynastic and meritocratic capital income. Standard errors obtained via bootstrap stratified by region (1000 replications). EU-SILC database.

Continuation of Table 4: Robustness analysis.

	Dynastic		Dynastic + meritocratic	
	2004	2010	2004	2010
Parental education cdf				
Average baseline IOP	0.02200	0.02030	0.02200	0.02030
Average capital IOP	0.02239	0.02083	0.01757	0.01688
Ratio of averages	0.98261	0.97437	1.25207	1.20215
Average baseline SE	0.00036	0.00035	0.00036	0.00035
Average capital SE	0.00033	0.00033	0.00023	0.00025
Ratio of average SEs	1.07092	1.04288	1.52590	1.39615
Pairwise correlation	0.89924	0.96963	0.91514	0.96089
Rank correlation	0.81744	0.87621	0.87145	0.91653
Four arbitrary groups				
Average baseline IOP	0.02200	0.02030	0.02200	0.02030
Average capital IOP	0.02912	0.02630	0.01778	0.01737
Ratio of averages	0.75544	0.77181	1.23713	1.16823
Average baseline SE	0.00036	0.00035	0.00036	0.00035
Average capital SE	0.00042	0.00042	0.00025	0.00026
Ratio of average SEs	0.84071	0.81946	1.45362	1.32659
Pairwise correlation	0.91733	0.94975	0.91211	0.95648
Rank correlation	0.86803	0.83145	0.86393	0.90161
Two arbitrary groups				
Average baseline IOP	0.02200	0.02030	0.02200	0.02030
Average capital IOP	0.02239	0.02083	0.01757	0.01688
Ratio of averages	0.98261	0.97437	1.25207	1.20215
Average baseline SE	0.00036	0.00035	0.00036	0.00035
Average capital SE	0.00033	0.00033	0.00023	0.00025
Ratio of average SEs	1.07092	1.04288	1.52590	1.39615
Pairwise correlation	0.89924	0.96963	0.91514	0.96089
Rank correlation	0.81744	0.87621	0.87145	0.91653
No capital income variable				
Average baseline IOP	0.02200	0.02030	0.02200	0.02030
Average capital IOP	0.01533	0.01411	0.01533	0.01411
Ratio of averages	1.43519	1.43884	1.43519	1.43884
Average baseline SE	0.00036	0.00035	0.00036	0.00035
Average capital SE	0.00011	0.00013	0.00011	0.00013
Ratio of average SEs	3.30847	2.60754	3.30847	2.60754
Pairwise correlation	0.92838	0.96299	0.92838	0.96299
Rank correlation	0.87077	0.92258	0.87077	0.92258

Note: 'Baseline' refers to IOP estimates obtained with a set of circumstances including parental education and occupation; 'capital' to estimates obtained with circumstances' sets including either one of our two measures of capital income. 'Dynastic' refers to the capital set of circumstances including the dynastic measure of capital income only; 'dynastic + meritocratic' to the capital set containing the simple measure of both dynastic and meritocratic capital income. Standard errors obtained via bootstrap stratified by region (1000 replications). EU-SILC database.

With the eighth check we see that using the Gini index as inequality measure returns results as good as when we use the MLD. The Gini index is not so popular in the IOP field as the MLD is, but we include it here because it is employed sometimes.

The following three tests performed are related to the way in which we group individuals when building our measures of capital income. Instead of using the algorithm described in subsection 3.2 to decide the groupings, we make arbitrary choices. The different possibilities shown are when our capital income variables' cumulative distribution functions a) mimic that of the variable parental education (which is different in each country and year), b) follow the pattern $[30, 60, 90, 100]$, and c) the pattern $[50, 100]$. It is reassuring to see that the accuracy of the capital income approach is rather robust to the way in which we group individuals, specially in the case of a) and c).

The last test of the robustness analysis consists of simply not including any measure of capital income in our capital set of circumstances. This is, to omit accounting for socioeconomic origin in any way. We do this by comparing the results of our baseline set composed of gender, immigrant status and parental education and occupation to a set that includes only gender and immigrant status. We perform this test because such strategy is an alternative to the capital income approach, followed for instance by Marrero, Rodríguez, and Weide (2016). Interestingly, the correlations do not change much, what can be interpreted as suggesting that the effect of family background on IOP remained, on average, constant between 2004 and 2010. While this is reassuring, in order to apply this approach in other periods we would have to assume that the role of socioeconomic background has still remained constant, what is probably stronger than assuming that the validity of capital income as proxy of socioeconomic background holds across time. On the other hand, the average IOP estimates and their standard errors are much lower than the baseline. Hence, this test shows that the capital income approach entails an improvement over another method previously employed for overcoming the data limitation imposed by the scarcity of information on family background.

In conclusion, after trying a large number of substantial methodological changes and mostly observed no major differences in the accuracy results, we conclude that the robustness analysis performed provides evidence that the results of our reliability analysis are not spurious, and hence further supporting the capital income approach.

5. Measuring IOP for the full length of the EU-SILC database

Once we have validated, in the previous section, the capital income approach, we now proceed to take advantage of it and obtain IOP estimates for the full length of the EU-SILC database. We are able to obtain a remarkable number of new IOP estimates. Figures 3 and 4 show, to the best of our knowledge, the most comprehensive estimation of lower-bound IOP in Europe produced so far. Figure 3 shows absolute IOP, fig. 4 displays relative estimates. For both figures we have used the dynastic measure of capital income, since it appears to perform better than the simple measure of capital income. Confidence intervals are shown as gray areas. These

figures include as well IOP estimates obtained using the baseline circumstances, with their confidence intervals shown in red brackets, for the only periods in which they can be estimated, 2004 and 2010. This superposition allows to rapidly verify to what extent the baseline and capital estimates are similar, and it also illustrates how large is the number of new data points available thanks to the capital income approach.

The main conclusion we can draw is that in many European countries the level of absolute IOP has not remained stable during the last two decades. Please bear in mind that since we use axes with a common scale it may be difficult to appreciate the extent of the changes occurred in some countries. To asses this in more detail consult tables 5 and 6.

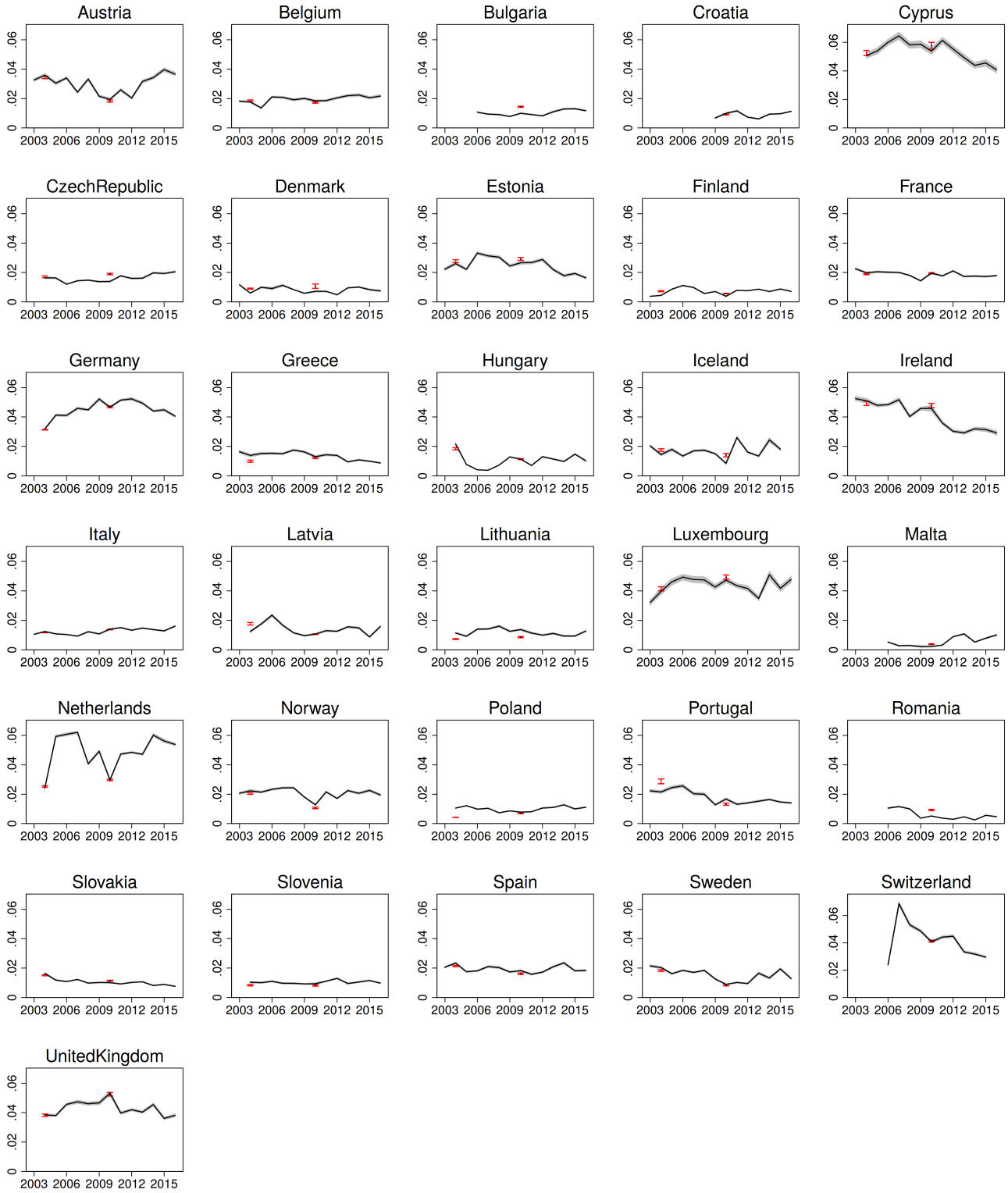
Since the Great Recession the absolute value of IOP has increased substantially in Austria and the Netherlands, and decreased in Cyprus, Estonia, Germany, Ireland, Portugal, Switzerland and the United Kingdom. Looking at relative IOP we observe a similar picture, although we could add Belgium and Italy to the list of countries with a rising level, and Greece and Spain to the ones with diminishing IOP.

This is, we believe, the first time that evidence on this matter can be offered for such a big number of European economies. However, we will not perform an exhaustive analysis of the evolution of IOP in Europe here, since this article is devoted to test the method proposed and to show the possibilities opened up by it—which are not restricted to the use of the EU-SILC database. Possible applications include obtaining historical estimates of IOP, studying the role of institutions, or analyzing the relationship of IOP with economic growth and political outcomes.

6. Concluding remarks

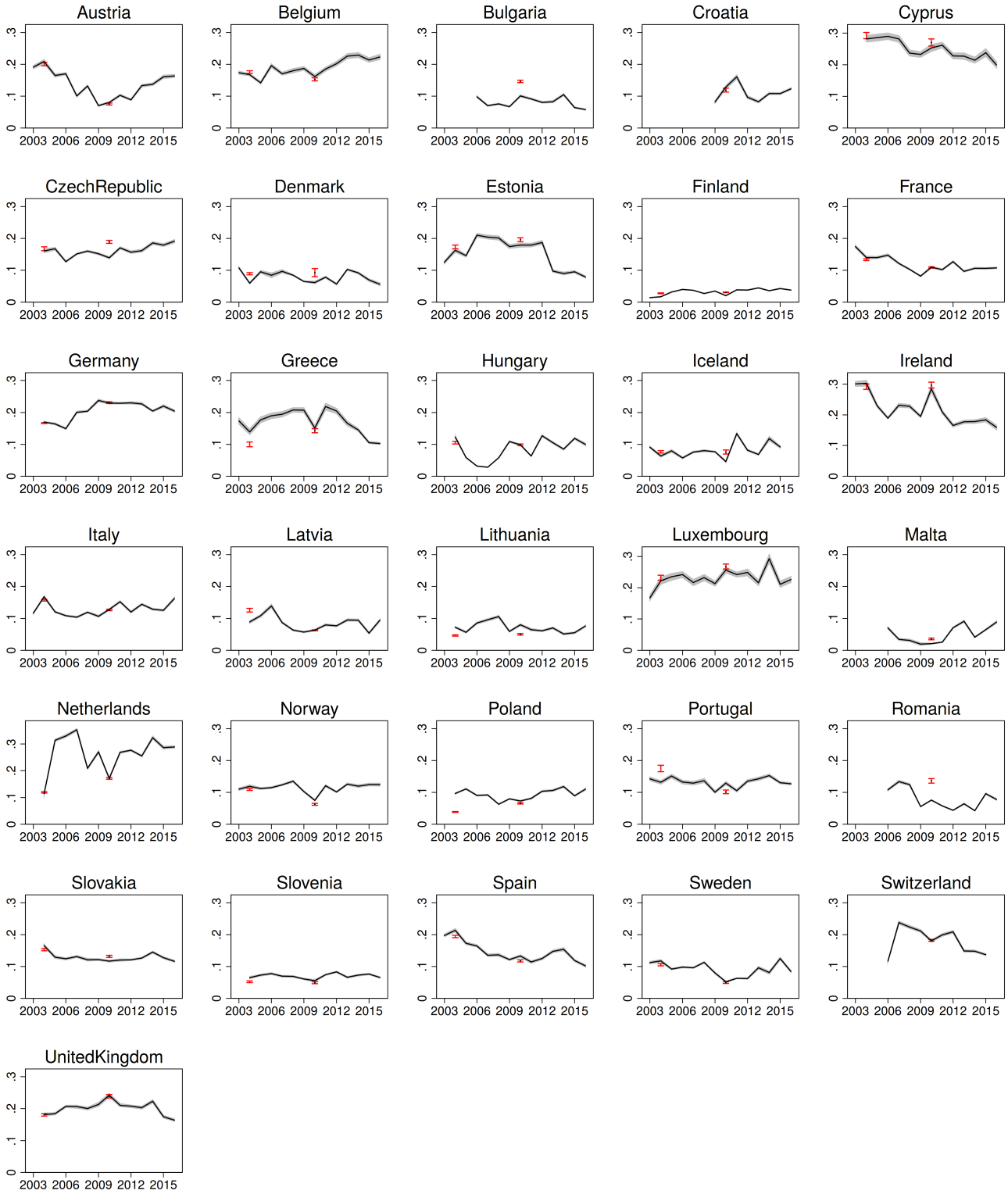
In this article we have proposed a new approach to measure IOP that does not rely on the availability of data on parental features. After testing this method by comparing its results to those of a standard approach, we conclude that it is sufficiently reliable to be used when we lack information on parental background. The results of the method proposed are not equal in all countries and periods to their baseline, what impels us to be cautious—yet, we believe they are similar enough to constitute an informative approximation. Furthermore, when taken on average, the IOP estimates returned by the capital income approach are nearly identical to those of their baseline. The visual test, the moments comparison and the correlation analysis provide strong support for the capital income approach, and in response to the concern that these metrics may be spurious, we have conducted an extensive robustness test that makes this possibility unlikely. We believe that, in light of the tests performed, the capital income approach can help foster the empirical measurement of IOP.

Figure 3: Evolution of absolute lower-bound IOP in Europe.



Note: Confidence intervals shown as gray areas for the IOP estimates obtained with the dynastic measure of capital income, and as red brackets for those obtained with the baseline set of circumstances. All have been calculated with standard errors computed via bootstrapping stratified by region (1000 replications). EU-SILC database.

Figure 4: Evolution of relative lower-bound IOP in Europe.



Note: Confidence intervals shown as gray areas for the IOP estimates obtained with the dynastic measure of capital income, and as red brackets for those obtained with the baseline set of circumstances. All have been calculated with standard errors computed via bootstrapping stratified by region (1000 replications). EU-SILC database.

Table 5: Absolute lower-bound IOP in Europe.

	2003	2004*	2004	2005	2006	2007	2008	2009	2010*	2010	2011	2012	2013	2014	2015	2016
Austria	0.0327	0.0345	0.0359	0.0304	0.0341	0.0244	0.0332	0.0216	0.0184	0.0195	0.0259	0.0203	0.0317	0.0343	0.0397	0.0367
Belgium	0.0183	0.0186	0.0177	0.0136	0.0211	0.0208	0.0192	0.0201	0.0174	0.0185	0.0186	0.0205	0.0220	0.0225	0.0206	0.0218
Bulgaria					0.0107	0.0094	0.0091	0.0079	0.0145	0.0100	0.0092	0.0083	0.0110	0.0130	0.0131	0.0118
Croatia								0.0068	0.0093	0.0101	0.0117	0.0074	0.0062	0.0095	0.0097	0.0114
Cyprus		0.0526	0.0507	0.0540	0.0600	0.0646	0.0582	0.0587	0.0576	0.0539	0.0613	0.0553	0.0493	0.0439	0.0455	0.0407
Czech Rep.		0.0170	0.0164	0.0163	0.0121	0.0144	0.0148	0.0138	0.0190	0.0140	0.0177	0.0160	0.0162	0.0197	0.0193	0.0205
Denmark	0.0116	0.0091	0.0060	0.0099	0.0091	0.0113	0.0083	0.0059	0.0107	0.0072	0.0071	0.0049	0.0096	0.0101	0.0084	0.0076
Estonia	0.0222	0.0277	0.0260	0.0222	0.0332	0.0313	0.0304	0.0245	0.0292	0.0267	0.0267	0.0289	0.0220	0.0178	0.0194	0.0163
Finland	0.0038	0.0072	0.0045	0.0087	0.0112	0.0098	0.0057	0.0071	0.0057	0.0038	0.0079	0.0076	0.0086	0.0070	0.0087	0.0072
France	0.0225	0.0189	0.0198	0.0205	0.0202	0.0200	0.0179	0.0143	0.0195	0.0196	0.0177	0.0210	0.0173	0.0175	0.0173	0.0179
Germany		0.0313	0.0319	0.0412	0.0410	0.0459	0.0448	0.0522	0.0469	0.0467	0.0515	0.0523	0.0494	0.0441	0.0448	0.0406
Greece	0.0164	0.0100	0.0139	0.0152	0.0153	0.0151	0.0175	0.0163	0.0123	0.0130	0.0144	0.0138	0.0096	0.0109	0.0099	0.0088
Hungary		0.0184	0.0215	0.0078	0.0041	0.0037	0.0073	0.0128	0.0113	0.0113	0.0070	0.0130	0.0114	0.0098	0.0147	0.0103
Iceland	0.0203	0.0175	0.0145	0.0179	0.0135	0.0170	0.0174	0.0150	0.0140	0.0084	0.0261	0.0161	0.0135	0.0244	0.0181	
Ireland	0.0526	0.0492	0.0510	0.0479	0.0484	0.0517	0.0404	0.0457	0.0478	0.0458	0.0359	0.0303	0.0292	0.0321	0.0314	0.0293
Italy	0.0105	0.0117	0.0124	0.0108	0.0103	0.0093	0.0122	0.0108	0.0138	0.0140	0.0150	0.0132	0.0147	0.0137	0.0128	0.0160
Latvia		0.0177	0.0125	0.0175	0.0234	0.0166	0.0114	0.0095	0.0106	0.0107	0.0129	0.0126	0.0156	0.0148	0.0087	0.0157
Lithuania		0.0073	0.0114	0.0092	0.0140	0.0141	0.0160	0.0125	0.0086	0.0138	0.0114	0.0099	0.0111	0.0093	0.0094	0.0127
Luxembourg	0.0321	0.0415	0.0397	0.0462	0.0493	0.0478	0.0475	0.0427	0.0494	0.0473	0.0435	0.0417	0.0349	0.0510	0.0417	0.0477
Malta					0.0052	0.0027	0.0029	0.0022	0.0037	0.0022	0.0032	0.0088	0.0108	0.0052	0.0079	0.0101
Netherlands		0.0253	0.0243	0.0593	0.0607	0.0621	0.0407	0.0491	0.0297	0.0297	0.0473	0.0485	0.0472	0.0602	0.0563	0.0539
Norway	0.0207	0.0205	0.0223	0.0215	0.0233	0.0243	0.0243	0.0180	0.0107	0.0128	0.0216	0.0171	0.0225	0.0206	0.0226	0.0195
Poland		0.0042	0.0106	0.0122	0.0098	0.0104	0.0074	0.0087	0.0070	0.0078	0.0081	0.0106	0.0111	0.0127	0.0100	0.0112
Portugal	0.0223	0.0286	0.0215	0.0246	0.0257	0.0204	0.0200	0.0128	0.0132	0.0168	0.0132	0.0141	0.0153	0.0165	0.0148	0.0141
Romania					0.0106	0.0116	0.0101	0.0038	0.0093	0.0052	0.0037	0.0029	0.0047	0.0025	0.0057	0.0047
Slovakia		0.0152	0.0164	0.0119	0.0109	0.0122	0.0098	0.0102	0.0114	0.0101	0.0093	0.0103	0.0107	0.0081	0.0089	0.0077
Slovenia		0.0084	0.0105	0.0101	0.0110	0.0097	0.0096	0.0093	0.0083	0.0093	0.0111	0.0130	0.0096	0.0106	0.0115	0.0098
Spain	0.0207	0.0213	0.0235	0.0175	0.0182	0.0210	0.0204	0.0174	0.0162	0.0183	0.0158	0.0173	0.0209	0.0236	0.0182	0.0185
Sweden	0.0215	0.0183	0.0204	0.0162	0.0184	0.0171	0.0184	0.0127	0.0084	0.0089	0.0103	0.0095	0.0165	0.0133	0.0195	0.0130
Switzerland					0.0239	0.0687	0.0533	0.0486	0.0413	0.0408	0.0442	0.0449	0.0334	0.0319	0.0295	
UK		0.0382	0.0384	0.0380	0.0456	0.0474	0.0461	0.0466	0.0525	0.0532	0.0397	0.0420	0.0404	0.0455	0.0361	0.0381

Note: Years followed by a star (*) indicate values obtained with the baseline set of circumstances, all other estimates were obtained with the set including a dynastic measure of capital income. EU-SILC database.

Table 6: Relative lower-bound IOP in Europe.

	2003	2004*	2004	2005	2006	2007	2008	2009	2010*	2010	2011	2012	2013	2014	2015	2016
Austria	0.1915	0.2007	0.2089	0.1652	0.1704	0.1009	0.1320	0.0707	0.0757	0.0803	0.1032	0.0890	0.1331	0.1376	0.1610	0.1637
Belgium	0.1738	0.1756	0.1674	0.1424	0.1960	0.1706	0.1802	0.1874	0.1528	0.1618	0.1850	0.2024	0.2256	0.2293	0.2137	0.2234
Bulgaria					0.0980	0.0707	0.0758	0.0674	0.1465	0.1012	0.0918	0.0810	0.0830	0.1051	0.0646	0.0582
Croatia								0.0824	0.1192	0.1289	0.1608	0.0970	0.0827	0.1085	0.1082	0.1234
Cyprus		0.2924	0.2819	0.2861	0.2902	0.2820	0.2373	0.2326	0.2705	0.2532	0.2623	0.2280	0.2272	0.2146	0.2387	0.1996
Czech Rep.		0.1677	0.1610	0.1674	0.1274	0.1513	0.1600	0.1518	0.1893	0.1394	0.1703	0.1567	0.1614	0.1856	0.1791	0.1911
Denmark	0.1074	0.0892	0.0595	0.0953	0.0842	0.0970	0.0847	0.0649	0.0925	0.0619	0.0784	0.0566	0.1024	0.0918	0.0696	0.0563
Estonia	0.1249	0.1733	0.1631	0.1457	0.2100	0.2042	0.2011	0.1746	0.1957	0.1789	0.1787	0.1872	0.0974	0.0899	0.0950	0.0788
Finland	0.0142	0.0275	0.0170	0.0318	0.0399	0.0375	0.0270	0.0349	0.0307	0.0207	0.0386	0.0379	0.0450	0.0360	0.0429	0.0377
France	0.1742	0.1333	0.1399	0.1397	0.1475	0.1214	0.1030	0.0815	0.1088	0.1095	0.1019	0.1270	0.0969	0.1064	0.1059	0.1076
Germany		0.1667	0.1697	0.1638	0.1495	0.2002	0.2041	0.2376	0.2307	0.2295	0.2289	0.2301	0.2271	0.2042	0.2202	0.2042
Greece	0.1732	0.0996	0.1391	0.1768	0.1894	0.1941	0.2078	0.2071	0.1427	0.1509	0.2185	0.2044	0.1656	0.1452	0.1054	0.1028
Hungary		0.1054	0.1231	0.0588	0.0316	0.0281	0.0577	0.1089	0.0984	0.0987	0.0636	0.1268	0.1050	0.0848	0.1188	0.0996
Iceland	0.0911	0.0767	0.0634	0.0797	0.0575	0.0759	0.0800	0.0768	0.0758	0.0456	0.1336	0.0817	0.0683	0.1184	0.0920	
Ireland	0.3008	0.2920	0.3028	0.2295	0.1894	0.2311	0.2282	0.1950	0.2968	0.2846	0.2092	0.1652	0.1772	0.1783	0.1840	0.1589
Italy	0.1166	0.1570	0.1677	0.1204	0.1084	0.1040	0.1190	0.1068	0.1260	0.1282	0.1523	0.1200	0.1444	0.1286	0.1256	0.1628
Latvia		0.1256	0.0887	0.1083	0.1391	0.0868	0.0631	0.0570	0.0625	0.0633	0.0795	0.0764	0.0949	0.0944	0.0538	0.0942
Lithuania		0.0461	0.0723	0.0565	0.0856	0.0958	0.1055	0.0591	0.0500	0.0800	0.0643	0.0610	0.0702	0.0508	0.0549	0.0759
Luxembourg	0.1680	0.2324	0.2225	0.2353	0.2421	0.2168	0.2326	0.2134	0.2681	0.2570	0.2422	0.2490	0.2158	0.2934	0.2116	0.2264
Malta					0.0702	0.0344	0.0310	0.0195	0.0352	0.0207	0.0258	0.0705	0.0911	0.0411	0.0646	0.0884
Netherlands		0.1187	0.1142	0.3132	0.3292	0.3525	0.2088	0.2703	0.1711	0.1710	0.2684	0.2764	0.2550	0.3233	0.2863	0.2886
Norway	0.1102	0.1095	0.1191	0.1122	0.1151	0.1240	0.1350	0.1029	0.0627	0.0754	0.1208	0.1013	0.1259	0.1198	0.1245	0.1245
Poland		0.0387	0.0967	0.1112	0.0906	0.0923	0.0630	0.0801	0.0658	0.0734	0.0812	0.1036	0.1062	0.1184	0.0897	0.1101
Portugal	0.1427	0.1750	0.1316	0.1513	0.1323	0.1290	0.1369	0.1010	0.1018	0.1291	0.1055	0.1353	0.1426	0.1531	0.1307	0.1272
Romania					0.1083	0.1342	0.1244	0.0557	0.1365	0.0757	0.0578	0.0440	0.0645	0.0429	0.0958	0.0782
Slovakia		0.1526	0.1653	0.1290	0.1240	0.1312	0.1212	0.1214	0.1318	0.1168	0.1201	0.1211	0.1266	0.1450	0.1276	0.1164
Slovenia		0.0518	0.0647	0.0730	0.0777	0.0694	0.0686	0.0606	0.0491	0.0554	0.0742	0.0831	0.0660	0.0729	0.0763	0.0657
Spain	0.1973	0.1941	0.2135	0.1725	0.1644	0.1351	0.1364	0.1216	0.1175	0.1327	0.1140	0.1247	0.1475	0.1540	0.1187	0.1018
Sweden	0.1122	0.1053	0.1172	0.0920	0.0981	0.0963	0.1130	0.0793	0.0492	0.0520	0.0627	0.0622	0.0961	0.0808	0.1246	0.0845
Switzerland					0.1166	0.2375	0.2237	0.2115	0.1821	0.1800	0.1993	0.2085	0.1484	0.1479	0.1370	
UK		0.1803	0.1812	0.1843	0.2070	0.2062	0.2002	0.2135	0.2390	0.2420	0.2106	0.2075	0.2030	0.2232	0.1746	0.1642

Note: Years followed by a star (*) indicate values obtained with the baseline set of circumstances, all other estimates were obtained with the set including a dynastic measure of capital income. EU-SILC database.

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