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Estimating Inequality of Opportunity in More Periods Than Ever Before: The Capital Income Approach

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Estimating Inequality of Opportunity in More Periods Than Ever Before: The Capital Income Approach

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Abstract

The measurement of Inequality of Opportunity has attracted a lot of attention in recent years, despite of the fact that it is very limited by the scarce availability of data on family background. In this paper we propose a method to overcome this limitation, which consists of using another variable, widely available, as a proxy of socioeconomic origin: capital income. Using data of 24 European countries we first show that capital income is strongly related to parental education and occupation. Secondly, we compare the results of our approach to estimate Inequality of Opportunity (which includes a measure of capital income in the set of circumstances) to those obtained with a "standard" procedure (i.e., including parental education in the circumstances set), and conclude that our method can be employed when we do not have information on parental background. Finally, we apply it to estimate Inequality of Opportunity for the full length of the EU-SILC database, which covers every year from 2003 to 2015. To the best of our knowledge, this method allows to measure Inequality of Opportunity in more countries and periods than ever before.

Keywords. Inequality, Social exclusion, Labor market outcomes, Assets, Methodology

JEL classification. D63 Equity, Justice, Inequality, and Other Normative Criteria and Measurement, D70 Analysis of Collective Decision-Making, I24 Education and Inequality

1 Introduction

Throughout all her life Sophie Germain had to face opposition to study mathematics just because she was born a woman. Germain had to self-taught herself during her youth and hide her gender with a pseudonym—Monsieur Le Blanc—once she grew up. Nevertheless, she broke through the hurdles posed by her family and society and eventually became a great mathematician. She obtained important results in number and elasticity theory, and impressed prominent mathematicians of her time like Joseph-Louis Lagrange and Carl Friedrich Gauss. Now we know that we owe her a number of contributions, but we do not know what else she could have achieved, should she had the *opportunity* to enjoy early access to formal education and social support. Notwithstanding, even

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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 she had to fulfill domestic tasks: she had time, which she used to study.

We believe that the life of Sophie Germain is interesting in its own right, but we recur to it now because it illustrates what the Equality of Opportunity approach pursues. This field follows the work of political philosophers who tried to define what a *fair* distribution is. Building upon the work of Rawls (1971), Sen (1979), Dworkin (1981a, 1981b), Arneson (1989) and Cohen (1989) sought to define a concept of equity that would accommodate for seemingly opposite concerns regarding advantages acquired through birth and results obtained by means of personal effort. The result is a method to systematically classify differences as fair or unjust.

In the field of (In)equality of Opportunity, IOP henceforth, inequalities with respect to any outcome—like income, wealth, health status or education attainment, to name a few—are deemed "fair" or "unfair" depending on where they stem from. Simply put, are considered fair inequalities those coming from causes that individuals can choose—like the degree of effort exerted—while unfair inequalities, on the contrary, come from sources that individuals cannot control—like gender or race. For example, Germain suffered discrimination due to her gender, something she cannot be hold responsible for. This is, being a woman did not complicate her path to become a mathematician because of her behavior, but 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. She did not choose that either, or had any responsibility on achieving it. Consequently, the IOP approach would consider the inequalities steaming from her gender and privileged socioeconomic origin as unfair, playing the former a negative influence and the latter being a head start. However, Germain attained greater levels of knowledge and (postmortem) prestige than most people, and some of that inequality is probably due to the greater amount of effort she must have exerted. Such inequalities, coming from variables individuals can choose, are deemed fair. For a survey on the philosophical grounds of the IOP approach, see Ferreira and Peragine (2015) or Roemer and Trannoy (2016).

The measurement of "fair" and "unfair" inequality is an appealing field that has been growing notably in the last years. However, the empirical measurement of IOP is markedly limited by the scarcity of a kind of information considered necessary to estimate it: family background of individuals.[1] This paper investigates how to overcome this limitation. Instead of using information on parental education or occupation, we propose to use data on capital income, since it can also be used to approximate socioeconomic origin.[2] The paper is organized as follows: in the next section we briefly review the literature of the empirical measurement of IOP; in section 3 we discuss the details of the proposed strategy to measure IOP when we do not have information on the parental background, and the methodology of the test we perform to assess its reliability; in section 4 we show the results of this test and in section 5 we take advantage of our method to measure IOP in a number of countries and periods for which, to the best of our knowledge, it has never been measured before. Section 6 concludes.

[1] The importance of socioeconomic origin in determining economic and social outcomes has been explored extensively by the literature on intergenerational mobility. An interesting recent paper that includes also genetic evidence is Papageorge and Thom (2018).

[2] I owe the idea of using capital income as a proxy of family background to my supervisor, Carlos Hervés-Beloso.

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, and only of, a set of circumstances C and a variable of effort e (and hence, all individuals with the same circumstances and degree of effort would have the same outcome):

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

- Circumstances are factors that might influence a given outcome but cannot be chosen by individuals, and therefore individuals cannot be held responsible for them. These include gender, race, geographical origin, family background and the sort. The set of circumstances implicitly include different forms of luck[3] and the effect of circumstances on effort.[4]
- Effort is the intensity with which individuals devote themselves to work, and can, on the contrary, be decided by them.

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

Following the contributions of Roemer (1993, 1998), Van de Gaer (1993), Van de Gaer et al. (1998) and Fleurbaey (1995), many authors have proposed different methods to empirically assess the degree of unfair inequality. In this article we will apply two of the most popular procedures: the parametric method proposed by Ferreira and Gignoux (2011) and the non-parametric *ex-ante between-types inequality*, variously proposed by Van de Gaer (1993), Peragine (2002), Checchi and Peragine (2010), and Ferreira and Gignoux (2011). We employ two methods rather than one for comprehensiveness and, most importantly, to test for robustness. For articles surveying the available methods to measure IOP, see Ramos and Van de Gaer (2016) or the already mentioned Ferreira and Peragine (2015). One of the problems the measurement of IOP faces is the lack of a widely accepted methodology, what includes, for instance, the measurement method, the selection of the set of circumstances or the outcome of choice. This results in notoriously different estimates of IOP across different studies, and the consequent difficulty of establishing country ranks. In respect to the choice of circumstances, an objective process of cross validation has been proposed by Brunori et al. (2018), who also highlight the inconsistency of IOP estimates across different studies.

However, the most important limitation of IOP measurement is the reduced amount of data points that can be estimated due to the relatively demanding quantity of data necessary. Of course, this is due to the need of information on family background. This limitation has led to many studies attempting to assess the evolution of IOP in Europe considering only two periods, 2004 and 2010, like Suárez Álvarez and López Menéndez (2017), who analyze changes of IOP in Spain, or Andreoli and Fusco (2017), who study the evolution of inequality of opportunity in 19 European countries. These two articles employ the EU-SILC database—which has information on parental background only in 2004 and 2010's waves—to simply compare estimations of these two periods, so we cannot learn anything about how IOP behaved in between, and probably more interesting, how has behaved after. Other studies have explored the relationship of IOP with a number of economic and social phenomena, such as Checchi, Peragine, and Serlenga (2016), who explore the role of institutions by performing regressions with around 50 observations, or Marrero and Rodríguez (2012), who perform a correlation analysis of IOP and education and labor market indicators with also a reduced number

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

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

of observations. Albeit these are great pieces of research that pursued relevant and interesting matters, they are constrained by the small amount of data points they could rely on. Furthermore, some studies like Marrero and Rodríguez (2013) and Marrero, Rodríguez, and Weide (2016) have related IOP to GDP growth using data of the US, country for which there are larger databases with information on parental background. For the case of Europe, however, it is currently not feasible to conduct these kind of studies using a "standard" set of circumstances, due to the small number of data points that can be obtained. We believe that the capital income approach, which allows to perform estimations of IOP in datasets that do not include information on parental background—as long as they count with information on capital income of households, which is the norm—, unfolds a new range of possibilities.

3 Methodology

This article presents a strategy that aims to allow the estimation of IOP in many more periods than what is currently possible. The strategy involves the selection of variables to be included as circumstances: instead of using information on parental background—which is scarce—to approximate individuals' socioeconomic origin, we propose to employ a measure of gross capital income of households—which is widely available. Different mechanisms may be at play: first, from the intergenerational mobility literature we know that more educated parents tend to transmit important social advantages, such as education, to their children (see for example Jäntti and Jenkins 2015); second, returns on investments are linked to education and financial literacy, what we know from the portfolio literature (Bucher-Koenen and Ziegelmeyer 2011; Gaudecker 2013); and third, savings and wealth ownership are strongly conditioned by the intergenerational transmission of bequests and human capital, what has been explored by the wealth inequality literature (De Nardi and Fella 2017).

That said, using capital income as a proxy of socioeconomic origin might seem adequate. However, an important concern arises: the amount of capital income received can be decided by individuals, at least to some extend. In the IOP approach only characteristics that are exogenous to individuals are included in the circumstances set, and that is precisely what justifies the qualification of any inequality stemming from these factors as unfair. Hence, we will take another approach. We can think of wealth ownership and consequently capital income as characteristics determined by two factors: a *dynastic* component, product of advantages acquired through birth such as access to good education and bequests, and a *meritocratic* component, coming from effort exerted by individuals during their lifetime. The evidence cited in the previous paragraph suggests that the dynastic component would be bigger than the meritocratic, and still, we would be concerned by the influence of the latter if we were to introduce a simple measure of capital income in the circumstance set. Therefore, we will try to remove the effort component before we include a measure of capital income in the circumstance set. We discuss the details of how we attempt to isolate the dynastic component in subsection 3.3, to subsequently test its validity as a proxy of socioeconomic origin in subsection 3.4. Finally, in section 4 we perform an empirical test of the overall validity of this whole strategy to measure IOP with capital income. But first, let us outline the structure of this project in the next paragraphs and detail the methodology employed to measure IOP in subsections 3.1 and 3.2.

Our project consists of two parts:

- Validating the method: we first study datasets of countries and periods in which data on both parental education and capital income are available, so we can obtain IOP measures with a "standard" set of circumstances (including parental education) and the set of circumstances we propose (excluding parental education but including a measure of capital income). Once we have the two estimates, we compare them to assess the accuracy of the method proposed. This kind of testing implies assuming that the "standard" method returns *perfect* results. This is surely not a realistic assumption, but since the "standard" procedure is widely accepted in the field, we use it as our baseline.

- Benefiting from the method: once the reliability of our new method has been assessed, we use it to estimate IOP in datasets for which we do not have information on parental background, but for which we do have information on capital income (which are many).

For comprehensiveness and robustness we make use of two databases: the Luxembourg Income Study , which offers harmonized data on income and circumstances at the individual and household level for several high and middle income countries, and the European Survey of Income and Living Conditions , which offers the same kind of data for up to 31 European countries in its most recent wave. The LIS database is specially fit for the validation purpose, as it has information on parental education for a relatively big number of periods in the case of two high income countries, Germany and Italy. We can use data of 23 periods—scattered between 1984 and 2015—in the case of Germany, and 7 periods—within 1995 and 2014—with Italy (totaling 30 data points). We must restrict our analysis to high income countries, since the capital income approach needs the presence of widely distributed capital ownership, what we will discuss in detail in subsection 3.3. The EU-SILC has information about parental background only in two waves—2004 and 2010—, but capital income of households is available in all waves and countries. Hence, the EU-SILC is specially fit to benefit from the method, as we could estimate IOP for all countries and periods, which at the time of writing this article range from 2003 to 2015.

Regarding the empirical methods to estimate IOP, we apply the Ferreira and Gignoux (2011)'s parametric approach and the ex-ante between-types inequality non-parametric approach. As inequality measures, we employ the Gini index and the Mean Log Deviation, but for brevity, and provided that results are robust to the choice of inequality measure, in the body of the article we will mostly report results using the MLD, leaving for the Appendix the results using the Gini index (we will comment on this and other robustness checks in section 4).

Now we will briefly describe the two empirical methods to estimate IOP that we are going to use in this article. The procedure proposed by Ferreira and Gignoux (2011) consists of regressing an outcome variable y_i against a set of circumstances C_i:

$$\ln y_i \;=\; \psi C_i + u_i$$

Actually, this equation is a reduced form of

$$\ln y_i \;=\; \alpha C_i + \beta E_i + v_i$$

where β would capture the influence of circumstances on the degree of effort exerted.

Then, to "remove" the effect of effort e_i on the outcome variable, we predict each individual's income $\hat{y}_i$ based only on the circumstances set C_i, and construct a counterfactual distribution. We finally apply an inequality measure to this distribution to get an absolute measure of IOP

$$\mathrm{IOP}_{abs} = I(\hat{y}_i)$$

and a relative one

$$\mathrm{IOP}_{rel} = \frac{I(\hat{y}_i)}{I(y)}.$$

The ex-ante between-types inequality approach consists of replacing the outcome of each individual by a feature of the outcome distribution of individuals who share the same circumstances, generally the mean value. Let us explain it with an example. 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 set of circumstances, and e an effort variable. 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, within which everyone shares 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.

[Table 1 about here.]

Now, to "remove" the effect of effort e_j on the outcome y_{ij} of all individuals in each type T_i, we replace the outcome y_{ij} by some feature of the outcome distribution of that type, like the mean value μ_i, as it is shown in table 2. By doing so any inequality withing types is eliminated, remaining only the inequality between types; this is, the inequality due to circumstances. Finally, we can apply an inequality measure such as the Gini index or the MLD to μ_i in order to obtain an absolute

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

and a relative measure of IOP

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

[Table 2 about here.]

3.1 Data description

We use two databases, the Luxembourg Income Study and the European Survey of Income and Living Conditions. These are well-known and researched databases for the study of inequality, poverty, and social exclusion. We restrict our sample to individuals aged 30 to 59 who declare to be economically active (working full or part-time or unemployed). As the outcome variable we use annual gross personal income. We can speak of a trade-off in relation to the choice of this outcome: on the one hand, personal income is defined at the individual level, and hence our analysis overlooks household bargain issues that influence labor market participation. On the other hand, part of the effect of circumstances in income works through labor supply decisions—specially that of the circumstance gender—and thus income at the individual level is required to capture it. We leave for future analyses the implications of choosing personal or household income as outcome. With the EU-SILC database we consider gross personal income.[5] In the case of LIS, we use net

[5]Defined as "Employee cash or near cash income (Gross)" plus "Non-Cash employee income (Gross)" plus "Cash benefits or losses from self-employment (Gross)" plus "Pension from individual private plans (Gross)" plus "Unemployment benefits (Gross)" plus "Survivor' benefits (Gross)" plus "Sickness benefits (Gross)" (setting all negatives values to zero). We exclude "Value of goods produced by own-consumption (Gross)" because it is not available in all countries, and "Disability benefits (Gross)", "Education-related allowances (Gross)" and "Old-age benefits (Gross)" because students, retired and disable people are excluded from the sample. Also, in the case of Italy this definition excludes "Sickness benefits (Gross)", since it is not available for this country in any period. Note that this exclusion does not entail a comparability problem, since we are only comparing each country to itself.

personal income.[6] In addition, apart from these outcome variables and the circumstances described in subsection 3.2, we will use information on individuals' education and occupation (coded in three levels following ISCED-97 and ISCO-88 classifications, respectively), as well as parental occupation (following ISCO-88), to assess to which extent our proxy of socioeconomic origin, a measure of capital income, is related to these individual characteristics.

3.2 Circumstances

As the "standard" or "baseline" set of circumstances we consider gender, immigrant status, population density of the living area, and parental education. We use the results of this "baseline" set to compare them to those of our proposed set, which we call "capital". These sets of circumstances only differ in the last circumstance, parental education, which is substituted by a measure of capital income of the household in the second set. Now we proceed to discuss these circumstances.

As first circumstance, binary gender is included in the set. Secondly, immigrant status, differentiating between individuals born in the country of residence and born outside. Thirdly, we include density of population of the area where individuals reside. Including in the circumstances set whether a person lives in a rural or an urban area is controversial. However, we consider that the economic prospects of individuals are conditioned by the place where they were born, even within their country.[7] Hence, we include a variable on the density of population where individuals live, distinguishing between rural and non-rural.[8] Nevertheless, aware as we are of the possible source of controversy that this choice entails, we have also conducted every analysis in this paper excluding population density from the circumstance set. Since the results hold and the conclusions remain unaltered we refer to them only in the Appendix. Finally, in respect to socioeconomic origin, it is common practice to include some information on parental background, usually educational attainment. Its scarce availability, and the problem that poses, is the leitmotif of this paper. To test our method by comparing its results with those of a "standard" approach, we consider three levels of parental education, representing the highest level attained by any parent: 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). We detail how our measure of capital income is constructed in the

[6]Variable "pi", which includes total monetary payments from labor, property, and social or private transfers, as well as total value of non-monetary goods and services received from labor and social or private transfers, excluding social transfers in kind such as universal health insurance, universal education benefits, and near cash benefits from public housing.

[7]Some authors state that living in a rural or an urban area can be chosen by individuals, and hence should be considered an effort. Yet, we argue that being born in the countryside is not responsibility of the individual, and it is relevant because people tend to develop ties to the place where they were born, in the form of emotional attachment or social networks, implying that the necessary effort to move to an urban area—where chances of economic success are higher—is greater than for those already born in the city. Also, those already born in the city may enjoy more time to develop their social capital in the area. We see this circumstance in a similar way as the immigrant status, since one can *choose* to emigrate or to stay in her home country.

[8]In the LIS database a dummy for rural area is provided. The classification of geographical areas into urban and rural follows the country-specific guidelines (i.e. the urban/rural classification is not based on absolute numbers across all countries, but the cutoff point changes from country to country and can change within the same country from year to year in order to retain the individual country's classifications). 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 only consider thinly-populated areas as rural ones, 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.

next subsection.

Therefore, with these sets of circumstances we have up to 24 types, product of 2 genders $\times$ 2 geographical origins $\times$ 2 population density areas $\times$ 3 levels of parental education/capital income. However, the number of types falls shorter than 24 in some datasets. This happens because some types rarely appear in the data, as they consist of infrequent combinations of circumstances such as for instance female immigrants living in rural areas. To prevent a misleading influence of very small types that may contain extreme values, we retain only those types with at least 50 observations.

3.3 Definition of the capital income variable

In this subsection is detailed how we construct our measure of capital income to be included in the circumstances set. As was mentioned at the beginning of section 3, capital income can be thought of as a product of two components, a dynastic and a meritocratic one, and for our purpose we would want to solely consider the dynastic factor. Hence, we will follow a procedure to isolate it. However, for the sake of the narrative, this subsection will begin with a simpler task. We will first discuss the construction of a discrete variable that classifies individuals according to the importance of their household's gross capital income in relation to their household's gross total income; this is, according to a simple ratio. Straightaway, building onto that process, we will detail how we proceed to separate the dynastic component of capital income.

The process to generate our ratio is the following:

- First, we look at the distribution of parental education. We have previously constructed a variable of parental education with three levels, and hence we can see how the education of parents (primary or less, secondary, and tertiary or more) is distributed across individuals. We look at the values of the cumulative distribution function in each country and period, and store them.
- Second, we generate a ratio of household gross capital income (setting all negative values to 0) to household gross total income for every household in the sample. This variables has values ranging from 0 (no capital income in the household) to 1 (all income of the household comes from capital returns). This is, we generate a measure of the relative importance of capital income in each household.
- Third, we find the exact values of this ratio at which its CDF takes the same values of the parental education's CDF in each country and period.
- Finally, we create a discrete variable of three levels that groups individuals according to where the ratio of their household gross capital income to household gross total income falls in respect to the values found in the previous step. This is, we obtain a classification of individuals into three groups regarding the importance of gross capital income in their households, having these groups the same size as the groups defined by the distribution of the variable parental education.

Let us explain it with an example: consider the fictitious distribution of parental education in a sample of 10,000 individuals displayed in table 3.

[Table 3 about here.]

First, we look at the values of the "Cumulative" column, which displays the values of the cumulative distribution function, and store them. Then, we construct a variable measuring the importance of household gross capital income in relation to household gross total income (a ratio). Then, we look at its distribution across the sample, and find the exact values at which this ratio's CDF reaches the exact values of the parental education's CDF (the "Cumulative" column in table 3). We are looking to get something like in table 4.

[Table 4 about here.]

Now, once we have obtained the exact values at which we can divide individuals into groups so that the CDF of the capital income's ratio coincides with the parental education's CDF (in this fictitious case would be 0.01 and 0.03), we construct an ordered discrete variable that groups every individual in the sample according to these levels of relative importance of capital income in her household ("Group 1" if the capital income of her household represents up to 1% of the household's total income, "Group 2" if it is between 1 and 3%, and "Group 3" if it is over 3%). For this fictitious case, a diagram of this ordered discrete variable, which we name capital income levels, is shown in (1).

$$\textit{Capital income levels} = \begin{cases} 1 & \text{if} \quad Kratio_i \leq 0.01 \\ 2 & \text{if} \quad 0.01 < Kratio_i \leq 0.03 \\ 3 & \text{if} \quad Kratio_i > 0.03 \end{cases} \tag{1}$$

Yet, creating groups of the same size as those of the parental education distribution has a problem: that parental education is more evenly distributed than capital returns. In some countries and periods, the proportion of individuals whose household receives any capital income is very small, not even reaching the 3%. This means that we cannot construct the variable capital income levels as we have described it in some cases. With the LIS database, from which we use data of Germany and Italy, this problem does not arise—we can construct the variable capital income levels just as described in all periods. However, using the EU-SILC this occurs with some datasets, namely Hungary and Poland in both 2004 and 2010, Estonia and Slovakia in 2004, and Ireland, Latvia, Lithuania, Bulgaria and Romania in 2010 (note that all, except Ireland, are countries which had a planned economy, what might have had an impact on the development of their capital markets thereafter. It is surprising to see, anyway, that the ownership of capital income became less widespread between 2004 and 2010 in Ireland). Find the CDF of parental education and capital income levels in tables 11 and 12, at the Appendix. This problem implies that we may not be able to use the capital income approach to estimate IOP in these countries and periods. In consequence, we have excluded them from our main sample, and we will report results on a selected set of countries of the EU-SILC database, those for which we can build the variable capital income levels either just as described, or with at least three levels. These group of countries include: Austria, Belgium, Cyprus, Czech Republic, Denmark, Finland, Germany, Iceland, Ireland, Luxembourg, the Netherlands, Norway, Slovenia, Sweden and the United Kingdom in the wave of 2004 (other countries, particularly France, Greece, Italy, Portugal and Spain, lack data on gross capital income before 2006's wave); and Austria, Belgium, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Iceland, Italy, Luxembourg, Malta, the Netherlands, Norway, Portugal, Slovakia, Slovenia, Spain, Sweden and the United Kingdom in 2010's wave (Switzerland is present in this wave, but it lacks data on personal income).

The variable capital income levels, which construction we just have described, could not be included in the circumstances set unless we would not be concerned about capital income being non-exogenous to individuals, at least not completely. In order to isolate its dynastic component we will run an OLS regression of gross capital income of households against a number of available individual characteristics that contain information about the effort exerted by individuals, namely education and occupation, and about their situation in their life cycle, namely age. Then, we take the residuals of this regression, which can be seen as the value of capital income once its non-dynastic component has been removed, and use them as input to construct two new discrete variables to be used as proxies of socioeconomic origin. This OLS regression takes the following form:

$$Kinc_i = \beta_0 + \beta_1 education_i + \beta_2 occupation_i + \beta_3 age_i + \varepsilon_i \qquad (2)$$

where $Kinc_i$ is the amount of gross capital income of individual's i household, $education_i$ is the highest educational level attained by individual i (primary or less, secondary or tertiary), $occupation_i$ is the occupational status of individual i ("unskilled worker" (ISCO 9), "skilled worker" (ISCO 4-8) or "professional" (ISCO 1-3)), and age_i determines to which age group individual i belongs (30 to 39, 40 to 49, or 50 to 59). This regression includes education and occupation because they are related to the responsibility of individuals. Of course, they are not perfect measures of the effort exerted, and in fact they are as well conditioned by family background, but we believe they represent a step in the right direction. We apply this procedure to "remove" the meritocratic component following the logic behind the Ferreira and Gignoux (2011)'s approach, used to "remove" the effect of effort. Nevertheless, it should be kept in mind that our variables of "effort" are a strict subset of all relevant information regarding personal effort. We also include age in the regression, despite of the fact that it is exogenous to individual's responsibility, to account for the life cycle, which influences decisions to invest and shall not be compensated for (see for example Modigliani 1966). While not being a perfect "isolation" of the dynastic component of capital income, following this procedure alleviates the concern of introducing characteristics non-exogenous to individuals in the circumstances set.

Once the residuals ε from (2) have been obtained, we use them to construct two new discrete variables following a process analogous the one just described for the variable capital income levels. Instead of grouping individuals according to a ratio of households' gross capital income to households' gross total income, $Kratio$, we employ the residuals in (2) that represent the "dynastic" component of capital income. We construct two different measures of the dynastic component of capital income: one is built by taking the residuals in their absolute value, to then generate three groups, or levels, of the size determined by parental's education CDF, in the same way as we did with $Kratio$. For the second new measure we take the ratio of the residuals ε to the households' gross total income, and analogously generate three groups of the size determined by parental's education distribution. We have constructed two different measures of the dynastic component of capital income to test for robustness, but since the results are not sensible to which one is selected, in this text we will only detail the results from the one that seems to perform slightly better[9], the measure that considers the absolute values of the residuals ε—we will return to this in subsection 4.1.

In this subsection we have detailed the construction of three measures of capital income: *capital income levels*, which is based on a simple measure of capital income, *absolute dynastic component of capital income levels*, which is based in the absolute values of the residuals from (2), and *relative dynastic component of capital income levels*, which is based in a ratio of the absolute values of the residuals from (2) to total household income. In the next subsection we test how the first two measures are related to family background using data from the EU-SILC and the LIS databases.

3.4 How does our measure of capital income relate to parental background?

We have constructed different measures of the importance of capital income of households in order to use it as a proxies of socioeconomic origin of individuals. At the beginning of section 3 we have

[9] All results available from the author.

referred to evidence from different literatures suggesting the existence of this link. But how does it appear in our samples? In this subsection we look at the relationship between our capital income measures and some individual characteristics.

[Table 5 about here.]

In table 5 we can see the results of an ordered logistic regression with *capital income levels* as dependent variable over our subset of countries from the EU-SILC, including observations from both the 2004 and 2010 waves. Regression (1) presents the average marginal effects of parental education and occupation on the three capital income levels, taking the lowest category of the regressors as reference ("pre-primary, primary or lower secondary education (levels 0, 1, and 2 of ISCED-97)" in the case of paternal education and "unskilled workers (ISCO 9)" for parental occupation). These results suggest that, in our sample from the EU-SILC, capital returns are linked to parental background, being its effect both statistically and economically significant. Little or no importance of capital income in the household appears to be related to less educated and less skilled parents. The average marginal effects are larger for parental education than for parental occupation, what may be relevant, as previous research has identified it as better proxy of family background than parental occupation (Marrero and Rodríguez 2013). In (2) we see that these effects hold after controlling for education, occupation and age of individuals. Looking at the average marginal effects, parental education seems more strongly related to capital income than personal education, perhaps surprisingly, provided that education and financial literacy are considered the main drivers of capital returns (Bucher-Koenen and Ziegelmeyer 2011; Gaudecker 2013). Also, the size effect of age or occupation seems not as important as that of parental education. Regarding parental occupation, its effect seems to be weaker. The marginal effect of its third level, "professionals (ISCO 1-3)" loses its significance in regression (2), and the effect size of its second level "skilled workers (ISCO 4-8)" diminishes. Also, we have included a year dummy, since we are using pooled cross-sectional data over two periods. Nevertheless, its average marginal effect does not appear significant in our regressions, which suggests that the link between capital income levels and the included regressors remained stable through 2004 and 2010. This is a relevant result, as it could be argued that the financial crisis of 2007 might had changed the predictive power of our variable capital income levels in regards to family background, yet it does not appear to be the case. This evidence suggests that parental background may explain capital income to a larger extent than personal characteristics do, what is a strong result. However, despite of the fact that *capital income levels* appears to be serve the purpose of proxy of family background, it does include a meritocratic component. Hence, we are interested in knowing if our isolated *absolute dynastic component of capital income levels* would serve the same purpose. We consequently proceed to run this same kind of regression with it as dependent variable, to test if it is also related to family background. We can see the results in table 6.

[Table 6 about here.]

In table 6 we can see that our measure of "dynastic" capital income appears to be strongly and positively correlated with parental education. The effect is significant at the 99% level or higher at all levels, and the effect size is considerable. Parental occupation, however, seems to lose importance; in this respect we refer again to previous research that identified it as a less relevant proxy of family background than parental education (Marrero and Rodríguez 2013). The rest of regressors, namely individual's education and occupation and age retain some significance, although the sign of their effect has been inverted with respect to the model with *capital income levels* as dependent variable. This means that the residuals of the OLS regression, which we use as the dynastic component, are not orthogonal to the regressors—education, occupation and age—, what should happen by construction. A possible reason for this is the presence of omitted variable bias in the OLS regression, what would cause this regressors to *capture* other effects not included. Nevertheless, this does not seem a relevant concern, provided that parental education retains its significance both in statistical and economic sense. Also, the fact that the individual characteristics education, occupation and age do not show a positive correlation with our measure of dynastic capital income supports its usage as a proxy of socioeconomic origin.

Overall, this analysis leads us to conclude that the variable *absolute dynastic component of capital income levels* appears to be a valid proxy of parental education. Consequently, in section 4 we include it in the circumstances set to estimate IOP following our proposed strategy, the capital income approach, and test the reliability of its results.

4 Results

In this section we present the results of IOP estimations using a “standard” set of circumstances, which includes parental education, and the “capital” set we propose. We will compare these results in a number of ways, trying to assess the reliability of the capital income approach. As we mentioned in section 3, this testing approach assumes that the “standard” method returns *perfect* results. We will do so in order to have a “baseline” estimates to compare with the results of our own approach.

[Figure 1 about here.]

[Figure 2 about here.]

[Figure 3 about here.]

[Figure 4 about here.]

The first four figures of this paper are line plots displaying the evolution of IOP measured with the “standard” and the “capital” sets of circumstances, using the LIS database and employing the mean log deviation as inequality measure. Figures 1 and 2 refer to Germany, and 3 and 4 to Italy. Concurrently, figures 1 and 3 show IOP estimates obtained using the Ferreira and Gignoux (2011) approach, while figures 2 and 4 display results from the ex-ante between-types inequality. Dashed lines represent estimates using the “baseline” set of circumstances, solid lines those obtained using the “capital” set. Estimates with both sets of circumstances follow very similar trends, with pairwise correlations close to 1, and the points estimates’ confidence intervals, obtained via bootstrapping, overlap in an important number of periods as well. Also, it appears that the results are robust to the measurement procedure.

[Figure 5 about here.]

[Figure 6 about here.]

Using the EU-SILC database we obtain the estimates shown in figures 5 to 8. On the contrary to what occurs using the LIS database, where we have few countries but many periods, using the EU-SILC we count with many countries but just a few periods. Therefore, instead of line graphs we employ scatter plots. On the vertical axises is displayed IOP measured using the baseline set of circumstances, and IOP using the capital set on the horizontal one. Figures 5 and 6 show the results in 2004's wave, which includes 15 countries. Figures 7 and 8 display the estimates of 2010, with 23 countries. In addition, 5 and 7 represent results of the Ferreira and Gignoux (2011) approach, while 6 and 8 those of the ex-ante between-types inequality. The measure of inequality employed is the mean log deviation. Once more, the different estimates obtained appear to be similar, with pairwise correlations close to 1. However, some countries such as Luxembourg or Estonia seem to behave as an outliers.

[Figure 7 about here.]

[Figure 8 about here.]

An important use of IOP measures are country rankings. It would be of course an interesting feature of the capital income approach to be a rank-preserving measure with respect to the baseline estimates, although it is not the case. Nevertheless, the rank correlations are also close to 1, which means that if a country ranks high when considering a "standard" IOP measure, it will rank high as well if measured with the capital income approach. To help put this in perspective, bear in mind that the rank correlations between the estimates of a number of published papers, all of which were obtained using a set of circumstances that included parental education, are notoriously lower than the ones presented here (Brunori et al. 2018). Figures 9 to 12 show IOP ranks comparisons using the EU-SILC database. These figures display the rank of the "baseline" set of circumstances in the vertical axis, and the "capital" set in the horizontal one, going from less unequal to more unequal. Again, figures 9 and 10 represent data from 2004's wave, and 11 and 12 from the one referring to 2010. Figures 9 and 11 were produced with Ferreira and Gignoux (2011)'s approach estimates, while 10 and 12 display estimates using the ex-ante between-types inequality method.

[Figure 9 about here.]

[Figure 10 about here.]

[Figure 11 about here.]

[Figure 12 about here.]

Another way of assessing the accuracy of the capital income approach is to compare the counterfactual distributions of income, $\hat{y}_i$, generated when we performed the regressions of the Ferreira and Gignoux (2011) approach. This is, the regressions $\ln y_i = \psi C_i + u_i$ with both the baseline, C_i^{base}, and the capital, C_i^K, circumstances sets. After all, to the extent these counterfactual distributions are similar, the closer from each other their degree of inequality will be. Let us call these counterfactual distributions $\hat{y}_i^{base}$ and $\hat{y}_i^K$, generated using the baseline and the capital sets of circumstances, respectively. A way to compare them is looking at their moments, which are presented in tables 7 to 10. Tables 7 and 8 come from the LIS database, figures 9 and 10 from the EU-SILC. We consider that the means of the counterfactual distributions estimated with the baseline and capital circumstances sets are very similar. In most cases, either *periods* with the LIS database or *countries* with the EU-SILC, the difference is under 1%. However, the median values and the standard deviations are not so similar, with substantial differences in some cases.

[Table 7 about here.]

[Table 8 about here.]

[Table 9 about here.]

4.1 Robustness

The reliability test of the capital income approach has consisted mainly in correlation analyses. While these correlations are high, speaking in favor of the reliability of the capital income approach, it could arise the concern of these correlations to be spurious, i.e., product of chance. Since a causal analysis has no place here (there is not such claim as that the "standard" estimates *cause* the "capital" ones, nor the other way around), an strategy to alleviate this concern is a robustness analysis. While IOP estimates with both sets of circumstances might be similar by chance with a particular methodology, it is unlikely that they remain similar when we vary different methodological aspects if they are truly similar due to chance, and for that reason we consider of great importance the numerous robustness tests performed. The results presented in section 4 hold when we vary the following parameters of the analysis:

- The database employed, LIS or EU-SILC. Their differences for our case are interesting, since with LIS we can study a small number of countries (Germany and Italy) during a relatively big number of periods (up to 23), while with the EU-SILC we have a relatively big number of countries (up to 23) but a small number of periods (2)
- The approach to measure IOP, either the parametric procedure proposed by Ferreira and Gignoux (2011) or the non-parametric ex-ante between-types inequality approach
- The inequality measure employed, either the MLD or the Gini index (find the results using the Gini index in the Appendix)
- Consider annual net personal income (outcome variable in LIS database) or gross (outcome variable in EU-SILC database). Also, net personal income is available in the EU-SILC database for a smaller number of countries, and employing it does not change the conclusions
- The sample selection: including people fulfilling domestic tasks or care responsibilities and not only individuals who are active in the labor market
- The way in which we construct the *dynastic component of capital income levels* variable: apart from the absolute measure, we have tested a relative one. And, as a matter of fact, even simply including *capital income levels* in the circumstance set, without isolating its dynastic component first, returns similar results
- The set of circumstances: we have conducted the same analysis but excluding "Population density" from the set of circumstances

For brevity and simplicity not all of these methodological variations have been included in this version of the article, but they available from the author, and soon will be freely accessible at github.com.

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 estimate IOP for the full length of the EU-SILC database. Figures 13 and 14 show the evolution of IOP in 23 European countries for, to the best of our knowledge, the longest span estimated so far. These IOP measurements have been obtained using the Ferreira and Gignoux (2011) approach. Figure 13 shows the evolution of IOP using MLD as inequality measure, and fig. 14 includes the evolution of personal income inequality as well. However, due to the very different magnitudes of these measures across countries, graphical visualization may be difficult. For that reason we include figs. 15 and 16, which show the indexed evolution of IOP and personal income inequality, taking as base year the first one available in each country. We do not observe a common trend, but quite different evolutions in each country. For example, these results point at a sharp rise in Austria and Sweden since the years of the financial crisis, and at the opposite in Luxembourg. Nevertheless, a high variability in IOP is observed, with changes of around 30% in most countries within the 13 years analyzed. An interesting finding is the relatively low correlation between IOP and personal income inequality, which is around 0.5. However, with this simple application of the capital income approach we do not intend to perform an exhaustive analysis of the evolution of IOP in Europe, but simply showing the possibility it offers to estimate IOP for so many new periods. This article is focused on testing the method proposed, future work will focus on the exploration of the new area unveiled with it.

[Figure 13 about here.]

[Figure 14 about here.]

[Figure 15 about here.]

[Figure 16 about here.]

6 Concluding remarks

In this article we have proposed a new approach to measure IOP that does not rely on the scarce availability of parental background information, which we call the capital income approach. After testing this method by comparing its results to those of a “standard” approach, we conclude that it is sufficiently reliable to benefit from it when we do not have information on parental background. The results of our method are not equal to those taken as baseline, yet we consider them to be an informative approximation. First of all, the ordered logit models provide strong evidence in support of the use of the measures of capital income constructed as proxies of socioeconomic origin; secondly, the pairwise correlations of the inequality of opportunity measures are close to 1, and so are the rank correlations; and finally, the counterfactual distributions appear to have similar patterns from the moments comparison. In respect to the possible concern of the correlations obtained being spurious, we have conducted numerous robustness tests that make this possibility unlikely, most importantly, but not limited to, the use of two different techniques to measure IOP, two different databases, and two different inequality measures. We believe that, in light of the tests performed, the capital income approach can entail a contribution to the field of IOP. Specially so if we take into account that, until now, we knew nothing about IOP levels aside from the periods in which we had information on parental background.

Appendix

[Figure 17 about here.]

[Figure 18 about here.]

[Figure 19 about here.]

[Figure 20 about here.]

[Figure 21 about here.]

[Figure 22 about here.]

[Figure 23 about here.]

[Figure 24 about here.]

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[Figure 26 about here.]

[Figure 27 about here.]

[Figure 28 about here.]

[Figure 29 about here.]

[Figure 30 about here.]

[Figure 31 about here.]

[Figure 32 about here.]

[Table 10 about here.]

[Table 11 about here.]

[Table 12 about here.]

[Table 13 about here.]

[Table 14 about here.]

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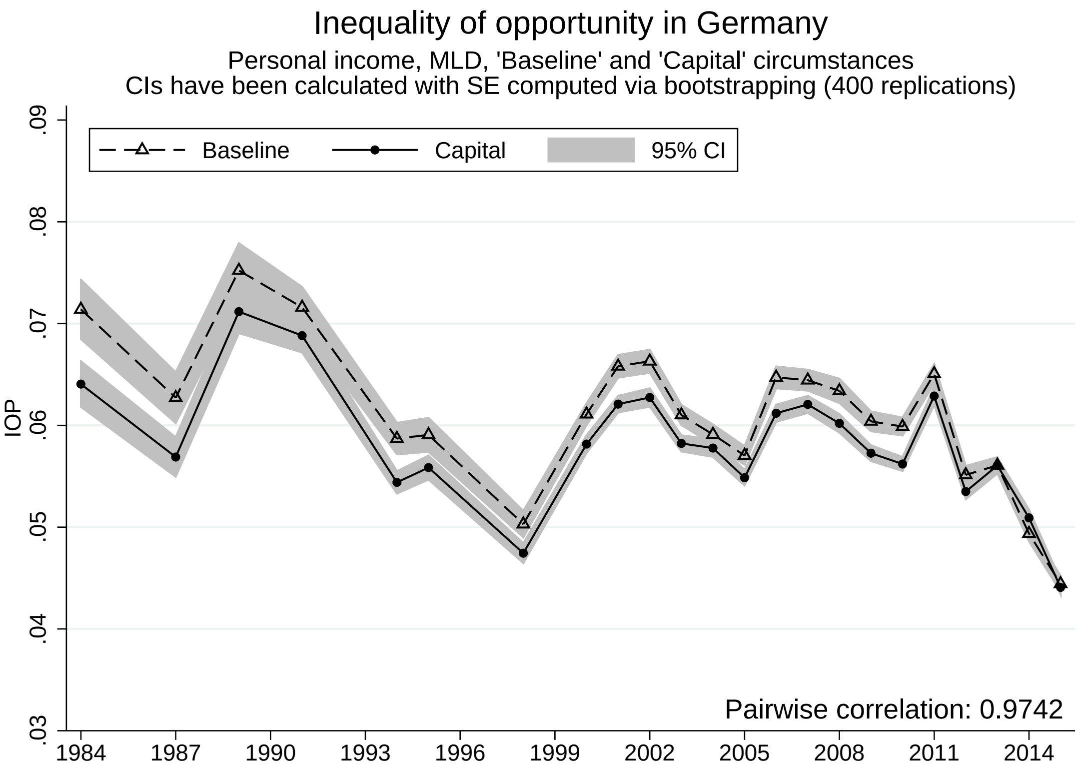


Figure 1: IOP with 'baseline' and 'capital' circumstances, Germany – MLD – Ferreira and Gignoux (2011) approach – LIS database

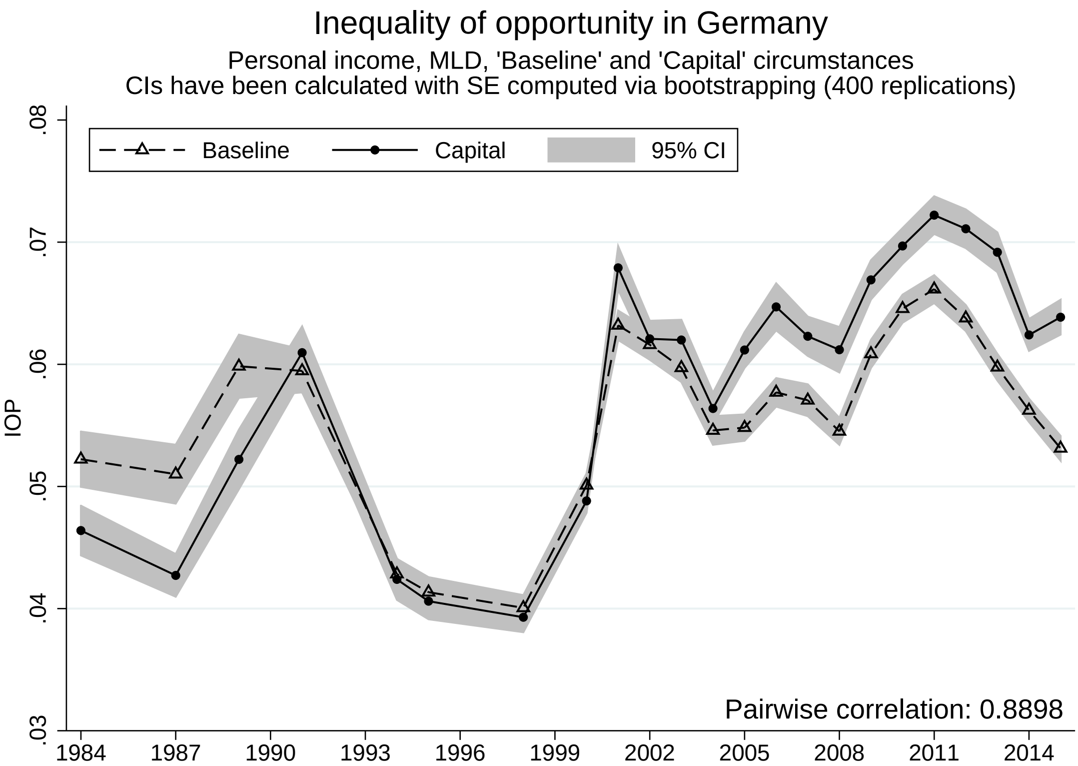


Figure 2: IOP with 'baseline' and 'capital' circumstances, Germany – MLD – Ex-ante between-types inequality – LIS database

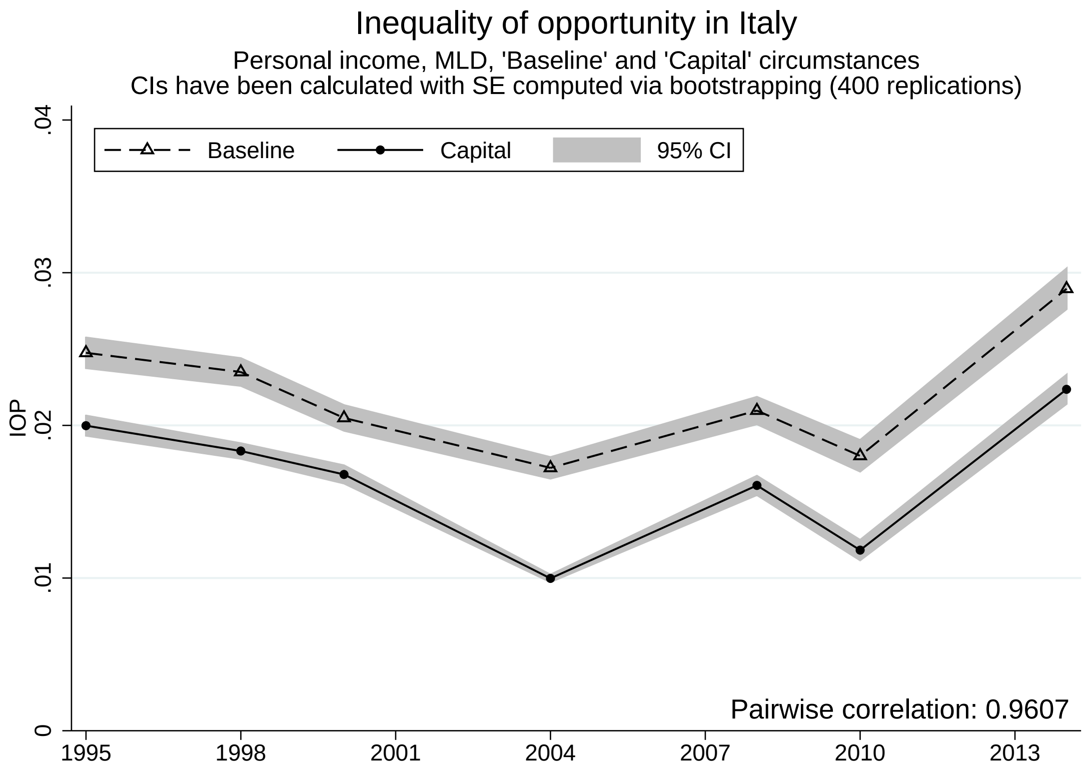
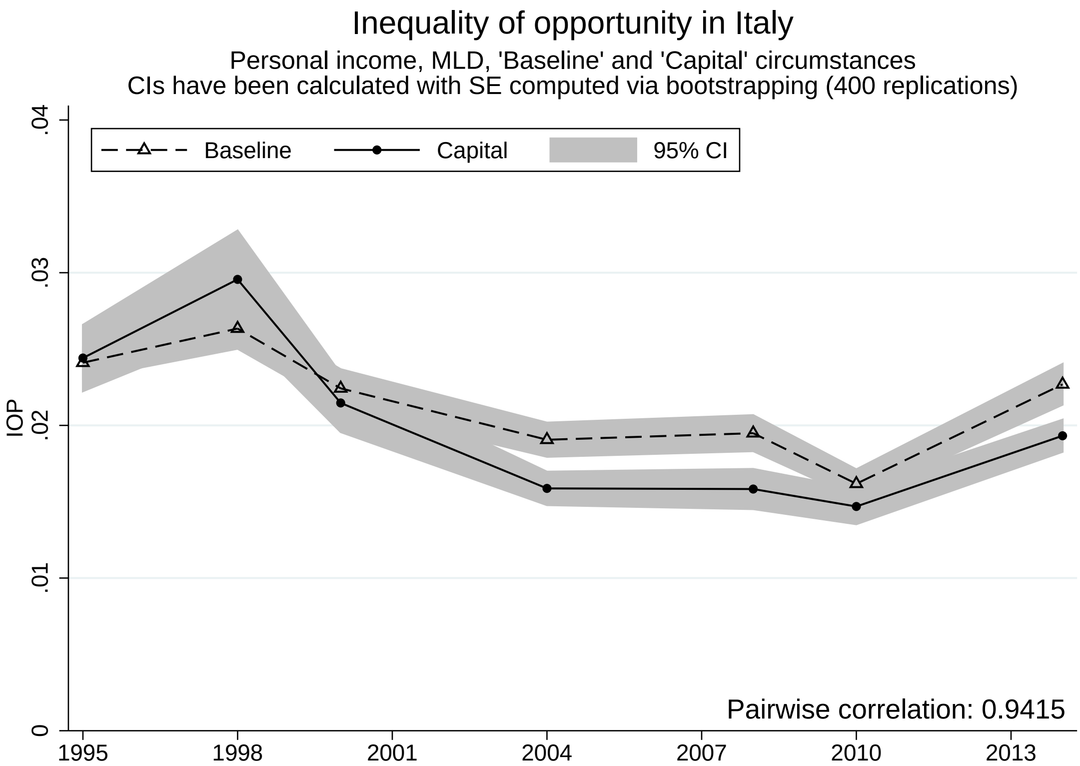


Figure 3: IOP with 'baseline' and 'capital' circumstances, Italy – MLD – Ferreira and Gignoux (2011) approach – LIS database



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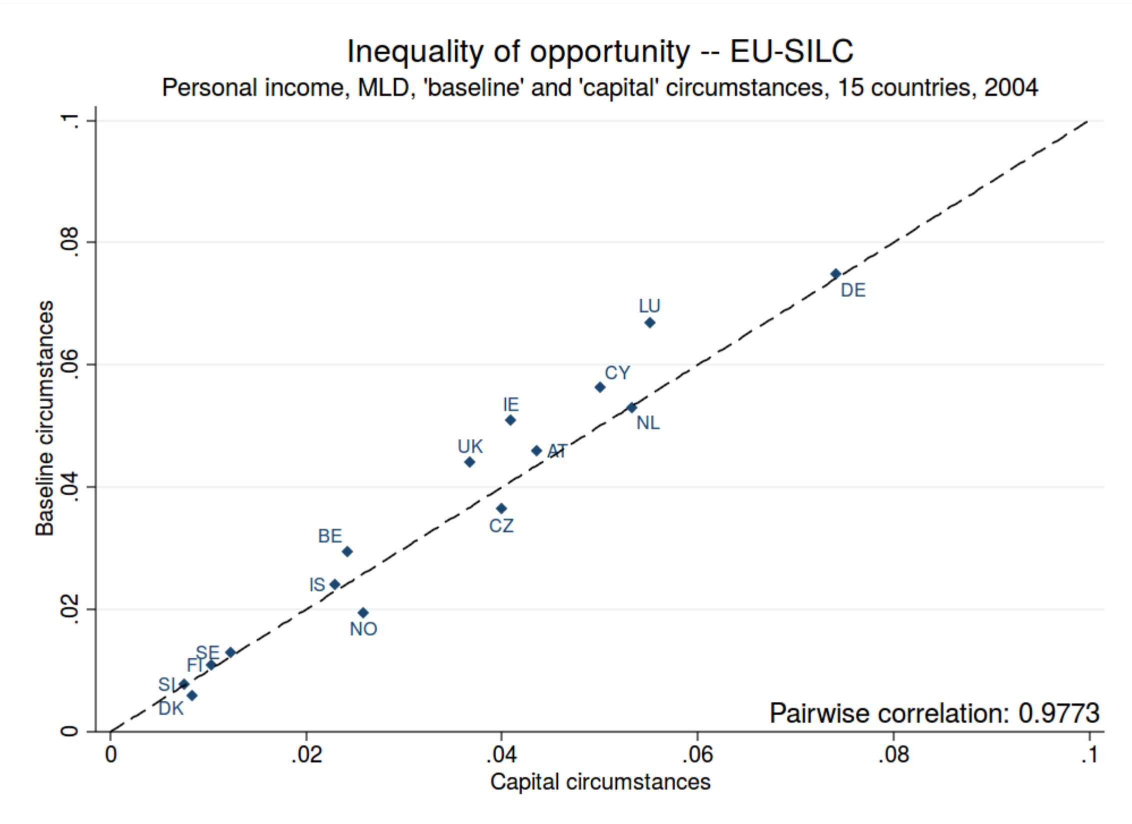

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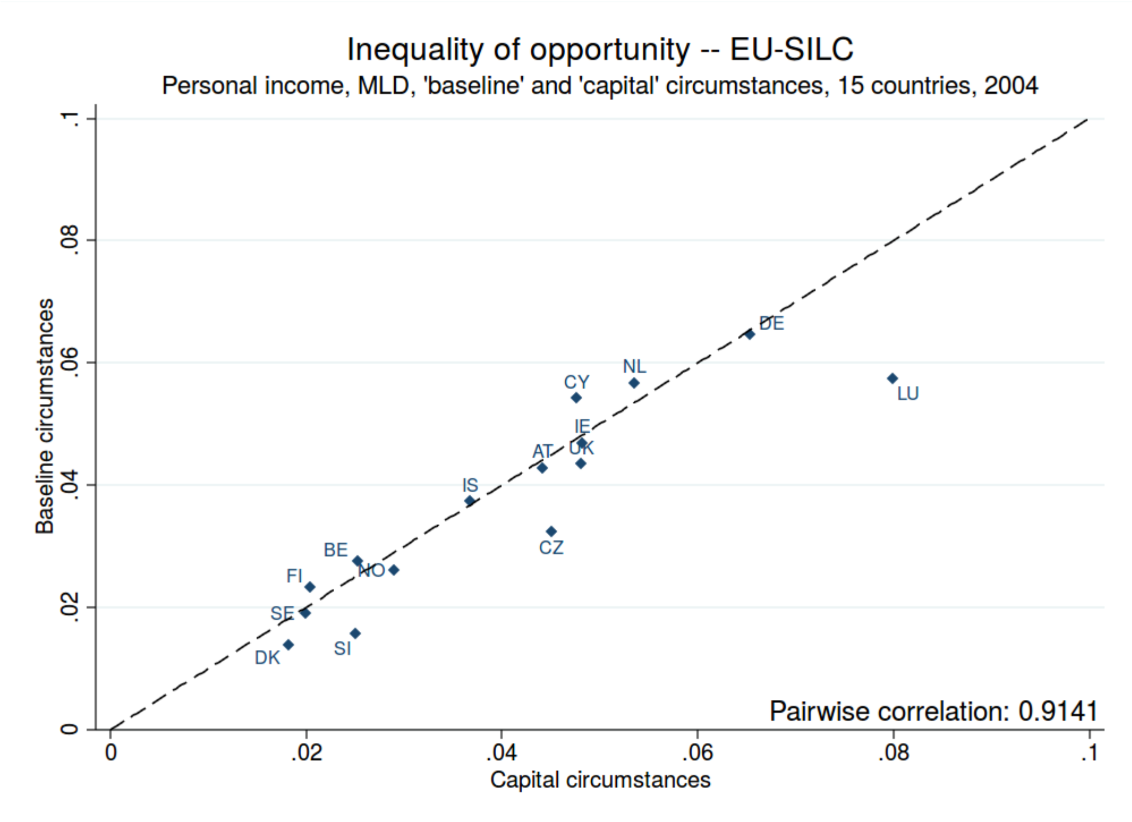


Figure 6: IOP with 'baseline' and 'capital' circumstances, 2004 (15 countries) – MLD – Ex-ante between-types inequality – EU-SILC database

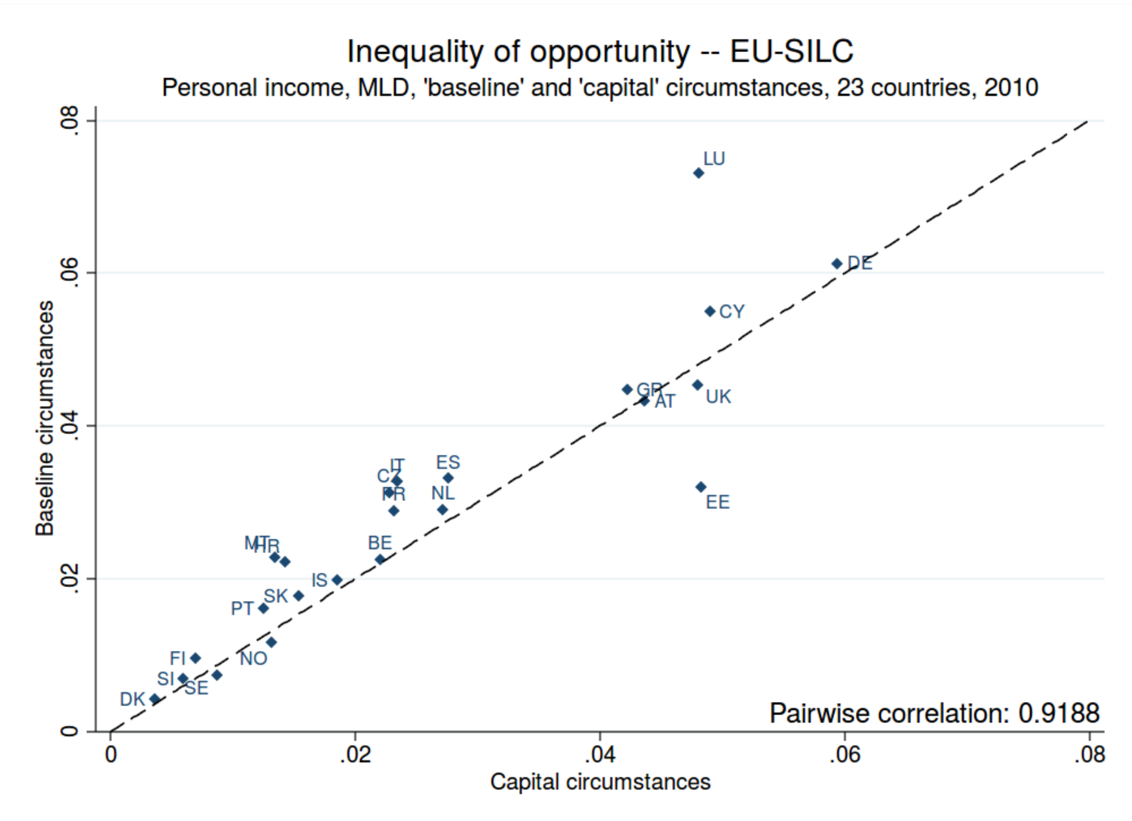


Figure 7: IOP with 'baseline' and 'capital' circumstances, 2010 (23 countries) – MLD – Ferreira and Gignoux (2011) approach – EU-SILC database

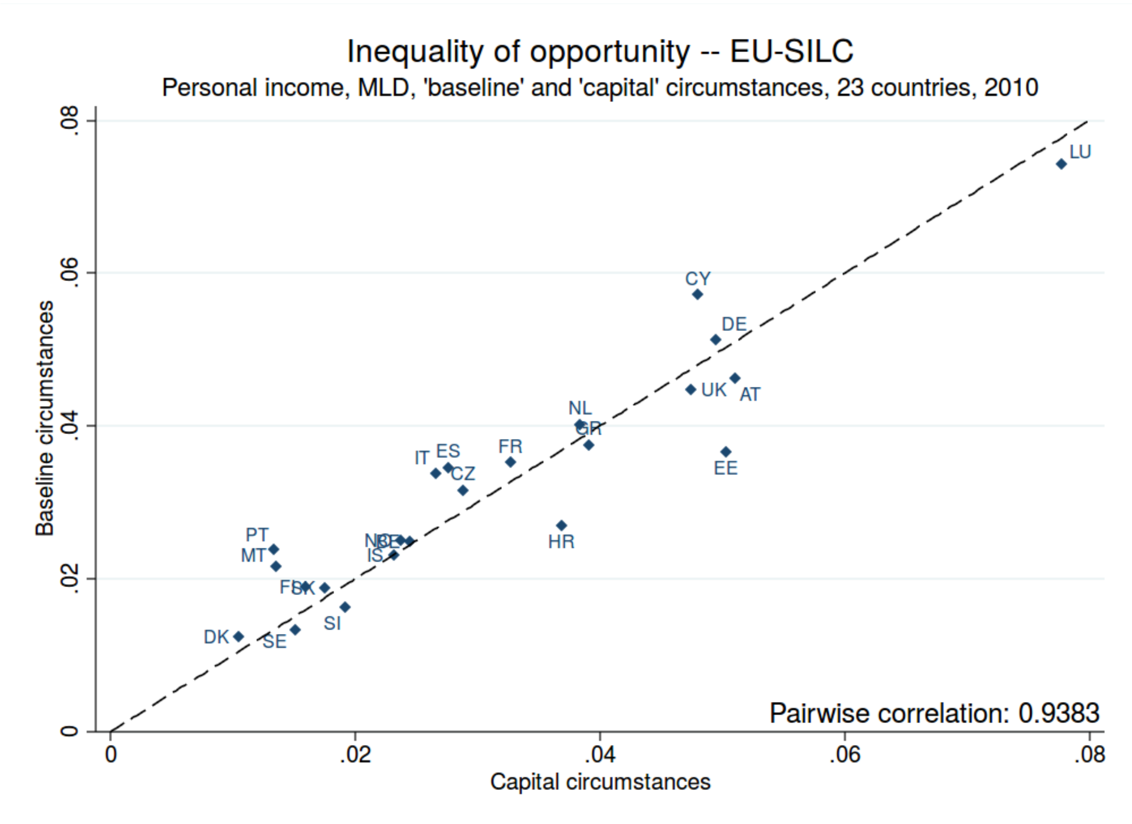
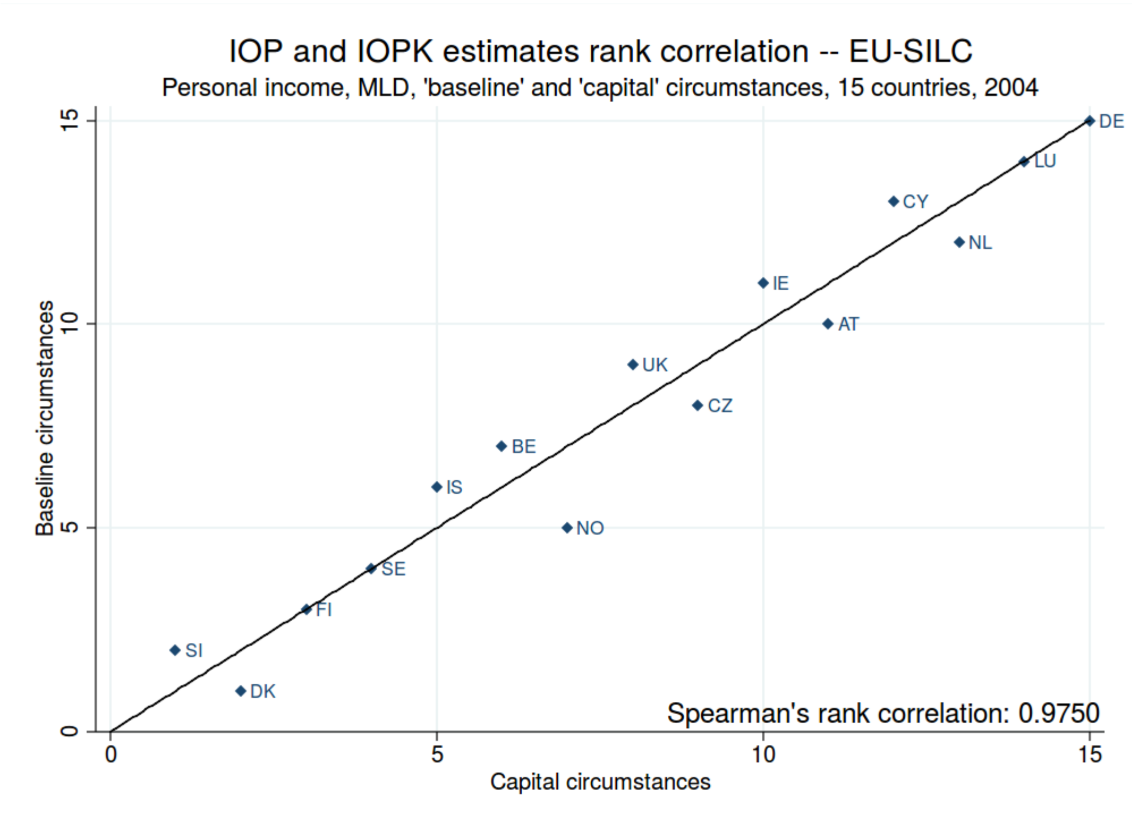


Figure 8: IOP with 'baseline' and 'capital' circumstances, 2010 (23 countries) – MLD – Ex-ante between-types inequality – EU-SILC database



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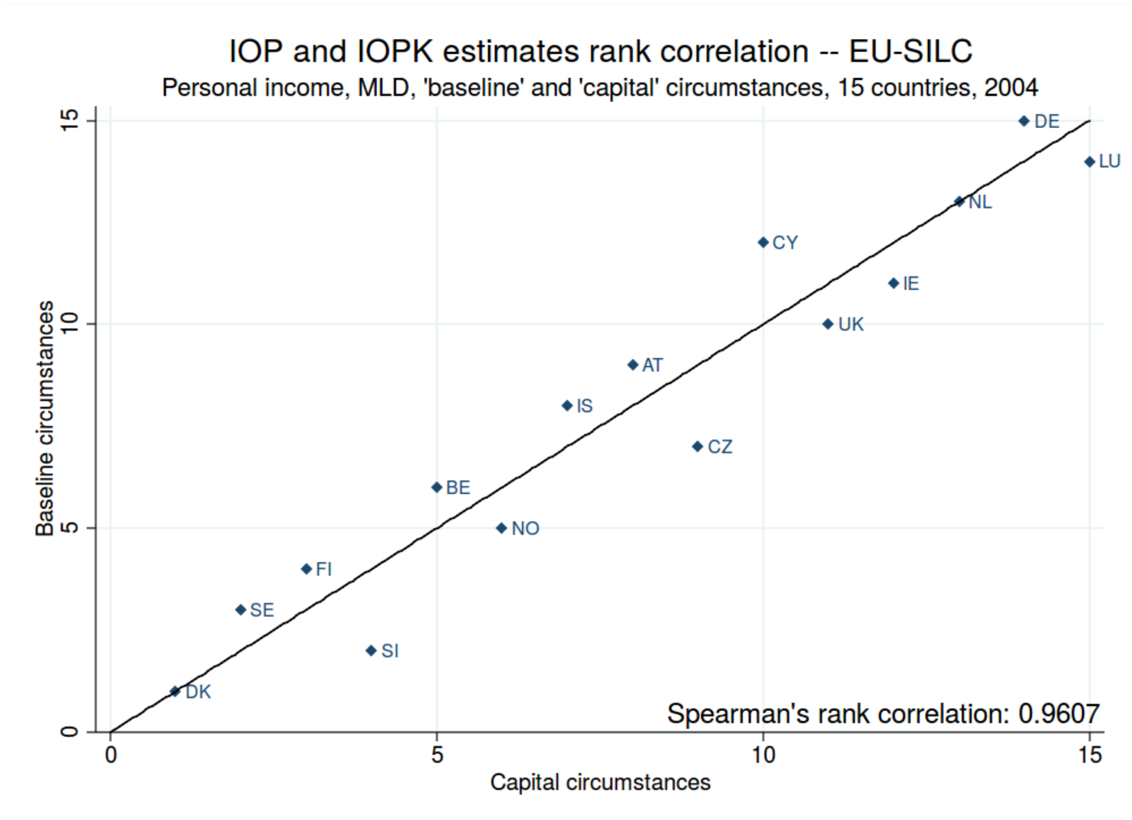

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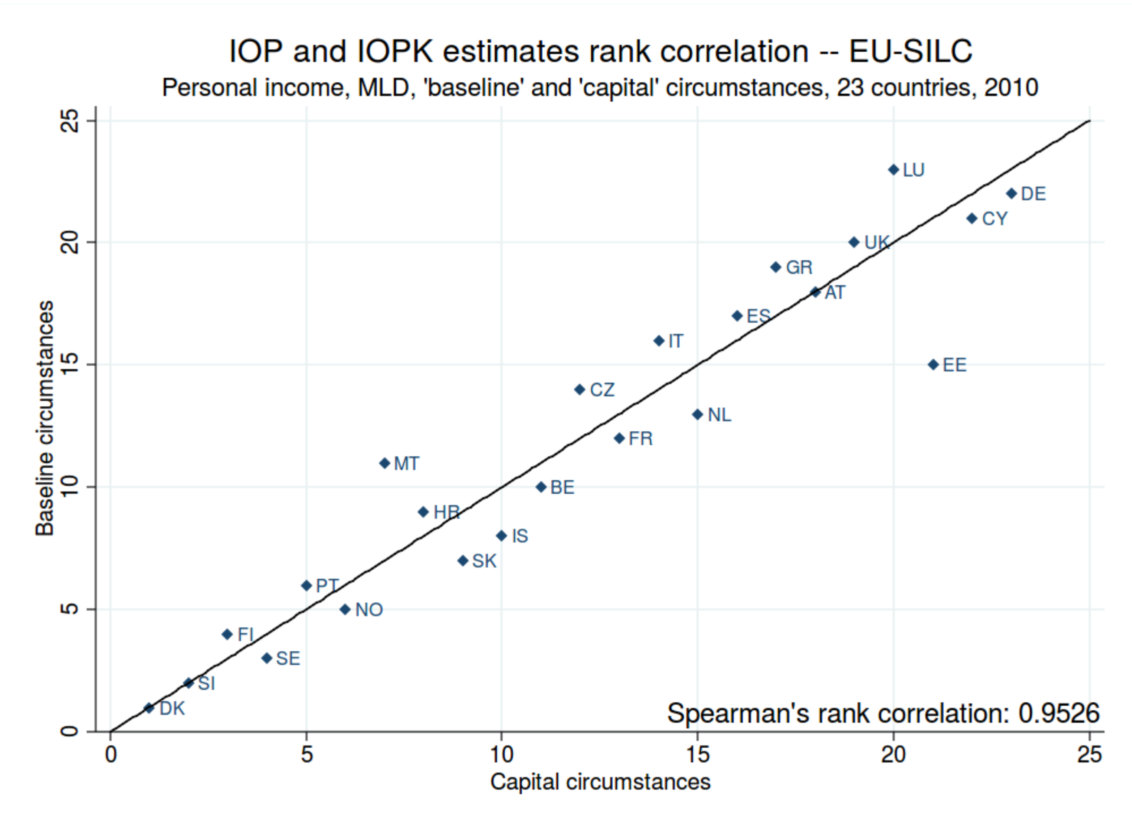

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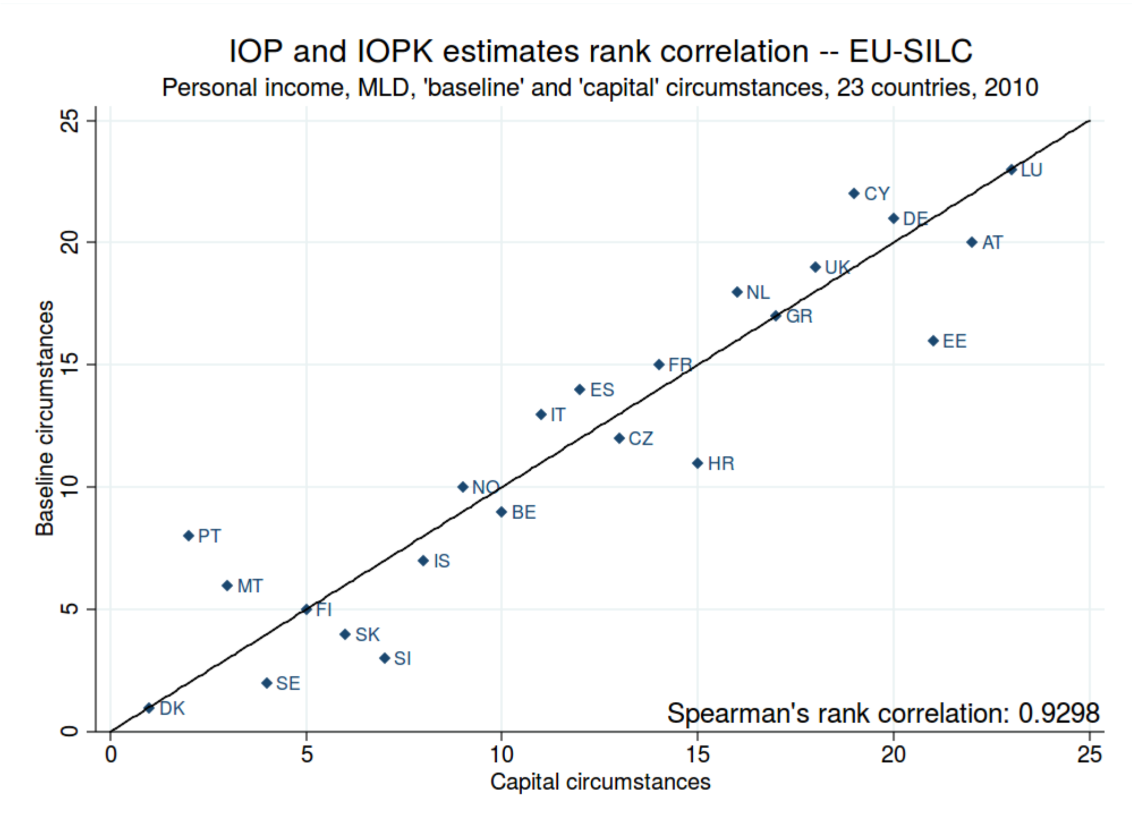


Figure 12: Ranks IOP with 'baseline' and 'capital' circumstances, 2010 (23 countries) – MLD – Ex-ante between-types inequality – EU-SILC database

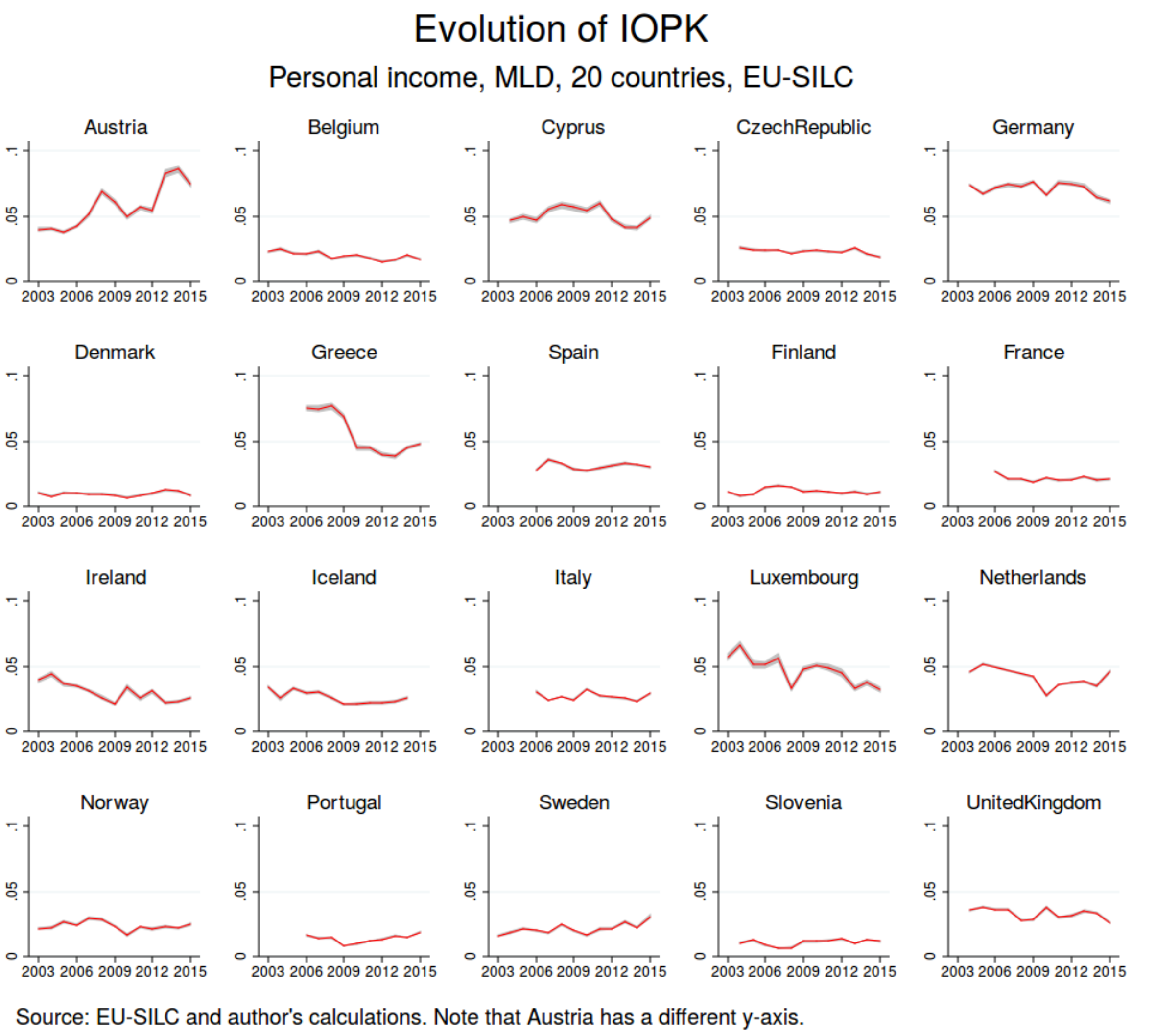
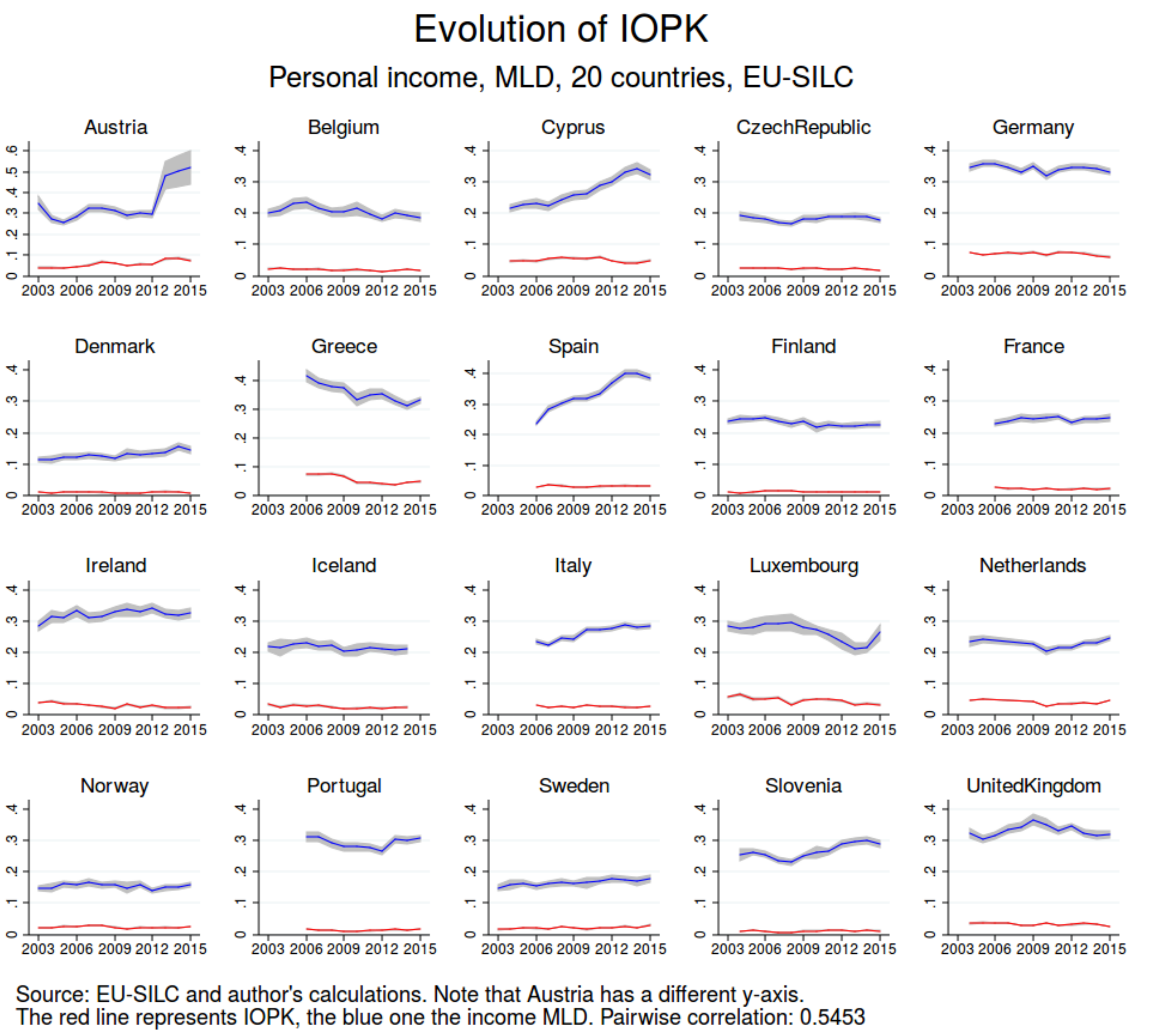


Figure 13: Evolution of IOP in Europe, estimated with 'capital' circumstances (23 countries) – MLD



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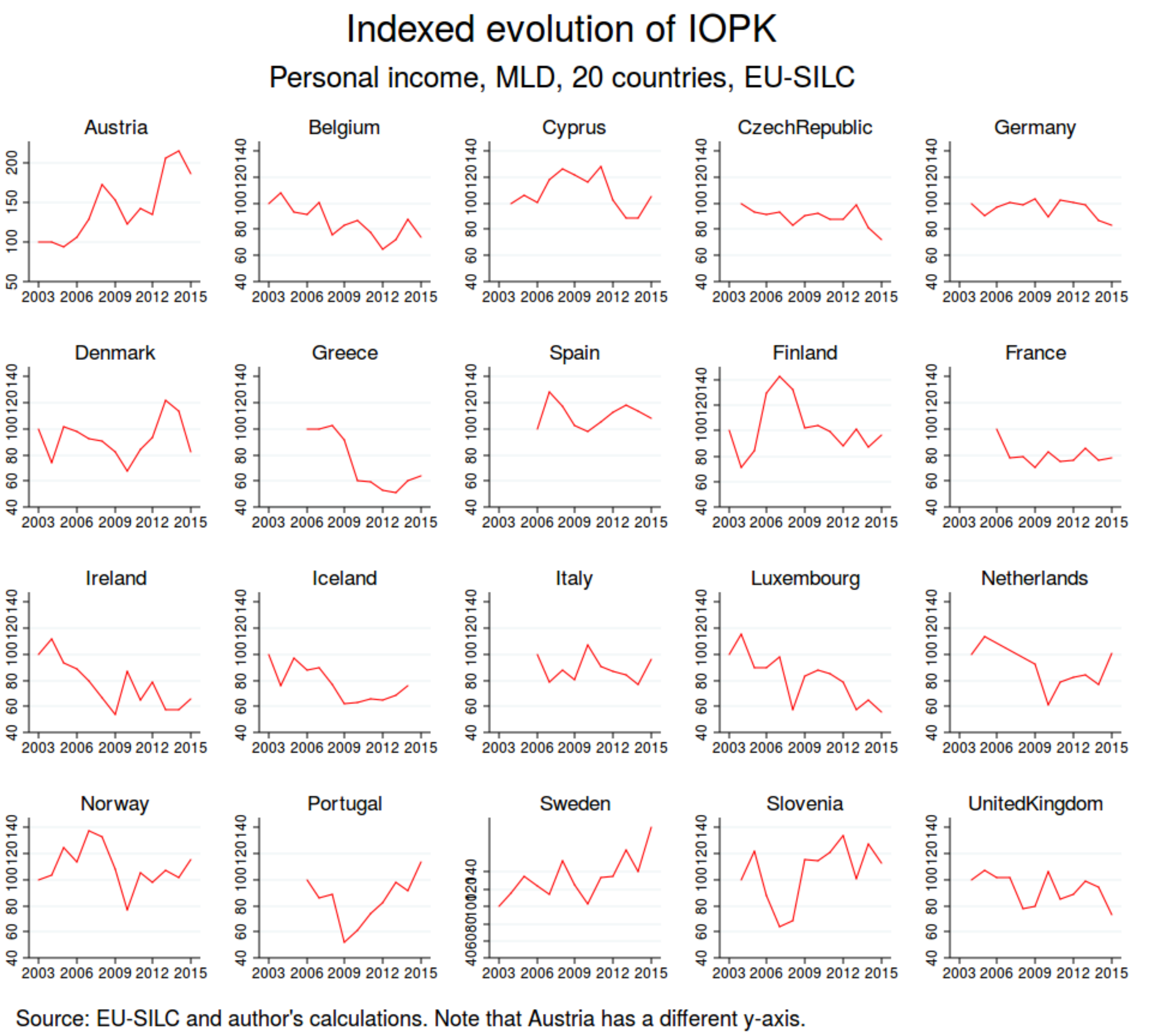


Figure 15: Indexed evolution of IOP in Europe, estimated with 'capital' circumstances (23 countries) – MLD

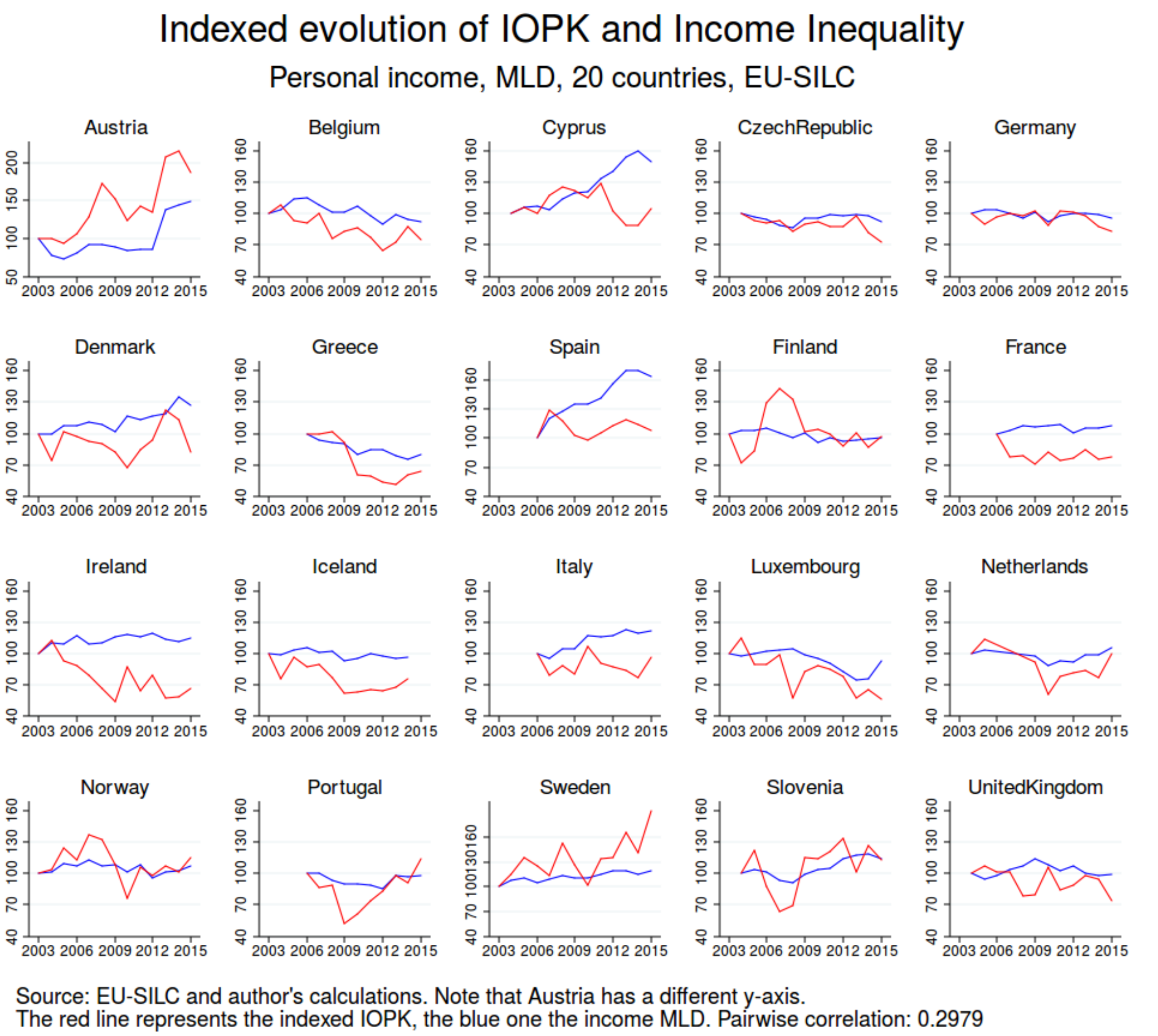


Figure 16: Indexed evolution of IOP and personal income inequality in Europe, IOP estimated with 'capital' circumstances (23 countries) – MLD

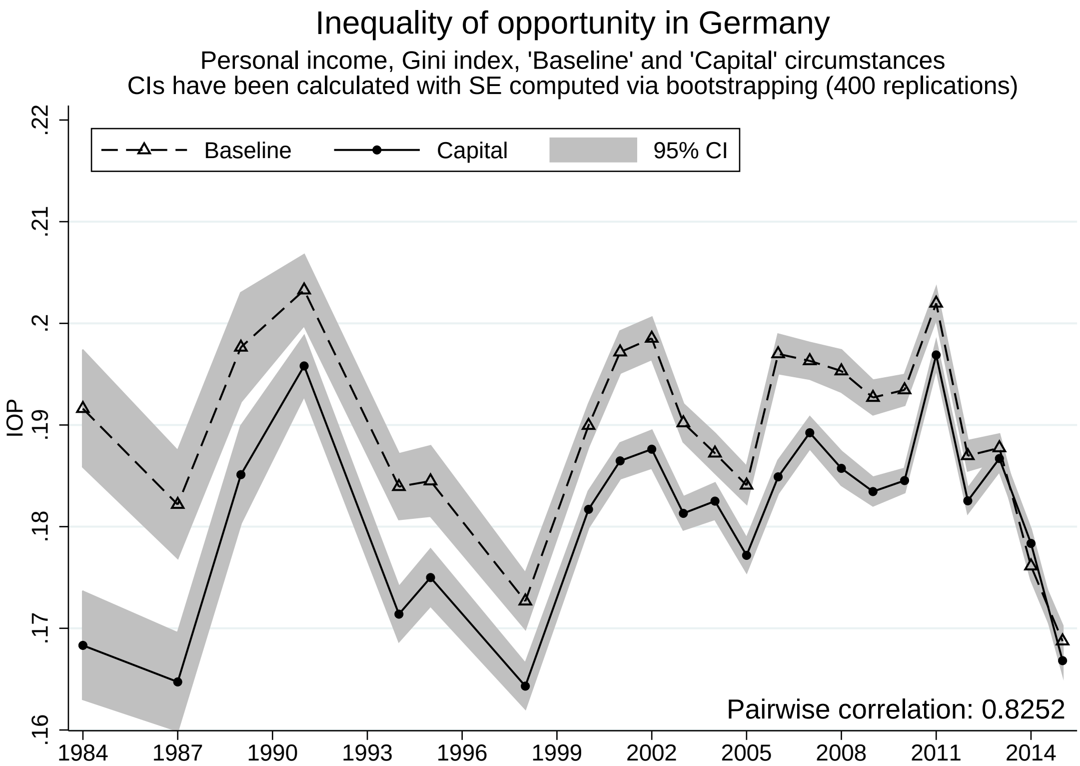
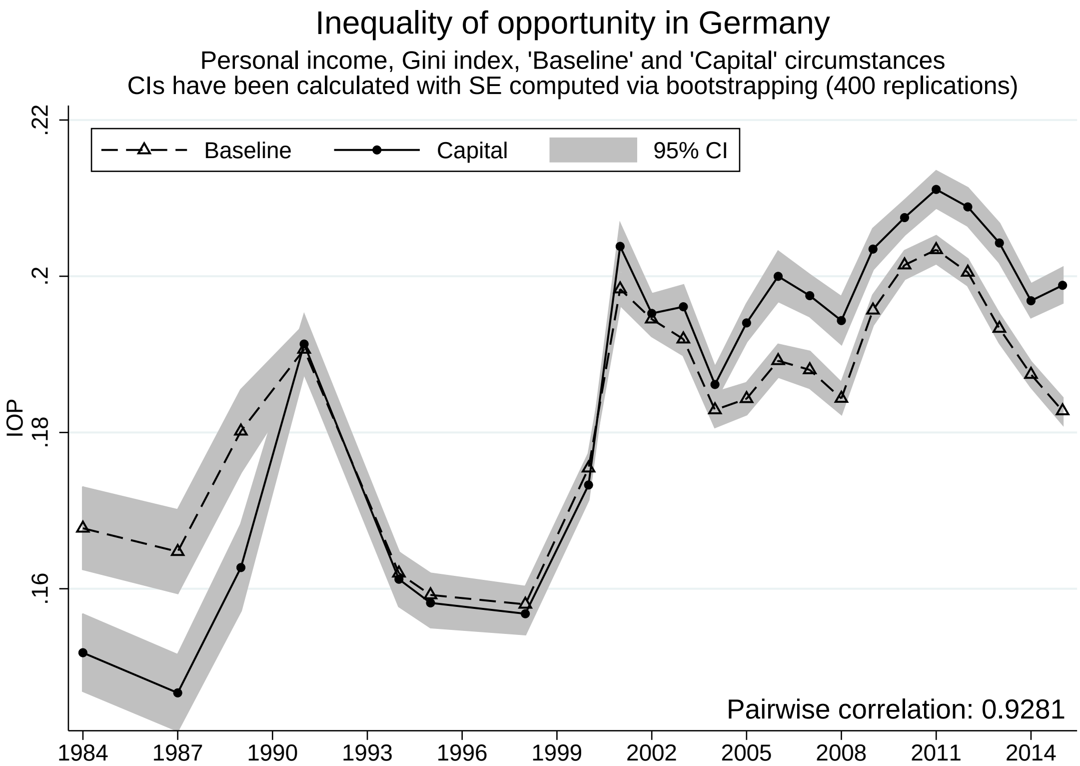


Figure 17: IOP with 'baseline' and 'capital' circumstances, Germany – Gini index – Ferreira and Gignoux (2011) approach – LIS database



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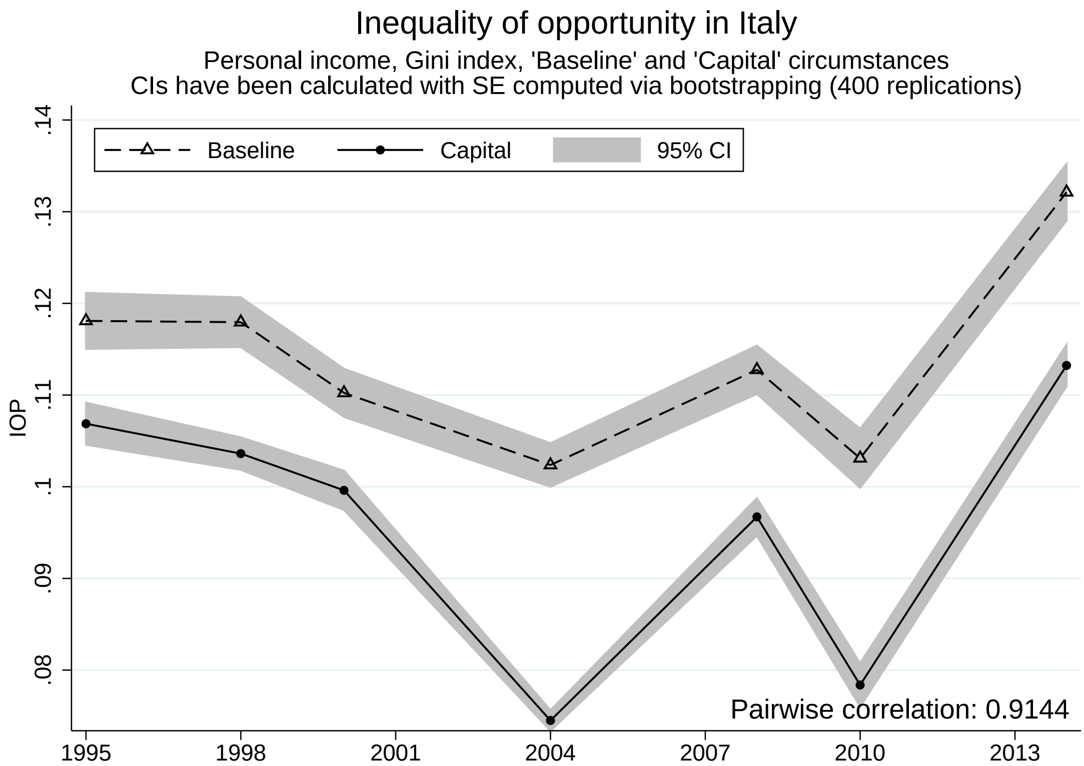

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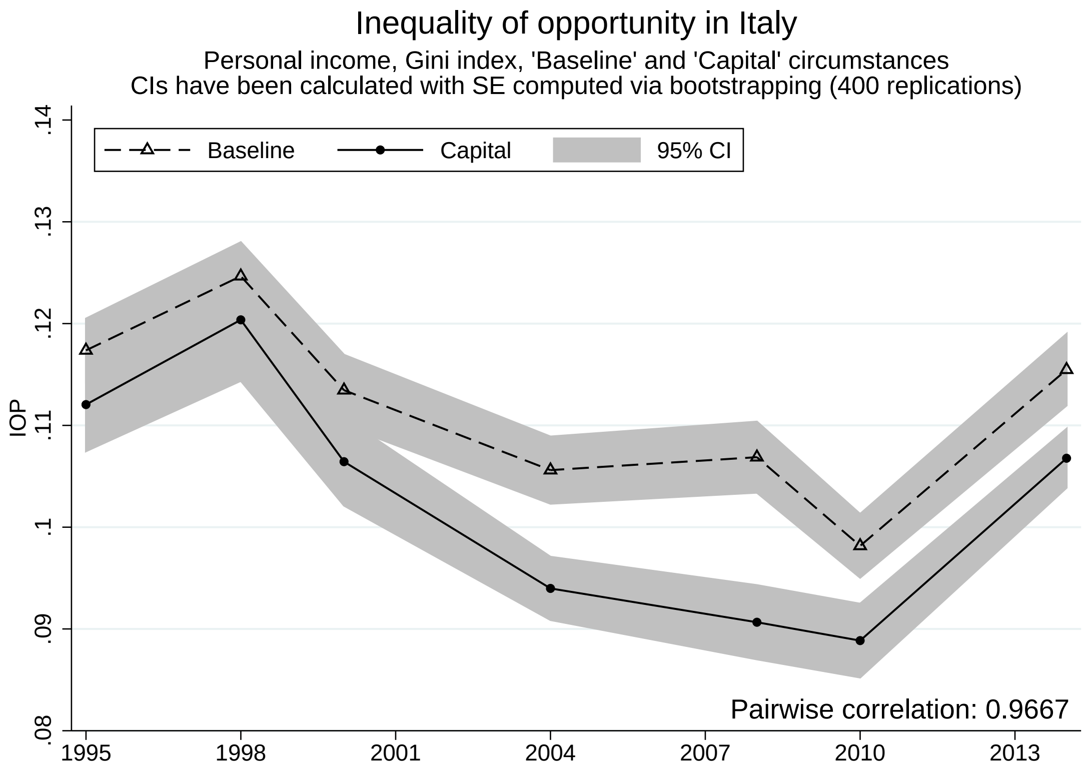

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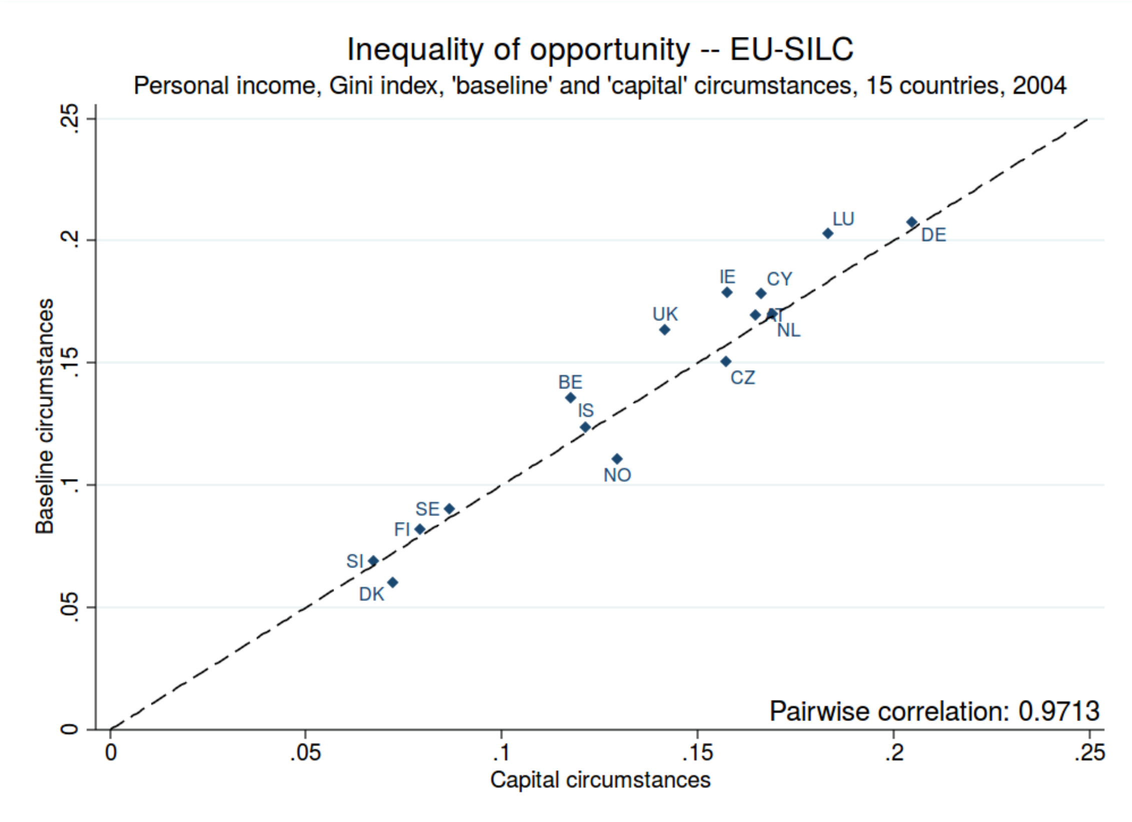

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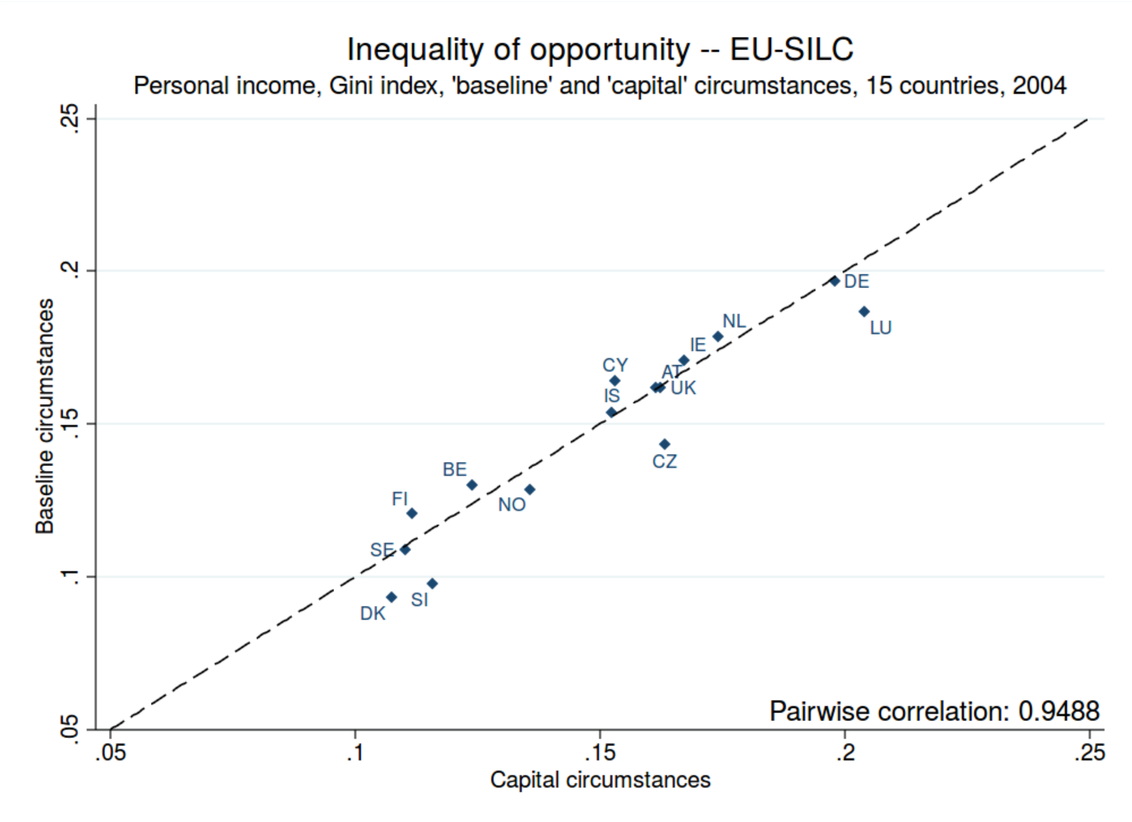

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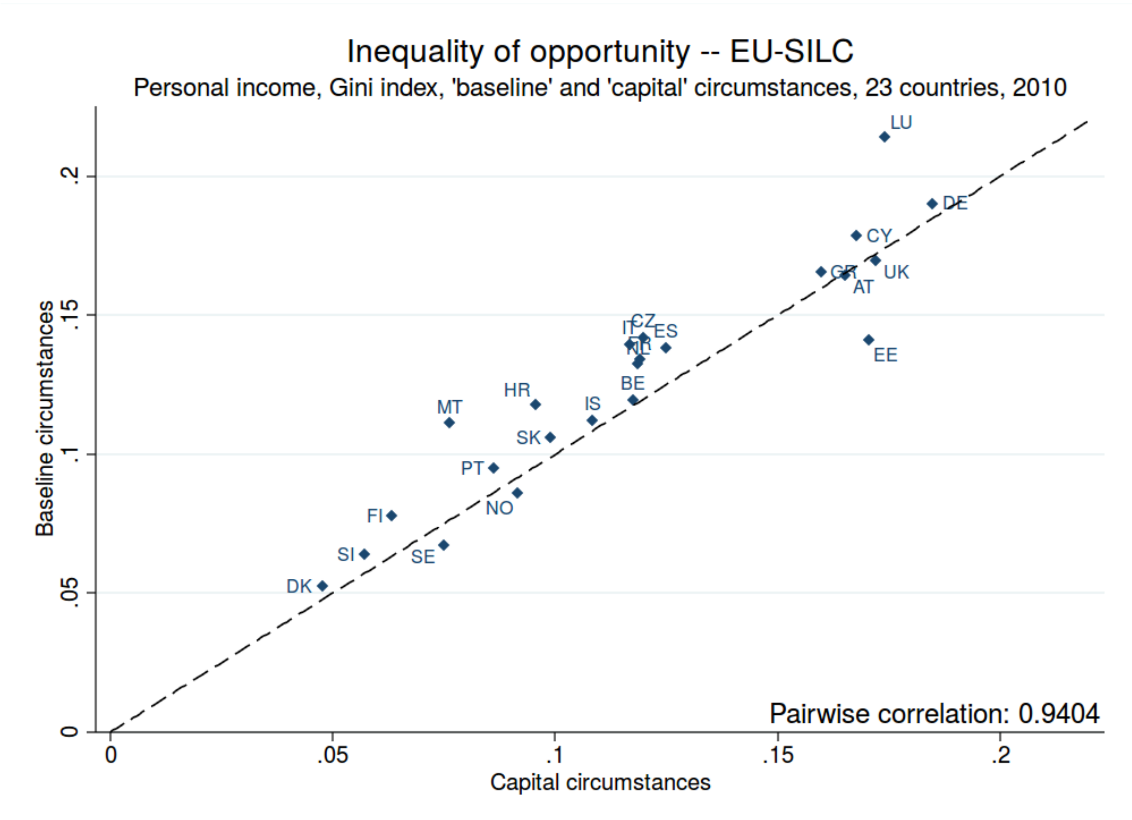

Figure 23: IOP with 'baseline' and 'capital' circumstances, 2010 (23 countries) – Gini index – Ferreira and Gignoux (2011) approach – EU-SILC database

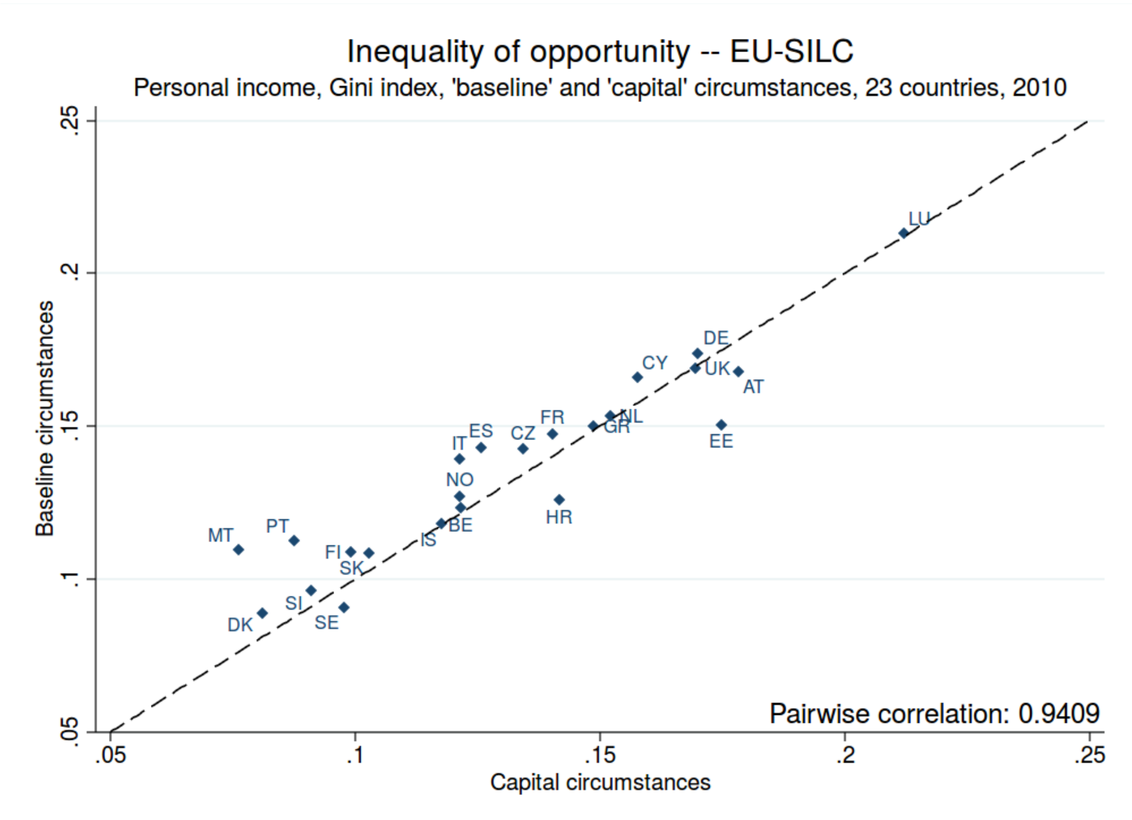

Figure 24: IOP with 'baseline' and 'capital' circumstances, 2010 (23 countries) – Gini index – Ex-ante between-types inequality – EU-SILC database

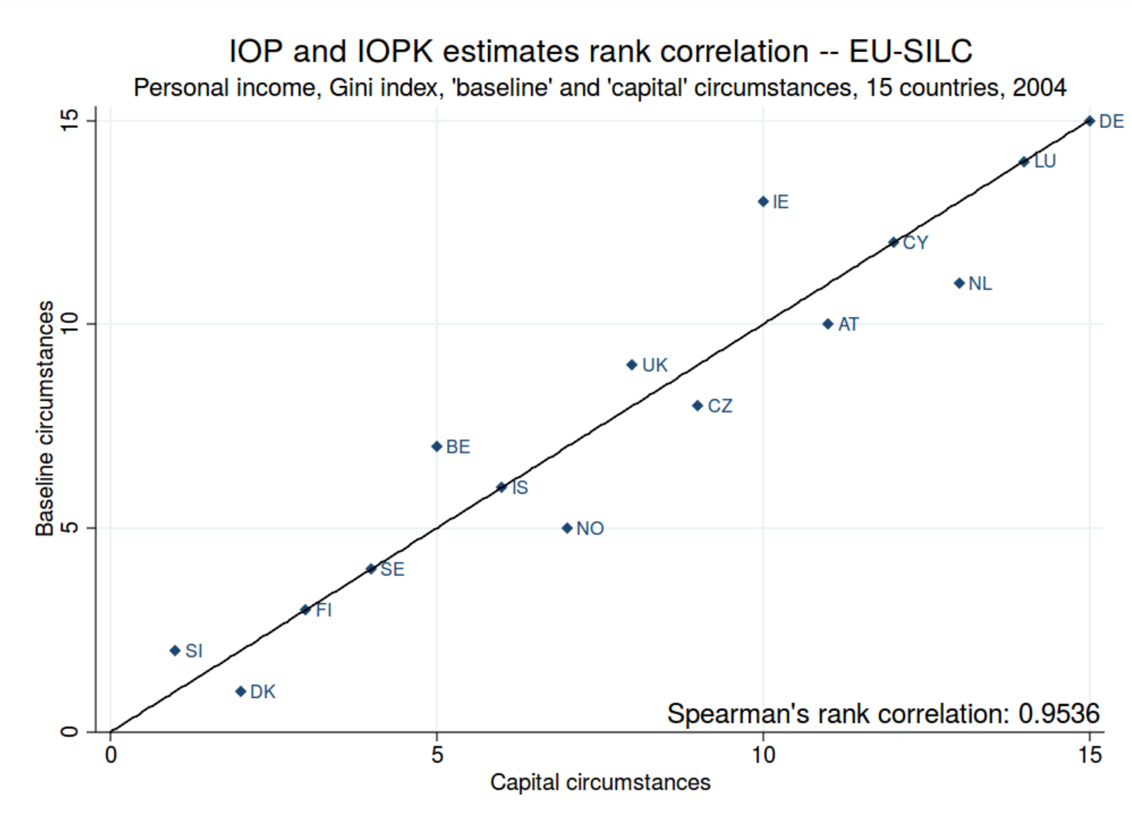

Figure 25: IOP with 'baseline' and 'capital' circumstances, 2004 (15 countries) – Gini index – Ferreira and Gignoux (2011) approach – EU-SILC database

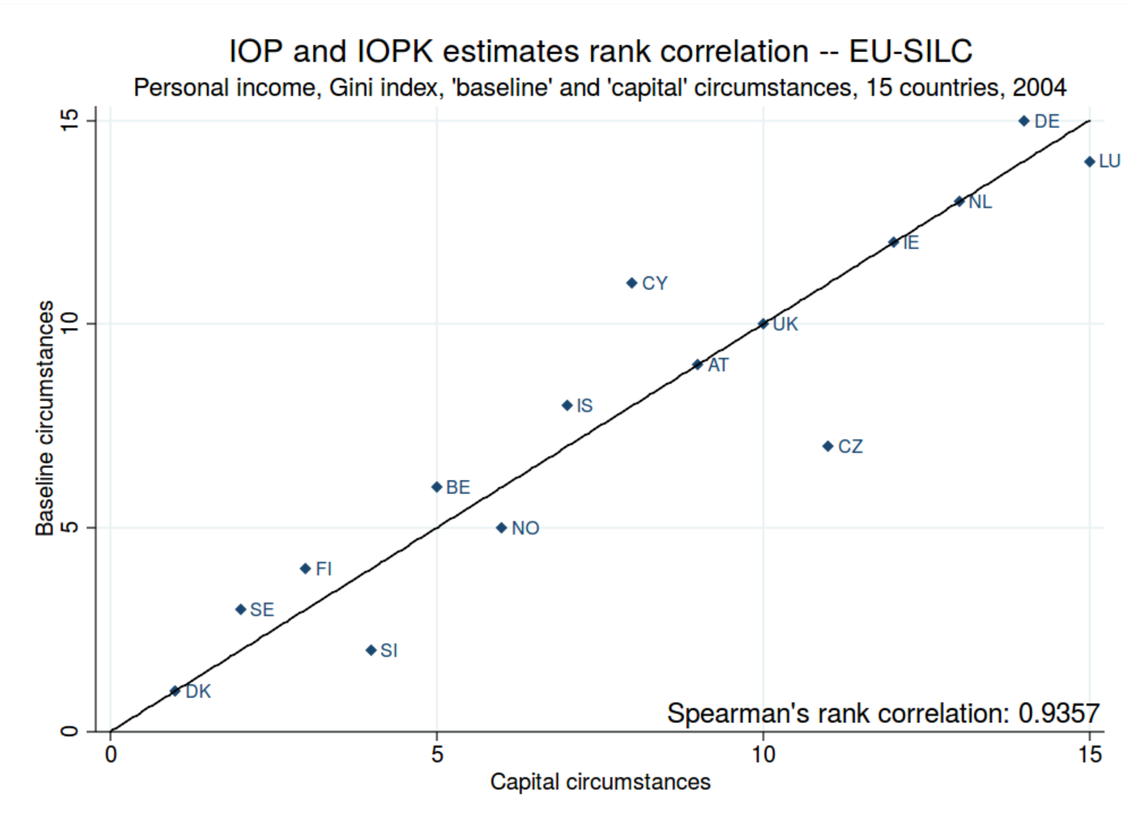

Figure 26: Ranks of IOP with 'baseline' and 'capital' circumstances, 2004 (15 countries) – Gini index – Ex-ante between-types inequality – EU-SILC database

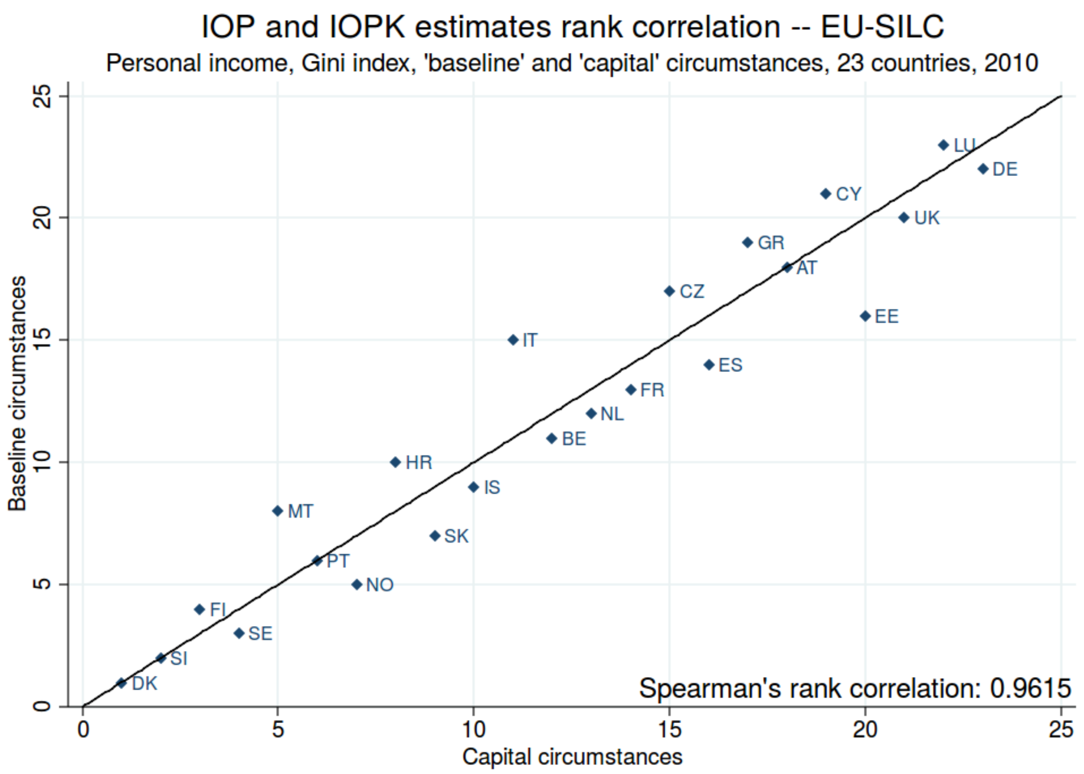

Figure 27: Ranks IOP with 'baseline' and 'capital' circumstances, 2010 (23 countries) – Gini index – Ferreira and Gignoux (2011) approach – EU-SILC database

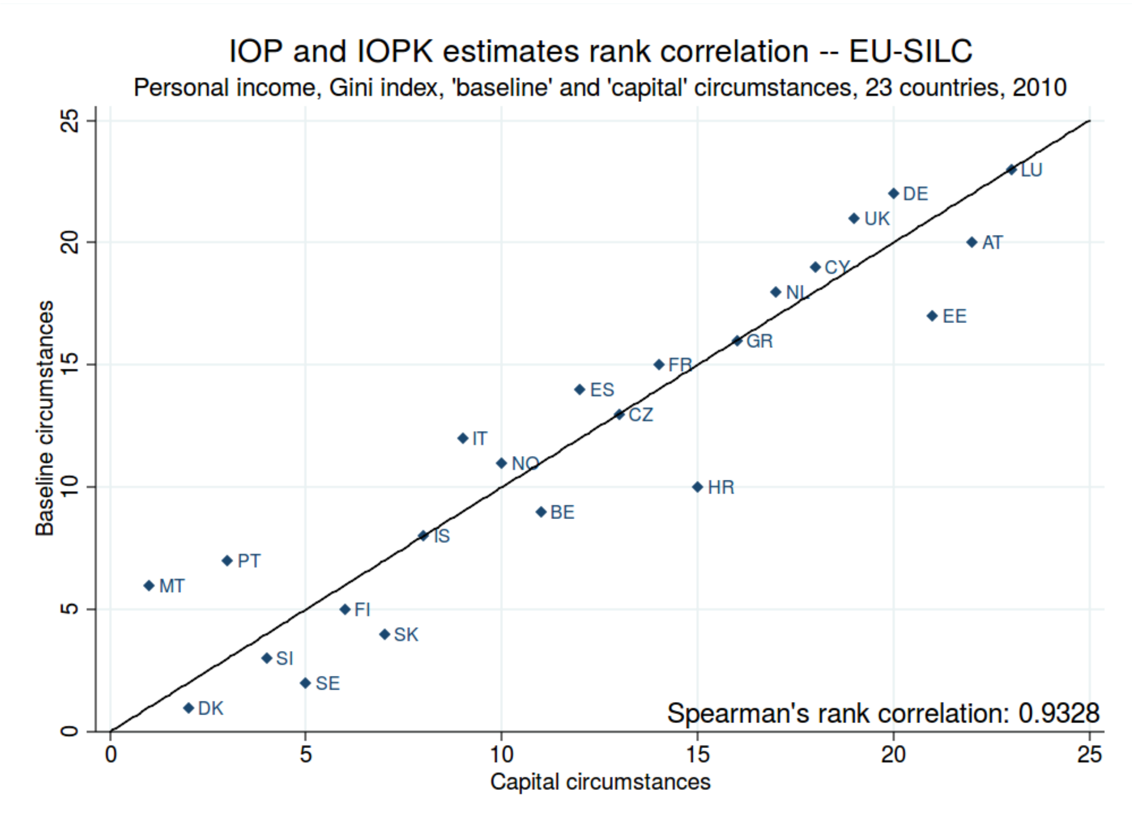

Figure 28: Ranks IOP with 'baseline' and 'capital' circumstances, 2010 (23 countries) – Gini index – Ex-ante between-types inequality – EU-SILC database

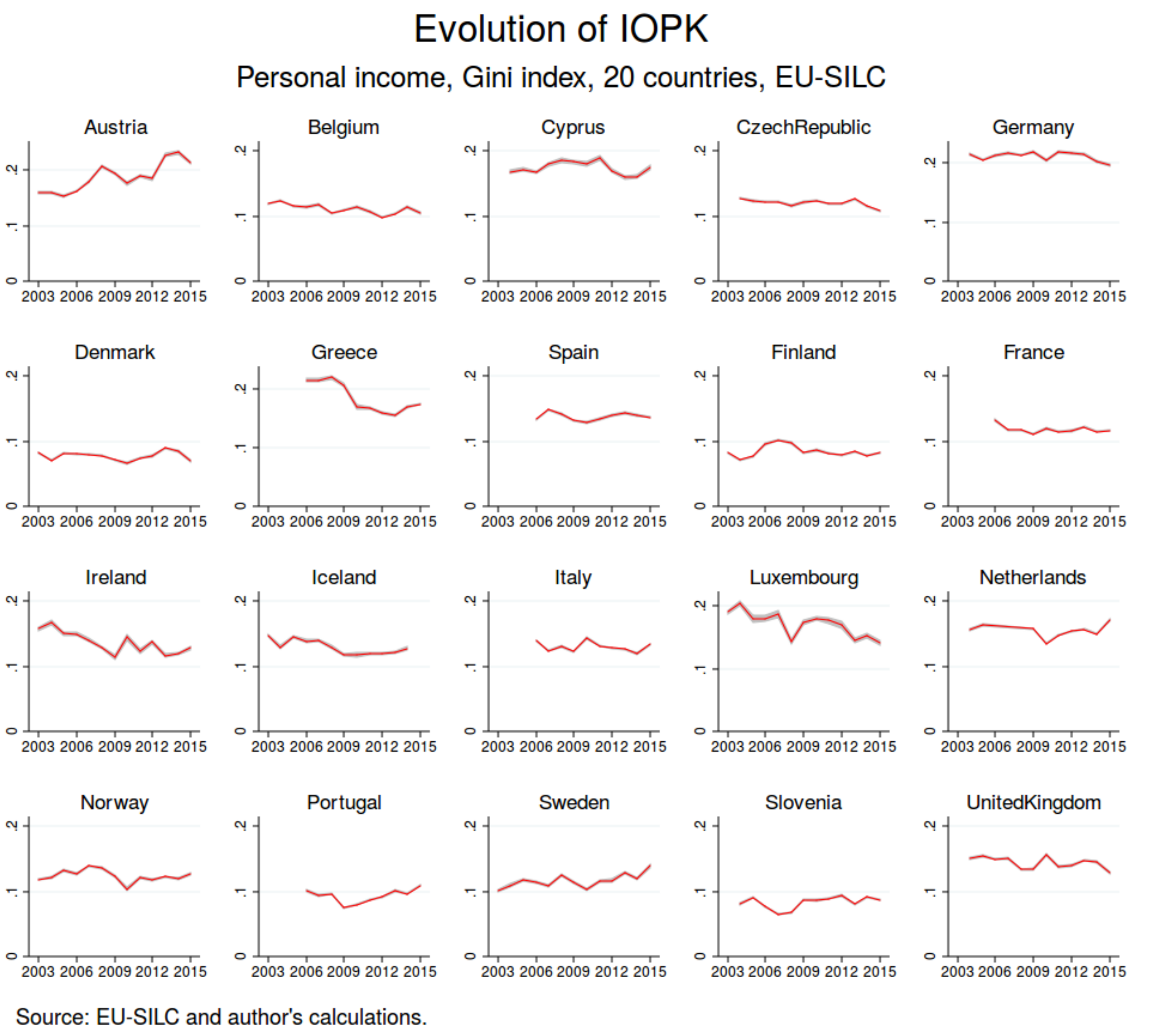

Figure 29: Evolution of IOP in Europe, estimated with 'capital' circumstances (23 countries) – Gini index

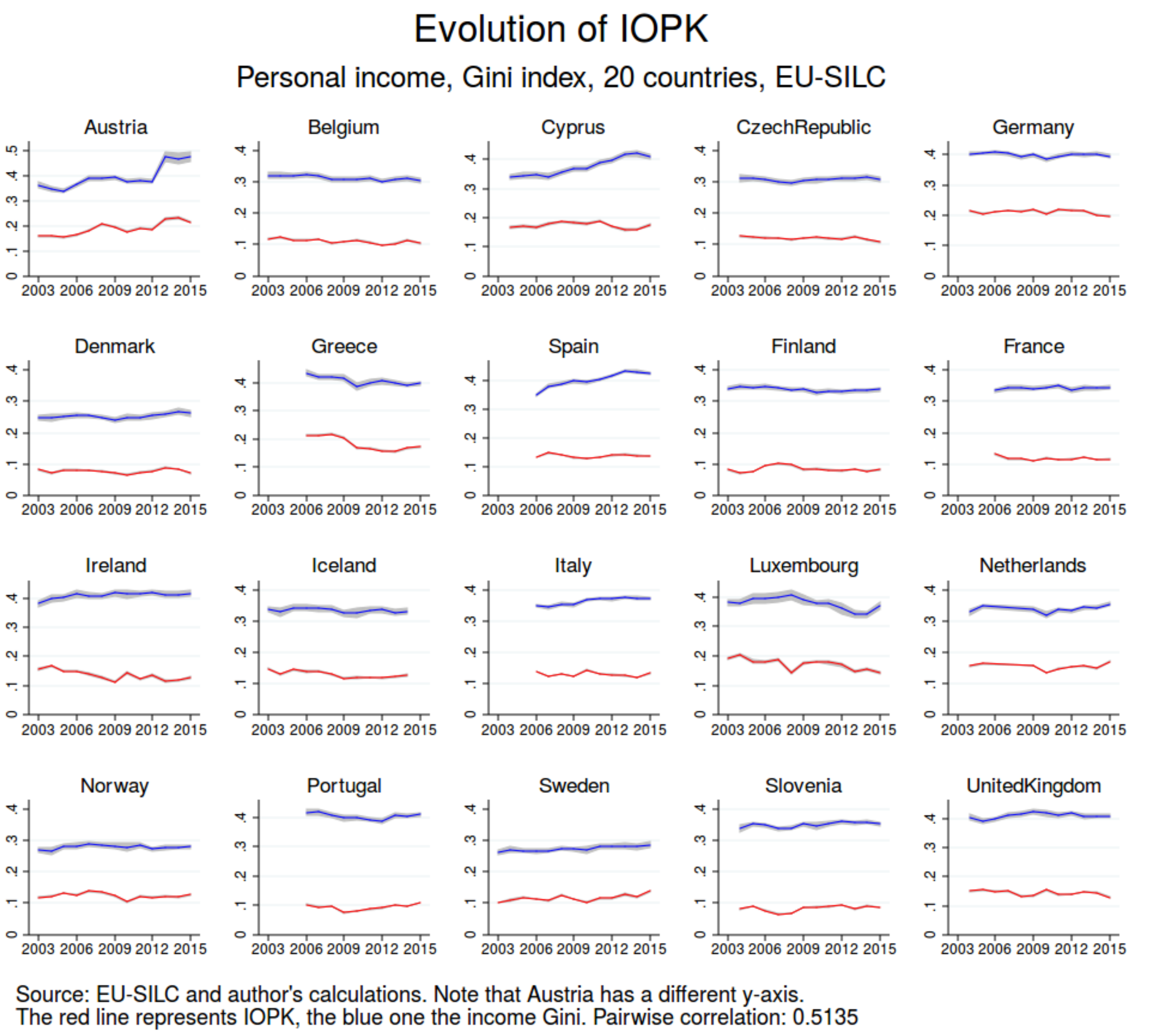

Figure 30: Evolution of IOP and personal income inequality in Europe, IOP estimated with 'capital' circumstances (23 countries) – Gini index

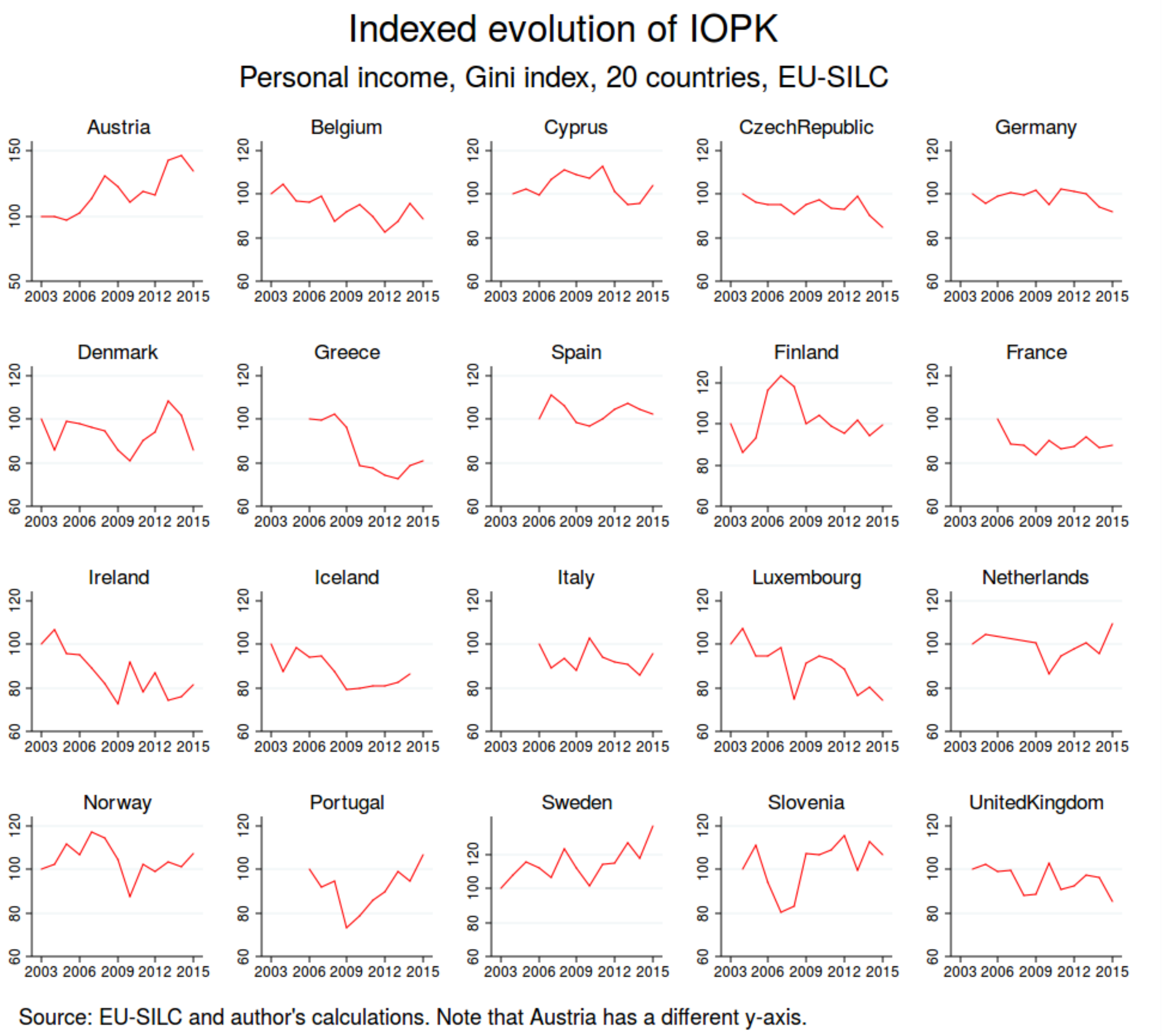

Figure 31: Indexed evolution of IOP in Europe, estimated with 'capital' circumstances (23 countries) – Gini index

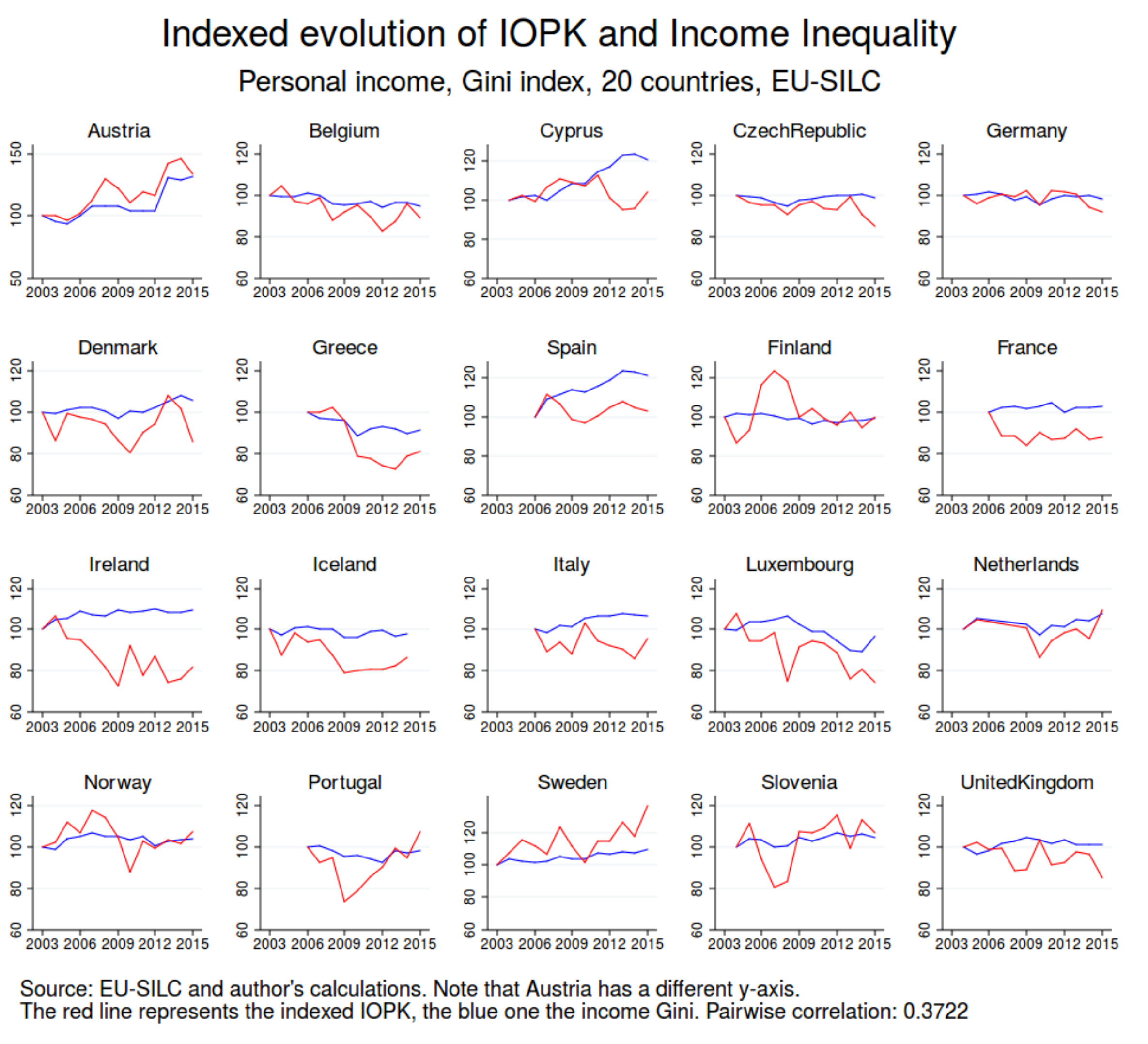

Figure 32: Indexed evolution of IOP and personal income inequality in Europe, IOP estimated with 'capital' circumstances (23 countries) – Gini index

List of Tables

Table 1: Distribution of an outcome according to circumstances and effort.

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

Table 2: Removing withing types inequality.

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

Table 3: A fictitious distribution of parental education

Parental education	Frequency	Percent	Cumulative
Primary or less	6,000	60	60
Secondary	3,000	30	90
Tertiary or more	1,000	10	100
Total	10,000	100	

The highest education level attained by any of the parents is considered.

Table 4: A fictitious distribution of capital income ratio

Capital income ratio	Frequency	Percent	Cumulative
$Kratio \leq 0.01$	6,000	60	60
$0.01 < Kratio \leq 0.03$	3,000	30	90
$Kratio > 0.03$	1,000	10	100
Total	10,000	100	

$Kratio$ is the ratio of household capital income to household total income.

Table 5: Average marginal effects after ordered logit. Dependent variable: capital income levels. EU-SILC database.

	(1) Average marginal effects			(2) Average marginal effects		
	Pr(=1)	Pr(=2)	Pr(=3)	Pr(=1)	Pr(=2)	Pr(=3)
Parental education						
Secondary	−0.2260**	0.0941**	0.1320**	−0.1990**	0.0807**	0.1183**
	(0.0756)	(0.0307)	(0.0465)	(0.0669)	(0.0268)	(0.0412)
Tertiary or more	−0.2610***	0.1024***	0.1585***	−0.2276***	0.0880***	0.1397***
	(0.0715)	(0.0277)	(0.0454)	(0.0640)	(0.0248)	(0.0401)
Parental occupation						
Skilled workers	−0.0746***	0.0295***	0.0451***	−0.0568***	0.0209***	0.0359***
(ISCO 4-8)	(0.0133)	(0.0057)	(0.0088)	(0.0148)	(0.0058)	(0.0095)
Professionals	−0.0547***	0.0223**	0.0324***	−0.0219	0.0085	0.0134
(ISCO 1-3)	(0.0165)	(0.0071)	(0.0098)	(0.0170)	(0.0067)	(0.0104)
Education						
Secondary				−0.1125***	0.0486***	0.0639***
				(0.0193)	(0.0090)	(0.0114)
Tertiary or more				−0.1449***	0.0598***	0.0851***
				(0.0242)	(0.0110)	(0.0145)
Occupation						
Skilled workers				−0.0828***	0.0358***	0.0469***
(ISCO 4-8)				(0.0103)	(0.0037)	(0.0072)
Professionals				−0.1302***	0.0527***	0.0775***
(ISCO 1-3)				(0.0119)	(0.0044)	(0.0093)
Age						
40 to 49				−0.0833***	0.0336***	0.0497***
				(0.0100)	(0.0058)	(0.0051)
50 to 59				−0.1693***	0.0587***	0.1106***
				(0.0154)	(0.0098)	(0.0106)
Year dummies						
2011	0.0567	−0.0202	−0.0365	0.0469	−0.0163	−0.0305
	(0.0423)	(0.0162)	(0.0263)	(0.0405)	(0.0149)	(0.0258)
Observations	158,423	158,423	158,423	155,859	155,859	155,859

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard clustered by country errors in parentheses.

Note: Average marginal effects on the three levels of the dependent variable *capital income levels*; effects with respect to the base category ("Primary or less" in the case of parental and individual education and "Unskilled workers (ISCO 9)" for occupation). These regressions include observations from 2004 and 2010 of Austria, Belgium, Croatia, Cyprus, Czech Republic, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, Malta, the Netherlands, Norway, Portugal, Sweden, Slovakia, Slovenia and the United Kingdom (24 countries).

Table 6: Average marginal effects after ordered logit. Dependent variable: absolute dynastic component of capital income levels. EU-SILC database.

	(1) Average marginal effects			(2) Average marginal effects		
	Pr(=1)	Pr(=2)	Pr(=3)	Pr(=1)	Pr(=2)	Pr(=3)
Parental education						
Secondary	−0.2641***	0.1051***	0.1590**	−0.2740***	0.1097***	0.1644**
	(0.0723)	(0.0259)	(0.0522)	(0.0676)	(0.0257)	(0.0500)
Tertiary or more	−0.2519**	0.1031***	0.1488**	−0.3047***	0.1132***	0.1914***
	(0.0802)	(0.0290)	(0.0546)	(0.0660)	(0.0246)	(0.0514)
Parental occupation						
Skilled workers (ISCO 4-8)	−0.0240	0.0079	0.0161	−0.0421*	0.0155	0.0266*
	(0.0193)	(0.0067)	(0.0130)	(0.0207)	(0.0084)	(0.0131)
Professionals (ISCO 1-3)	0.0475*	−0.0182	−0.0292*	−0.0048	0.0019	0.0029
	(0.0223)	(0.0094)	(0.0137)	(0.0258)	(0.0102)	(0.0156)
Education						
Secondary				−0.0399	0.0121	0.0278
				(0.0341)	(0.0110)	(0.0241)
Tertiary or more				0.1097**	−0.0458***	−0.0639**
				(0.0348)	(0.0131)	(0.0236)
Occupation						
Skilled workers (ISCO 4-8)				0.0846*	−0.0178	−0.0668*
				(0.0362)	(0.0122)	(0.0293)
Professionals (ISCO 1-3)				0.2029**	−0.0632*	−0.1396**
				(0.0652)	(0.0261)	(0.0462)
Age						
40 to 49				0.0679**	−0.0219**	−0.0460*
				(0.0256)	(0.0073)	(0.0211)
50 to 59				0.1424**	−0.0538***	−0.0886*
				(0.0483)	(0.0133)	(0.0365)
Year dummies						
2011	0.1142*	−0.0384	−0.0758*	0.1164*	−0.0391	−0.0773*
	(0.0521)	(0.0220)	(0.0324)	(0.0510)	(0.0212)	(0.0323)
Observations	158,423	158,423	158,423	155,859	155,859	155,859

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard clustered by country errors in parentheses.

Note: Average marginal effects on the three levels of the dependent variable *residuals of capital income levels*; effects with respect to the base category ("Primary or less" in the case of parental and individual education and "Unskilled workers (ISCO 9)" for occupation). These regressions include observations from 2004 and 2010 of Austria, Belgium, Croatia, Cyprus, Czech Republic, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, Malta, the Netherlands, Norway, Portugal, Sweden, Slovakia, Slovenia and the United Kingdom (24 countries).

Table 7: Comparison of moments – Counterfactual distributions of personal income obtained with the Ferreira and Gignoux (2011) method, based on "baseline" and "capital" circumstances – Germany – LIS database

	Mean		Median		Standard deviation	
	Baseline	Capital	Baseline	Capital	Baseline	Capital
1984	36,086.52	35,845.31	43,180.01	39,535.23	12,696.29	11,632.66
Diff. (%)	*-0.67*		*-8.44*		*-8.38*	
1987	39,662.42	39,513.50	44,919.16	46,774.78	13,184.77	12,250.47
Diff. (%)	*-0.38*		*4.13*		*-7.09*	
1989	41,644.70	41,503.58	49,108.17	45,980.79	14,995.49	14,345.97
Diff. (%)	*-0.34*		*-6.37*		*-4.33*	
1991	39,285.18	39,274.81	40,384.84	41,418.90	14,235.09	13,814.95
Diff. (%)	*-0.03*		*2.56*		*-2.95*	
1994	45,106.28	45,072.57	48,904.54	50,684.77	14,891.79	14,101.01
Diff. (%)	*-0.07*		*3.64*		*-5.31*	
1995	47,773.10	47,793.01	51,905.78	53,306.31	15,829.34	15,169.57
Diff. (%)	*0.04*		*2.70*		*-4.17*	
1998	48,657.81	48,727.79	51,895.63	53,392.55	14,973.42	14,387.65
Diff. (%)	*0.14*		*2.88*		*-3.91*	
2000	50,447.10	50,459.52	54,764.32	56,222.36	17,069.19	16,468.32
Diff. (%)	*0.02*		*2.66*		*-3.52*	
2001	50,761.83	50,211.02	55,352.83	56,438.80	17,815.03	16,912.74
Diff. (%)	*-1.09*		*1.96*		*-5.06*	
2002	27,333.02	27,154.87	29,861.49	30,855.65	9,638.54	9,213.07
Diff. (%)	*-0.65*		*3.33*		*-4.41*	
2003	26,635.99	26,438.85	29,709.47	29,179.24	9,018.59	8,672.35
Diff. (%)	*-0.74*		*-1.78*		*-3.84*	
2004	27,185.09	26,992.01	30,330.44	29,940.08	9,056.16	8,836.34
Diff. (%)	*-0.71*		*-1.29*		*-2.43*	
2005	26,745.56	26,600.80	27,543.67	29,315.89	8,781.74	8,510.15
Diff. (%)	*-0.54*		*6.43*		*-3.09*	
2006	26,679.60	26,497.14	26,850.69	28,167.15	9,348.12	8,951.59
Diff. (%)	*-0.68*		*4.90*		*-4.24*	
2007	27,113.31	26,947.34	28,589.06	29,110.56	9,486.30	9,192.80
Diff. (%)	*-0.61*		*1.82*		*-3.09*	
2008	27,288.01	27,121.77	24,781.91	25,689.17	9,505.59	9,125.43
Diff. (%)	*-0.61*		*3.66*		*-4.00*	
2009	28,123.54	27,762.50	28,221.19	29,561.26	9,571.68	9,131.70
Diff. (%)	*-1.28*		*4.75*		*-4.60*	
2010	27,871.79	27,513.61	24,785.08	24,508.80	9,530.92	9,037.20
Diff. (%)	*-1.29*		*-1.11*		*-5.18*	
2011	28,797.59	28,431.66	25,496.96	22,404.87	10,303.04	9,934.32
Diff. (%)	*-1.27*		*-12.13*		*-3.58*	
2012	29,213.53	28,932.40	26,434.13	23,458.48	9,679.21	9,380.04
Diff. (%)	*-0.96*		*-11.26*		*-3.09*	
2013	30,268.84	29,966.83	26,657.11	24,235.51	10,090.06	9,946.84
Diff. (%)	*-1.00*		*-9.08*		*-1.42*	
2014	30,573.01	30,291.25	26,786.46	24,990.36	9,543.88	9,579.09
Diff. (%)	*-0.92*		*-6.71*		*0.37*	
2015	31,541.98	31,115.76	29,386.99	26,405.83	9,399.39	9,179.42
Diff. (%)	*-1.35*		*-10.14*		*-2.34*	

Baseline refers to the set of circumstances including *parental education*, Capital to the one including *capital income levels.*

Table 8: Comparison of moments – Counterfactual distributions of personal income obtained with the Ferreira and Gignoux (2011) method, based on "baseline" and "capital" circumstances – Italy – LIS database

	Mean		Median		Standard deviation	
	Baseline	Capital	Baseline	Capital	Baseline	Capital
1995	24,736,902.15	24,561,798.98	26,263,348.00	26,625,848.00	5,490,548.41	4,825,106.69
Diff. (%)	*-0.71*		*1.38*		*-12.12*	
1998	26,550,162.05	26,360,161.65	28,405,088.00	29,214,788.00	5,726,572.08	4,934,870.95
Diff. (%)	*-0.72*		*2.85*		*-13.83*	
2000	27,343,304.64	27,344,173.34	28,812,148.00	29,763,452.00	5,584,199.73	4,959,557.55
Diff. (%)	*0.00*		*3.30*		*-11.19*	
2004	15,341.56	15,259.49	15,898.75	15,738.24	2,872.44	2,120.08
Diff. (%)	*-0.53*		*-1.01*		*-26.19*	
2008	17,341.59	17,365.86	18,532.78	19,092.06	3,518.51	3,021.94
Diff. (%)	*0.14*		*3.02*		*-14.11*	
2010	17,288.56	17,295.55	17,875.74	19,064.64	3,246.11	2,564.38
Diff. (%)	*0.04*		*6.65*		*-21.00*	
2014	16,856.72	16,873.72	15,948.75	15,232.89	3,998.49	3,440.42
Diff. (%)	*0.10*		*-4.49*		*-13.96*	

Baseline refers to the set of circumstances including *parental education*, Capital to the one including *capital income levels.*

Table 9: Comparison of moments – Counterfactual distributions of personal income obtained with the Ferreira and Gignoux (2011) method, based on "baseline" and "capital" circumstances – 2004 – 15 countries – EU-SILC database

	Mean		Median		Standard deviation	
	Baseline	Capital	Baseline	Capital	Baseline	Capital
Austria	21,909.18	21,891.78	22,834.33	23,001.31	6,567.12	6,308.69
Diff. (%)	*-0.08*		*0.73*		*-3.94*	
Belgium	26,091.10	25,968.26	24,809.15	26,419.84	6,285.44	5,593.34
Diff. (%)	*-0.47*		*6.49*		*-11.01*	
Cyprus	17,326.55	17,312.89	19,604.69	15,868.11	5,564.92	5,183.50
Diff. (%)	*-0.08*		*-19.06*		*-6.85*	
Czech Rep.	5,256.24	5,288.40	5,069.97	5,471.65	1,416.89	1,497.03
Diff. (%)	*0.61*		*7.92*		*5.66*	
Denmark	36,394.31	36,655.74	35,639.46	36,511.54	3,903.45	4,697.45
Diff. (%)	*0.72*		*2.45*		*20.34*	
Finland	22,910.36	22,793.34	22,296.27	23,930.38	3,433.66	3,262.27
Diff. (%)	*-0.51*		*7.33*		*-4.99*	
Germany	23,744.80	23,771.51	17,099.35	17,082.15	8,977.97	8,937.84
Diff. (%)	*0.11*		*-0.10*		*-0.45*	
Iceland	32,359.60	32,238.86	30,697.77	31,222.35	7,060.82	6,863.25
Diff. (%)	*-0.37*		*1.71*		*-2.80*	
Ireland	25,844.46	25,678.69	25,711.40	21,347.15	8,434.73	7,278.72
Diff. (%)	*-0.64*		*-16.97*		*-13.71*	
Luxembourg	38,651.19	37,929.71	36,342.77	39,741.98	13,918.50	12,162.21
Diff. (%)	*-1.87*		*9.35*		*-12.62*	
Netherlands	26,510.33	26,636.79	33,104.26	32,995.27	8,388.20	8,433.43
Diff. (%)	*0.48*		*-0.33*		*0.54*	
Norway	36,314.67	36,581.35	37,644.18	36,186.41	7,089.81	8,313.58
Diff. (%)	*0.73*		*-3.87*		*17.26*	
Slovenia	11,455.25	11,556.96	11,159.17	11,315.74	1,439.16	1,391.09
Diff. (%)	*0.89*		*1.40*		*-3.34*	
Sweden	26,653.11	26,649.54	27,810.36	26,104.74	4,298.44	4,155.51
Diff. (%)	*-0.01*		*-6.13*		*-3.33*	
U. Kingdom	28,535.00	28,316.70	32,511.53	32,833.46	8,434.12	7,515.18
Diff. (%)	*-0.77*		*0.99*		*-10.90*	

Baseline refers to the set of circumstances including *parental education*, Capital to the one including *absolute dynastic component of capital income levels*.

Table 10: Comparison of moments – Counterfactual distributions of personal income obtained with the Ferreira and Gignoux (2011) method, based on ’Baseline’ and ’Capital’ circumstances – 2010 – 23 countries – EU-SILC database

	Mean			Median			Standard deviation		
	Baseline		Capital	Baseline		Capital	Baseline		Capital
Austria	27,925.00		27,894.47	26,069.74		25,441.68	8,061.20		8,072.90
Diff. (%)		*-0.11*			*-2.41*			*0.15*	
Belgium	28,237.86		28,236.51	28,180.47		26,572.94	5,995.69		5,860.84
Diff. (%)		*-0.00*			*-5.70*			*-2.25*	
Croatia	8,163.45		8,255.85	7,316.05		8,473.76	1,783.03		1,395.30
Diff. (%)		*1.13*			*15.82*			*-21.75*	
Cyprus	21,115.16		21,140.01	20,675.76		19,064.92	6,718.83		6,263.02
Diff. (%)		*0.12*			*-7.79*			*-6.78*	
Czech Rep.	9,067.25		9,051.05	9,319.80		7,907.08	2,324.79		1,934.71
Diff. (%)		*-0.18*			*-15.16*			*-16.78*	
Denmark	42,759.08		42,857.28	43,329.25		42,514.90	3,977.50		3,626.30
Diff. (%)		*0.23*			*-1.88*			*-8.83*	
Estonia	6,637.28		6,686.46	6,230.00		7,308.87	1,680.34		2,064.49
Diff. (%)		*0.74*			*17.32*			*22.86*	
Finland	29,427.57		29,376.69	27,983.69		29,406.61	4,127.71		3,467.63
Diff. (%)		*-0.17*			*5.08*			*-15.99*	
France	23,614.06		23,503.63	23,866.90		21,874.32	5,754.30		5,003.85
Diff. (%)		*-0.47*			*-8.35*			*-13.04*	
Germany	24,853.53		24,763.26	21,965.36		23,867.40	8,497.86		8,315.04
Diff. (%)		*-0.36*			*8.66*			*-2.15*	
Greece	15,133.33		15,245.89	14,549.06		14,494.17	4,595.00		4,421.62
Diff. (%)		*0.74*			*-0.38*			*-3.77*	
Iceland	25,403.07		25,393.92	24,581.21		25,252.41	5,029.74		4,843.47
Diff. (%)		*-0.04*			*2.73*			*-3.70*	
Italy	22,976.47		22,717.71	22,464.18		22,952.73	5,921.79		4,759.72
Diff. (%)		*-1.13*			*2.17*			*-19.62*	
Luxembourg	42,596.67		41,603.16	40,909.39		40,577.95	16,581.22		12,785.76
Diff. (%)		*-2.33*			*-0.81*			*-22.89*	
Malta	15,719.68		15,615.29	16,056.12		17,130.93	3,364.03		2,444.74
Diff. (%)		*-0.66*			*6.69*			*-27.33*	
Netherlands	32,519.65		32,530.93	31,654.29		34,021.62	7,750.97		7,468.39
Diff. (%)		*0.03*			*7.48*			*-3.65*	
Norway	52,927.52		53,207.74	53,220.52		52,201.10	7,990.91		8,546.69
Diff. (%)		*0.53*			*-1.92*			*6.96*	
Portugal	11,134.00		11,148.16	10,672.83		10,637.87	2,161.11		1,804.82
Diff. (%)		*0.13*			*-0.33*			*-16.49*	
Slovakia	6,950.93		6,962.24	6,666.58		6,909.06	1,317.37		1,220.76
Diff. (%)		*0.16*			*3.64*			*-7.33*	
Slovenia	14,965.00		15,061.66	14,309.27		15,908.07	1,818.89		1,590.57
Diff. (%)		*0.65*			*11.17*			*-12.55*	
Spain	16,653.85		16,616.71	15,479.02		15,482.88	4,263.33		3,764.40
Diff. (%)		*-0.22*			*0.02*			*-11.70*	
Sweden	29,304.97		29,363.61	29,428.32		29,064.01	3,555.06		3,896.45
Diff. (%)		*0.20*			*-1.24*			*9.60*	
U. Kingdom	23,606.16		23,764.13	22,336.47		20,296.88	7,171.92		7,307.86
Diff. (%)		*0.67*			*-9.13*			*1.90*	

Baseline refers to the set of circumstances including *parental education*, Capital to the one including *absolute dynastic component of capital income levels.*

Table 11: Distributions of parental education and capital income levels by country – 2004 – EU-SILC database

	Parental education			Capital income levels		
	Frequency	Percent	Cumulative	Frequency	Percent	Cumulative
Austria						
1	2,697	54.79	54.79	2,697	54.79	54.79
2	1,965	39.92	94.72	1,965	39.92	94.72
3	260	5.28	100.00	260	5.28	100.00
Total	4,922	100.00		4,922	100.00	
Belgium						
1	2,638	55.23	55.23	2,638	55.23	55.23
2	1,168	24.46	79.69	1,168	24.46	79.69
3	970	20.31	100.00	970	20.31	100.00
Total	4,776	100.00		4,776	100.00	
Cyprus						
1	3,362	74.76	74.76	3,846	85.52	85.52
2	777	17.28	92.04	294	6.54	92.06
3	358	7.96	100.00	357	7.94	100.00
Total	4,497	100.00		4,497	100.00	
Czech Rep.						
1	735	17.27	17.27	3,265	76.72	76.72
2	3,131	73.57	90.84	601	14.12	90.84
3	390	9.16	100.00	390	9.16	100.00
Total	4,256	100.00		4,256	100.00	
Denmark						
1	1,348	38.55	38.55	2,317	66.26	66.26
2	1,466	41.92	80.47	497	14.21	80.47
3	683	19.53	100.00	683	19.53	100.00
Total	3,497	100.00		3,497	100.00	
Estonia						
1	1,740	39.77	39.77	4,132	94.45	94.45
2	1,772	40.50	80.27	0	0.00	94.45
3	863	19.73	100.00	243	5.55	100.00
Total	4,375	100.00		4,375	100.00	
Finland						
1	3,860	62.69	62.69	3,860	62.69	62.69
2	1,295	21.03	83.73	1,295	21.03	83.73
3	1,002	16.27	100.00	1,002	16.27	100.00
Total	6,157	100.00		6,157	100.00	
Germany						
1	1,718	14.71	14.71	4,239	36.28	36.28
2	6,127	52.44	67.15	3,606	30.87	67.15
3	3,838	32.85	100.00	3,838	32.85	100.00
Total	11,683	100.00		11,683	100.00	
Hungary						
1	2,793	42.37	42.37	6,411	97.25	97.25
2	3,127	47.44	89.81	0	0.00	97.25
3	672	10.19	100.00	181	2.75	100.00
Total	6,592	100.00		6,592	100.00	
Ireland						
1	2,548	73.09	73.09	2,936	84.22	84.22
2	537	15.40	88.50	149	4.27	88.50
3	401	11.50	100.00	401	11.50	100.00
Total	3,486	100.00		3,486	100.00	
Iceland						
1	638	38.55	38.55	638	38.55	38.55
2	792	47.85	86.40	792	47.85	86.40
3	225	13.60	100.00	225	13.60	100.00
Total	1,655	100.00		1,655	100.00	

Continuation of table 11: distributions of parental education and capital income levels by country – 2004

	Parental education			Capital income levels		
	Frequency	Percent	Cumulative	Frequency	Percent	Cumulative
Luxembourg						
1	1,950	53.19	53.19	2,854	77.85	77.85
2	1,139	31.07	84.26	236	6.44	84.29
3	577	15.74	100.00	576	15.71	100.00
Total	3,666	100.00		3,666	100.00	
Netherlands						
1	2,929	61.10	61.10	2,929	61.10	61.10
2	995	20.76	81.85	995	20.76	81.85
3	870	18.15	100.00	870	18.15	100.00
Total	4,794	100.00		4,794	100.00	
Norway						
1	841	24.31	24.31	841	24.31	24.31
2	1,433	41.42	65.72	1,433	41.42	65.72
3	1,186	34.28	100.00	1,186	34.28	100.00
Total	3,460	100.00		3,460	100.00	
Poland						
1	8,649	50.89	50.89	16,406	96.54	96.54
2	7,214	42.45	93.34	0	0.00	96.54
3	1,131	6.66	100.00	588	3.46	100.00
Total	16,994	100.00		16,994	100.00	
Slovakia						
1	2,129	32.52	32.52	6,112	93.37	93.37
2	3,719	56.81	89.34	0	0.00	93.37
3	698	10.66	100.00	434	6.63	100.00
Total	6,546	100.00		6,546	100.00	
Slovenia						
1	2,072	50.75	50.75	2,652	64.95	64.95
2	1,817	44.50	95.25	1,237	30.30	95.25
3	194	4.75	100.00	194	4.75	100.00
Total	4,083	100.00		4,083	100.00	
Sweden						
1	2,155	67.68	67.68	2,155	67.68	67.68
2	476	14.95	82.63	476	14.95	82.63
3	553	17.37	100.00	553	17.37	100.00
Total	3,184	100.00		3,184	100.00	
United K.						
1	3,575	61.42	61.42	3,575	61.42	61.42
2	1,176	20.20	81.62	1,176	20.20	81.62
3	1,070	18.38	100.00	1,070	18.38	100.00
Total	5,821	100.00		5,821	100.00	

Table 12: Distributions of parental education and capital income levels by country – 2010

	Parental education			Capital income levels		
	Frequency	Percent	Cumulative	Frequency	Percent	Cumulative
Austria						
1	1,841	33.55	33.55	1,841	33.55	33.55
2	2,709	49.37	82.92	2,708	49.35	82.91
3	937	17.08	100.00	938	17.09	100.00
Total	5,487	100.00		5,487	100.00	
Belgium						
1	2,228	45.25	45.25	2,229	45.27	45.27
2	1,360	27.62	72.87	1,359	27.60	72.87
3	1,336	27.13	100.00	1,336	27.13	100.00
Total	4,924	100.00		4,924	100.00	
Bulgaria						
1	3,042	46.58	46.58	6,208	95.07	95.07
2	2,595	39.74	86.32	0	0.00	95.07
3	893	13.68	100.00	322	4.93	100.00
Total	6,530	100.00		6,530	100.00	
Croatia						
1	2,482	50.32	50.32	4,350	88.20	88.20
2	1,971	39.96	90.29	102	2.07	90.27
3	479	9.71	100.00	480	9.73	100.00
Total	4,932	100.00		4,932	100.00	
Cyprus						
1	2,887	66.60	66.60	3,493	80.58	80.58
2	966	22.28	88.88	360	8.30	88.88
3	482	11.12	100.00	482	11.12	100.00
Total	4,335	100.00		4,335	100.00	
Czech Rep.						
1	3,223	56.01	56.01	4,502	78.24	78.24
2	1,886	32.78	88.79	607	10.55	88.79
3	645	11.21	100.00	645	11.21	100.00
Total	5,754	100.00		5,754	100.00	
Denmark						
1	798	30.85	30.85	1,720	66.49	66.49
2	1,069	41.32	72.17	147	5.68	72.17
3	720	27.83	100.00	720	27.83	100.00
Total	2,587	100.00		2,587	100.00	
Estonia						
1	1,233	28.46	28.46	2,399	55.37	55.37
2	2,003	46.23	74.68	837	19.32	74.68
3	1,097	25.32	100.00	1,097	25.32	100.00
Total	4,333	100.00		4,333	100.00	
Finland						
1	2,030	46.08	46.08	2,030	46.08	46.08
2	1,330	30.19	76.28	1,330	30.19	76.28
3	1,045	23.72	100.00	1,045	23.72	100.00
Total	4,405	100.00		4,405	100.00	
France						
1	6,833	72.74	72.74	6,833	72.74	72.74
2	1,118	11.90	84.64	1,117	11.89	84.63
3	1,443	15.36	100.00	1,444	15.37	100.00
Total	9,394	100.00		9,394	100.00	
Germany						
1	817	8.62	8.62	1,309	13.82	13.82
2	5,587	58.97	67.60	5,095	53.78	67.60
3	3,070	32.40	100.00	3,070	32.40	100.00
Total	9,474	100.00		9,474	100.00	

Continuation of table 12: distributions of parental education and capital income levels by country – 2010

	Parental education			Capital income levels		
	Frequency	Percent	Cumulative	Frequency	Percent	Cumulative
Greece						
1	2,915	71.15	71.15	3,199	78.08	78.08
2	753	18.38	89.53	469	11.45	89.53
3	429	10.47	100.00	429	10.47	100.00
Total	4,097	100.00		4,097	100.00	
Hungary						
1	6,055	55.85	55.85	10,525	97.08	97.08
2	3,447	31.79	87.64	0	0.00	97.08
3	1,340	12.36	100.00	317	2.92	100.00
Total	10,842	100.00		10,842	100.00	
Ireland						
1	1,001	40.92	40.92	1,987	81.23	81.23
2	965	39.45	80.38	0	0.00	81.23
3	480	19.62	100.00	459	18.77	100.00
Total	2,446	100.00		2,446	100.00	
Iceland						
1	412	26.88	26.88	412	26.88	26.88
2	835	54.47	81.34	835	54.47	81.34
3	286	18.66	100.00	286	18.66	100.00
Total	1,533	100.00		1,533	100.00	
Italy						
1	12,562	72.77	72.77	12,562	72.77	72.77
2	3,644	21.11	93.88	3,644	21.11	93.88
3	1,056	6.12	100.00	1,056	6.12	100.00
Total	17,262	100.00		17,262	100.00	
Latvia						
1	2,098	37.09	37.09	5,496	97.17	97.17
2	2,536	44.84	81.93	0	0.00	97.17
3	1,022	18.07	100.00	160	2.83	100.00
Total	5,656	100.00		5,656	100.00	
Lithuania						
1	2,320	52.45	52.45	3,840	86.82	86.82
2	1,466	33.14	85.60	0	0.00	86.82
3	637	14.40	100.00	583	13.18	100.00
Total	4,423	100.00		4,423	100.00	
Luxembourg						
1	2,832	49.29	49.29	2,832	49.29	49.29
2	2,013	35.03	84.32	2,013	35.03	84.32
3	901	15.68	100.00	901	15.68	100.00
Total	5,746	100.00		5,746	100.00	
Malta						
1	2,216	68.42	68.42	2,216	68.42	68.42
2	759	23.43	91.85	759	23.43	91.85
3	264	8.15	100.00	264	8.15	100.00
Total	3,239	100.00		3,239	100.00	
Netherlands						
1	1,608	33.77	33.77	1,608	33.77	33.77
2	1,859	39.04	72.81	1,859	39.04	72.81
3	1,295	27.19	100.00	1,295	27.19	100.00
Total	4,762	100.00		4,762	100.00	
Norway						
1	506	21.27	21.27	506	21.27	21.27
2	982	41.28	62.55	982	41.28	62.55
3	891	37.45	100.00	891	37.45	100.00
Total	2,379	100.00		2,379	100.00	

Continuation of table 12: distributions of parental education and capital income levels by country – 2010

	Parental education			Capital income levels		
	Frequency	Percent	Cumulative	Frequency	Percent	Cumulative
Poland						
1	5,215	41.52	41.52	11,939	95.05	95.05
2	6,212	49.45	90.97	0	0.00	95.05
3	1,134	9.03	100.00	622	4.95	100.00
Total	12,561	100.00		12,561	100.00	
Portugal						
1	4,763	91.30	91.30	4,763	91.30	91.30
2	216	4.14	95.44	216	4.14	95.44
3	238	4.56	100.00	238	4.56	100.00
Total	5,217	100.00		5,217	100.00	
Romania						
1	4,741	80.04	80.04	5,853	98.82	98.82
2	937	15.82	95.86	0	0.00	98.82
3	245	4.14	100.00	70	1.18	100.00
Total	5,923	100.00		5,923	100.00	
Slovakia						
1	1,957	29.79	29.79	5,250	79.91	79.91
2	3,939	59.95	89.74	647	9.85	89.76
3	674	10.26	100.00	673	10.24	100.00
Total	6,570	100.00		6,570	100.00	
Slovenia						
1	2,726	62.68	62.68	2,926	67.28	67.28
2	1,034	23.78	86.46	834	19.18	86.46
3	589	13.54	100.00	589	13.54	100.00
Total	4,349	100.00		4,349	100.00	
Spain						
1	10,629	80.74	80.74	10,629	80.74	80.74
2	1,109	8.42	89.17	1,108	8.42	89.16
3	1,426	10.83	100.00	1,427	10.84	100.00
Total	13,164	100.00		13,164	100.00	
Sweden						
1	808	31.03	31.03	808	31.03	31.03
2	1,068	41.01	72.04	1,068	41.01	72.04
3	728	27.96	100.00	728	27.96	100.00
Total	2,604	100.00		2,604	100.00	
United K.						
1	2,700	51.78	51.78	3,531	67.72	67.72
2	1,289	24.72	76.51	459	8.80	76.52
3	1,225	23.49	100.00	1,224	23.48	100.00
Total	5,214	100.00		5,214	100.00	