INHERITANCES AND INEQUALITY OF OPPORTUNITY IN WEALTH*

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"There's nothing wrong with inherited wealth... if you melt the silver yourself"
The upper classes. Luke Haines (The Auteurs)

Abstract

While the analysis of inequality of opportunity (IO) in income has flourished in recent years, the study of wealth opportunity has not seen the same development. Recent findings about the historical trends and levels of wealth inequality have not been accompanied by advances in the study of the 'unfairness' of that inequality.

This paper tries to contribute to that task using unique data from Spain that contain information about income, wealth and external circumstances (gender, parental occupation and inheritances) and applying a non-parametric version of the ex-post IO method proposed by Lasso de la Vega et al. (2017) to compute IO in wealth and income for Spain in 2011.

We find wealth IO to be higher than IO in income, even in terms relative to their respective total inequality (IO ratio). IO in wealth can represent up to 48.97% of wealth inequality, compared to a 33.46% IO ratio in income. Our results also show that this higher level of IO in wealth is mostly caused by the effect of inheritances, who can be associated to more than one third of overall IO in wealth.

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1 Introduction

The debate about inequality has traditionally focused on the analysis of income. Originally, centered only on the levels and trends of inequality of the income distribution and, more recently, also on the 'unfair' part of income inequality associated with initial circumstances and not with individual decisions or effort, i.e., inequality of opportunity (IO). In inequality and IO analysis wealth has traditionally played a rather minor role. Firstly because statistics on income, both at the macro level (from national accounts) and at the micro level (from the relatively abundant income surveys) were more accessible to researchers than those on wealth. And, secondly, because the impact of income on subjective well-being was thought to be far more important than that of wealth.[1]

However, in the last few years, wealth inequality is attracting the attention of researchers and the general public. New administrative datasets including historic data of national wealth have recently begun to be exploited, revealing unsettling findings about wealth inequality and its dynamics. Saez and Zucman (2016) show that wealth inequality in the United States has been increasing since the late 1970s, after having had a decreasing trend since the 1930s, while Piketty and Zucman (2014) find that, in the main western economies (U.S., U.K., Germany and France), the wealth-income ratio has also began to increase steadily since the 1970s, reaching back the levels of the XVIIIth and XIXth centuries. At the same time, the link between wealth and well-being is being revisited, and some advantages derived from a higher wealth level are now being explicitly acknowledged. Hochman and Skopek (2013) show that there is a subjective well-being premium for wealthier individuals, even within rich countries like Germany or Israel. Shapiro (2004) and Oliver and Shapiro (2006) point at the far more important and persistent racial wealth gap between whites and blacks in the U.S. -compared to the income racial gap- linking this gap to access to loans or to education. In this line, Johnson (2014) highlights the importance that family wealth has in the United States educational system, for it can -among other things- provide access to better schools located in more expensive neighborhoods or secure funding for higher education. Finally, global statistics on wealth inequality and on the accumulated share of wealth owned by the top 1% of the world's population [Davies

[1] In the classic discussion about the relative or the absolute nature of subjective well-being, economists and sociologists have always used income as the proxy for fulfillment of material needs [Easterlin (1974), Veenhoven (1991), Diener et al. (1993)].

et al. (2016)] have had a shocking impact on social media (partly due to their diffusion through the Oxfam's report on [Hardoon (2017)) and have put wealth inequality in the spotlight.

Similarly to what has happened in the study of income inequality, a natural evolution of the concern about the distribution of wealth is to move from the mere analysis of inequality to the analysis of inequality of opportunity. It is relevant to know not only how unevenly wealth is distributed, but to what extent that inequality is the consequence of effort and talent or, else, is related to external prior circumstances that the individual is not responsible for. However, the scarcity of joint data of wealth and circumstances has probably caused such analysis to be overlooked by researchers and practitioners up to date. To the best of our knowledge, no systematic work has yet analyzed IO in wealth using the theoretical framework [Roemer (1993), Fleurbaey (2008), Roemer (2009)] that is already being used extensively for IO in income [e.g. Lefranc et al. (2008), Checchi and Peragine (2010), Ferreira and Gignoux (2011), Marrero and Rodríguez (2012)].

Aiming to fill that gap, in this paper we take advantage of the unique data collected by the Spanish Central Bank in the Spanish Survey of Household Finances (which, in addition to wealth, includes the parental occupational category and the inheritances received by the household) and we apply a non-parametric smoothing method to calculate IO, recently proposed by Lasso de la Vega et al. (2017). This method allows for a more precise measurement of IO compared to the traditional ex-post methodology based on fixed intervals (see Section 2).

Our results show that -even with a limited set of circumstances- IO in wealth can represent 50% of total wealth inequality. Differences gender, parental occupation and the amount of inheritances received imply different levels of expected wealth, and all of these circumstances matter to inequality of opportunity. In particular, we find that -controlling for gender and for parental occupation- considering inheritances can double the measure of inequality of opportunity in wealth.

The rest of the paper is structured as follows. In Section 2, we present the non-parametric methodology that we will use to estimate IO. Section 3 describes the properties of our database and our choices in the selection of circumstances and in the aggregation of wealth and income. In Section 4 we show the results of our IO estimations using different choices and methods. Finally, Section 5 concludes.

2 Methodology

The literature has approached the concept of inequality of opportunity from two different perspectives: the ex-ante and the ex post [Fleurbaey (2008)]. The ex-ante approach refers to equality of opportunity if all individuals face the same set of opportunities regardless of their circumstances, that is, if the expected outcome for individuals with different sets of circumstances is the same. The ex-post approach, on the other hand, states that there is equality of opportunity if all individuals who exert the same degree of effort obtain the same outcome.[2] In our analysis, we will implement a non-parametric version of the ex-post approach proposed by Lasso de la Vega et al. (2017), which tries to overcome some conflicts in the ex-post estimation generally overlooked by the literature.

In the IO literature, a *type* is defined as a subset of the population that shares the same set of circumstances.[3] According to Roemer's pragmatic approach (1993), two people belonging to different types have tried equally hard if and only if they are on the same rank of their respective effort distributions. As a consequence, there will be no IO in society when there is not dispersion of outcome across types for all degrees of effort.

The first step of the ex-post approach is identifying individuals who are comparable in terms of their degree of effort. Traditionally, scholars have adopted the quantile or tranche criterion, which assumes that all individuals belonging to different types but in the same tranche (section of the outcome distribution ordered by effort) exert the same degree of effort. However, the probability of considering individuals with different degrees of effort as close-equals increases with the size of the tranche considered. Inversely, choosing narrower tranches ranges reduces the number of individuals that can be considered close-equals in terms of effort (and, ultimately, the tranche can be so small that all individuals could be considered essentially different and, therefore, there will be no close-equals to compare with.) To find a satisfactory solution for this problem is not easy, but it seems reasonable to look for a statistical criterion instead of using a discretional division in standard

[2]The results obtained using one of the other approach are not always equal and in certain scenarios could be formally inconsistent (see Fleurbaey and Peragine (2013) and Ramos et al. (2015)).

[3]As we will see in Sections 2 and 4 in our application, if we consider only gender, parental occupational class (low, medium or high) and having or not having received inheritance we would have a total of twelve types, and one of them would be, for instance, men whose parental occupational class was medium and who have not received any inheritance.

tranches like deciles, ventiles or centiles is as often the case in the literature.

A second related issue arises from the fact that researchers typically consider as the scale of the dispersion of outcomes among individuals belonging to the same type and tranche normative irrelevant (Checchi and Peragine, 2010). Thus, the outcomes of observations in the same type and tranche are collapsed to their unweighted mean value. By doing this, however, dispersion among those individuals belonging to the same type and tranche -which implicitly contains potential information about 'effort'- is ignored.

To deal with these problems, the non-parametric regression framework proposed by Lasso de la Vega et al. (2017) uses the overlapping optimal bandwidth h to determine which individuals exert a similar degree of effort. Technically, h is chosen to minimize a distance measure like the Mean Integrated Squared Error (MISE) in the non-parametric regression of outcome Y on effort (rank) E. But, what is the economic rationale behind it? Non-parametric regression takes into account two elements: first, a good fit to the 'true' curve, which means a low bias (the difference between the actual and the expected estimated value); and second, the reduction of the volatility of the estimates (the variance is the standard criterion to measure volatility). These two elements have a conflicting interpretation in terms of equality of opportunity. The smaller the size of the tranches or the bandwidth h, the lower the bias. In this case, as we mentioned above, the probability of considering individuals with similar degrees of effort as different, increases. At the limit, there are no close-equals and if there is any IO, it is due only to the exact equals (if there is any). On the contrary, the larger the size of the tranche, the lower the variance. In this case, the probability of considering individuals with quite different degrees of effort to be similar, increases. At the limit, all individuals are close-equals and the IO is at its maximum. Optimal bandwidth is computed as a balance between both elements. Hence, despite that there is no normatively superior criterion to identify close-equals, using a statistically-optimal based criterion that balances variance and bias seems better than the ad hoc subjective researcher's criterion that is typically applied in the literature. Also, the fact that the non-parametric regression works with overlapping intervals avoids the paradox that two close observations in terms of effort be considered as different levels of effort just because they fall at two different sides of the ad-hoc tranche threshold (deciles, centiles, etc.). In the non-parametric regression, the influence of each observation in determining the expected value of the outcome variable for each level of effort only depends on the distance to the estimation point and the kernel function used, and no longer on whether it falls in or out of a discretional tranche division.

Essentially, a non-parametric regression estimates $Z = Y|X$, a vector comprising all the weighted local averages of Y at each point $x \in X$. These averages are obtained using neighboring observations, which are weighted using a smoothing function that relates negatively to the distance (measured in terms of X) that separates them from the evaluated observation. At each point $x \in X$:

$$z(x) = \sum_{i=1}^{n} W_i(x) \cdot Y_i \tag{1}$$

Among the possible smoothing functions, we will use the classic Nadaraya–Watson estimator [Nadaraya (1964), Watson (1964)]. The Nadaraya–Watson (NW) weighting estimator is:

$$Z_i = W_i^{NW}(x) = \frac{\sum_{i=1}^{n} K_h(x - x_i) \cdot y_i}{\sum_{i=1}^{n} K_h(x - x_i)} \tag{2}$$

where K_h is a kernel function K with a bandwidth h. The shape of the kernel weights is determined by K, whereas the size of the estimation is parameterized by h. We will use the NW estimator with a normal or gaussian kernel function and an optimal bandwidth h. Lasso de la Vega et al. (2017) show that the Nadayara-Watson non-parametric regression smoothing has the desirable property of dominance: the theoretical outcome distribution $Z = Y|E$ Lorenz-dominates the original Y distribution, avoiding any misinterpretation of the difference in inequality between both distributions. To obtain the optimal bandwidth h we minimize the mean integrated squared error using a normal operator for the kernel weighting, and including also the sampling weights of the survey in the computation.[4]

The optimal bandwidth and the overlapping intervals allow to the non-parametric regression method to tackle the problem of discretional tranche selection and to account for the dispersion of the

[4]We have used the npksum function in the R 'np' package [Hayfield et al. (2008)] in order to obtain the optimal bandwidth using cross-validation and, in the second step, to produce our non-parametric regressions. We are grateful for technical advice to Jean Opsomer and, in particular, to Luc Clair and Jeffrey Racine for their valuable help in programming the optimal bandwidth and regressions computation accounting for the sampling weights.

effort, while still being able to decompose overall inequality in inequality of effort and inequality of opportunity. In fact, Lasso de la Vega et al. (2017) show that this method generalizes previous standard ex-post decompositions used in the literature, and that the traditional ex-post method could be a considered a particular case of non-parametric regression (the regressogram) in which the weighting function is a constant that gives all observations in the tranche the same importance (thus obtaining the mean value as an estimate) and that considers non-overlapping ad-hoc intervals (deciles, centiles, etc.). [5]

Applying non-parametric regression to our data, the smoothed distribution $Z = Y|E$ is obtained conditioning the outcome variable to our effort proxy (the outcome rank of the individual within circumstance-peers). This distribution can therefore be considered circumstance-free, and its inequality can be considered inequality of effort (IE):

$$IE = I(Z), \tag{3}$$

where $I(Z)$ is the inequality index of our choice applied to variable Z. Subsequently, inequality of opportunity will be the remaining part of total inequality obtained subtracting $I(Z)$ from overall inequality of the outcome variable $I(Y)$:

$$IO = I(Y) - I(Z), \tag{4}$$

In relative terms, dividing all the expression by $I(Y)$ we can decompose total inequality into its effort and opportunity components:

$$1 = \frac{IE)}{I(Y)} + \frac{IO}{I(Y)}, \tag{5}$$

[5]For reference, we have in the results section included the estimations with this type of estimation (regressogram) together with our non-parametric regression estimates. We have used two ad-hoc tranches division: deciles and the optimal bandwidth tranche. Note that the regressogram, even when it uses the optimal bandwidth tranche, misses two key features of the non-parametric regression estimation: accounting for the dispersion of effort via the weighting function, and considering overlapping intervals. See Tables 5 to 8 for the estimations of the non-parametric regression method, Tables 9 to 12 for the estimation using the regressogram with deciles, and Tables 13 to 16 for the estimation using fixed tranches with the optimal bandwidth range.

3 Database

The 2011 Spanish Survey of Household Finances (Encuesta Financiera de las Familias or EFF) is the fourth wave of a series of surveys run by the Spanish Central Bank, which collects detailed information on consumption, income and wealth from a representative sample of the Spanish population. A remarkable feature of this survey is that, thanks to the collaboration of the Tax Office and the National Statistics Institute (INE), the EFF is able to oversample wealthy households on the basis of individual wealth tax records. Since the distribution of wealth is strongly skewed and certain types of assess are held by only a small share of the population, oversampling is crucial for the representativeness of the population and of aggregate wealth [Bover et al. (2014)]. In addition, the Spanish EFF gathers unique information on parental occupation and on received inheritances and gifts, which is fundamental in the analysis of inequality of opportunity.[6]

We have included in our sample all households whose head -defined in the survey as the 'reference person' responsible of the economic affairs of the household- is over 30 years old, leaving out younger families who could still not be fully integrated in the labor market. Aiming to gather all possible information about inheritances, we have not established an upper threshold for age. Moreover, since receiving or not an inheritance depends not only on your parental wealth but also on your age, we have replicated our analysis in a subsample of only individuals older than 60, in order to account for the effect of inheritances among comparable individuals that are old enough to be very likely to inherit.

Our main target variable is net household wealth, which we compute aggregating wealth from different sources: historic value of real state (including main house and other properties), actual value of durable goods (equipment and transportation means), jewelry, businesses and financial assets (stocks, shares in funds, public and private bonds, pension plans). We subtract the pending value of outstanding loans in order to obtain net wealth (see descriptives for the net wealth variable in Table 2). Our secondary target variable is income, which we have computed adding different

[6]The EFF is included in the European Household Finance and Consumption Survey (HFCS) run by the Eurosystem. Unfortunately, questions about parental occupation have not been included in the core homogeneous questionnaire of the European survey and is not available for all the other European countries. As long as these variables are available, our analysis could be extended to other countries in the Eurosystem.

sources of annual income referring to the previous year: labor income (both monetary and in kind), unemployment benefits, income from self-employment, income from retirement benefits or other pensions, interests from accounts, net profits from business managed and participated by household members, and dividends from stocks. In order to better approach to the 'permanent' income and avoid transitory shocks, we have excluded extraordinary sources of income, such as lottery, inheritances, prizes, job-firing compensations or transfers received from third parties or the government that were not included in the concepts stated above. The basic descriptives for the income distribution are in Table 3.[7]

Out of the 6106 households in the EFF, 5996 had a head over 30 years old. From that sample we also leave out households that had negative wealth or income, which represent 162 observations (2.7% of the sample). This excludes atypic observations of wealth and income in the bottom part of the distribution, and allows us to use inequality indices that only admit positive values (such as the Mean Logarithmic Deviation or Theil-0 index). Thus, our main sample will then be formed of 5834 observations, while the subsample of individuals older than 60 will include 3198 observations (see Table 1).

The circumstances that we consider are the gender, the highest parental occupational class of the household head, and the inheritances received by the household. Since having too many values for a certain circumstance would produce a high number 'types' with an reduced number of observations per type, we obtain three occupational classes collapsing the broad occupational categories of the Spanish Clasificación Nacional de Ocupaciones (CNO).[8] The first group is formed by the categories 1, 2 and 3 of the CNO, that include management, scientific and intellectual technicians and professionals, and support technicians and professionals. The second group includes an ample range of middle occupational class categories: clerical workers, sales workers, skilled agricultural workers, qualified handcraft workers, machine operators, and armed forces. The low occupational

[7]We found that equivalizing wealth and income with the squared root scale did not alter significantly our results. Consistently with what Bover (2010) finds for inequality measures, wealth distribution is affected by household structure, but it is not sensitive to considering the *size* of the household. We have therefore used household as the unit of analysis throughout.

[8]The CNO is based on the International Standard of Occupations (ISCO-08). Our aggregation in three occupational groups is similar to the one proposed by Erikson et al. (1979) when collapsing their occupational class schema into three occupational levels.

class group includes unskilled workers and housekeepers. Considering only gender and parental occupation would result in 6 different types of households (2 genders, 3 occupational classes). The share of the sample belonging to each group of parental occupational level is displayed in Table 1.

For the aggregation of inheritances, we have aggregated the actual net value of real state obtained through inheritance or gift , the value of jewelry inherited, and the historic value of business inherited or received as a donation. In all cases, the value of partial bequests has only been accounted for the share received. The reception of inheritances has been categorized first as a binomial variable (which would make a total of 12 types of households according to circumstances: 2 genders, 3 occupational classes, 2 inheritance categories). Trying to capture the difference influence of different amounts of inherited wealth, we alternatively divide the inheritance variable into 5 categories using its quartiles: no inheritance, low quartile, mid-low quartile, mid-high quintile and top quartile (see Table 2 for information about the quartile thresholds). This translates into splitting the sample in 30 types: 2 genders, 3 occupational classes, 5 inheritance categories. In section 4 we will present our results for each set of circumstances (6, 12 or 30 types) and both our general sample and for the subsample of individuals older than 60.

4 Results

4.1 Preliminary evidence: gender and parental occupation

The ex-post IO method requires in a first step to split the sample in groups of people with homogeneous circumstances. As explained above, a higher number of circumstances increases the number of types, which englobe all the possible combinations of the different levels or categories that each circumstance can have. For that reason, prior to incluiding inheritances in our set of circumstances and increase the number of types to 30, we found quite clarifying to run a preliminary visual analysis of the relation of parental occupation and gender with the wealth distribution ordered by rank within the type ('effort'). The top graphs in Figure 1 show the distribution of net wealth for each of the 6 types created using gender and parental occupational level. For a given gender, a higher level of parental occupation implies a higher amount of net wealth, the difference being especially relevant between households whose head has parents with a high-class occupation and those with mid and low parental occupational class. The relation is similar if we look at the income distributions per type (bottom two figures).

On the other hand, for a given level of parental occupation, households with a male head consistently have a higher amount of wealth (and income) than households with a female head. In fact, the distribution for the type of 'men with low-class parental occupation' is even slightly above the type of 'women with mid-class parental occupation', highlighting the importance of the gender circumstance.

4.2 Non-parametric regression and the ad-hoc tranches ex-post method

As pointed out in the methodology, the non-parametric regression method overcomes the problems of accounting for the dispersion within tranches and of the discretional classification of effort in ad-hoc tranches. In 2 it can be visualized the difference between the the non parametric estimation (black line) and the fixed tranches estimation (red segments), both using deciles or the lenght of the optimal bandwith for each outcome variable.

However, despite its qualitative advantages, it remains to see how this methodological changes can quantitatively affect the results and measurements of IO compared with the standard discretional ex-post methods. In order to check the robustness of our results we have included the results for the estimation with decile tranches (Tables 9 to 12) and bandwidth lenght tranches (Tables 13 to 16) in addition to our main non-parametric regression results (5 to 8). Although there are minor differences in the values of IO, the main findings are robust and hold in all three different methods: there is a higher level of IO in wealth than of IO in income and inheritances -and the amount inherited- are key circumstances for inequality of opportunity in wealth.

4.3 IO estimates and the role of inheritances

We turn now to a more detailed analysis of the results of our preferred especification. Using the non-parametric regression methodology described in Section 2, we have regressed wealth and income on each household's rank in its respective type, running Equation 2. The inequality of each smoothed distribution Z represents the value of 'inequality of effort', and it is included in columns 4-6 of Tables

5 and 7. These tables also include total inequality (IT) of the wealth and income distributions in the first three columns (Theil-0, Atkinson and Gini indices), while the final three columns reflect the inequality of opportunity level (IO), obtained using Equation 4. Finally, tables 6 and 8 reflect the IO ratios for wealth and income respectively obtained using Equation 5.

As explained in Section 2, the whole analysis has been run on two different subsets of the population depending on age. Our baseline estimation (first three rows of each table) includes all individuals of age 30 or older, while our second estimation (three bottom rows of each table) considers only individuals of age 60 or older, excluding there younger population less likely to receive inheritances due to age reasons, regardless of any rationale about their dynastic economic conditions. Also, in order to capture the contribution of inherited wealth to inequality of opportunity, we have run our estimations sequentially, considering three different groups of circumstances that produce different partitions of the population in types. In a first instance, we have excluded inheritances and used only gender (two categories) an parental occupational class (three categories), obtaining six different types for the population. In a second iteration, we have included inheritances as a dichotomic variable, splitting the previous 6 types depending on whether individuals had or had not received any inheritance, and therefore analysing 12 types. In the last iteration, we also consider the amount inherited and, using the quartiles of the distribution of inheritance amounts- we split each of the original 6 types in five (no inheritance, low, mid-low, mid-high and high inheritance), obtaining a total of 30 types. Each division corresponds to a different row in each table.

A first glance at the first two columns of tables 5 and 7 reveals that, consistently with many other studies, wealth inequality is greater than income inequality for both of the samples considered and for all the three inequality indices used. The level of IO is also higher for wealth than for income, which not surprising given a higher level of total inequality in the distribution. What is more revealing, however, is the comparison of the IO ratios (6 and 8): in the 6 types specification that does not include inheritances in the circumstances, the share that IO represents over total inequality is very similar or even higher for income. When we include inheritances, in the 12 types specification and, especially in the 30 types (that consider different inheritance sizes), the IO ratio for wealth increases much more than the IO ratio for income. As we can see in the results, it is the Theil-0 index which presents the highest variations between the results with different data specifications, followed by the Atkinson (1) index, and with the Gini index (less sensitive to inequality concentrated in the tails of the distribution) showing smaller and steadier values. Although the results are qualitatively consistent with all three indices used, we will focus on the analysis of the Theil-0 index values, which is the most broadly used index in IO literature.

Using the Theil-0 inequality index, in the global sample the IO ratio when considering only gender and parental occupation is 21.63% for wealth and 23.56% for income; in contrast, when we consider the size of the inheritance received (30 types) the IO ratio for wealth (38.09%) is far bigger than the ratio for income (24.66%) which is only very slightly higher. It seems that the possible 'income effect' of inheritances is smaller than the direct 'wealth effect'. The importance of the amount of the inheritance received in the wealth of the household and be graphically visualized in Figures 3 and 3 where are depicted the distributions of wealth and income for each different inheritance type (by amount), given the other circumstances (men with mid-level parental education in Figure 3 and men with high-level parental education in 4). The type with higher amounts of inheritances received (in the top quartile) clearly show a higher net wealth than any other type (even those that have received a inheritance for a smaller amount) and, to a lesser extent, a higher income. The effect of a high amount inherited on income is smaller among men with high-class parental education, but remains relevant when net wealth is the outcome considered.

The age threshold of the subsample has a clear effect on the results. In general, all measures of IO (tables 5 and 7) and of IO Ratio (tables 6 and 8) are higher for the restricted sample than for the whole sample counterpart. We believe the results of the older subsample reflect better the potential effect of inheritances on inequality of opportunity in wealth, for it compares equivalent individuals who are all potential receivers of bequests.[9] This increase is again really significant when we consider our richest set of circumstances (30 types) that includes inheritance sizes, making the IO ratio for wealth go up from 38.09% to 48.97%.

[9] Analysing the effect of inheritances in relatively young people's wealth is like analysing the effect of tertiary education on the income of people under 30. Some of them may already be working and earning according to their educational level, but most of them will not.

5 Concluding Remarks

It is a well established fact that wealth inequality is higher than income inequality, but little is known about inequality of opportunity in wealth. Our analysis reveals a higher level of IO in wealth than in income, even in terms relative to their respective total inequality (IO ratio). In our preferred specification (excluding younger individuals unlikely to receive potential inheritance, and considering the size of the inheritance) IO in wealth can represent up to half of total wealth inequality (48.97%), compared to a 33.46% IO ratio in income.

This higher level of IO in wealth is mostly caused by the effect of inheritances. Without taking them into account (6 types specification) the IO ratios of wealth and income are very similar (27.55% and 25.77%). The relatively small increase in IO in wealth when including the variable of inheritance as a 'yes/no' binary (from 27.55% to 33.11%), compared to the bigger increase when the amount of the inheritances is taken into account (up to 48.97%) points at the crucial role of the amount inherited in wealth inequality of opportunity.

We believe these results add another relevant ingredient to debate about inequality in the wealth distribution. They show that, even with a limited set of circumstances, up to one half of wealth inequality can be considered beyond the responsibility sphere of the individual, and that inheritances -especially those of a relatively high amount- represent a key component of inequality of opportunity in wealth.

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6 Tables and Figures

Table 1: Database Descriptive Statistics

	Sample over 30 years old	Sample over 60 years old
Observations	5834	3198
Share of women (%)	39.68	37.52
Share with high parental occupational class (%)	27.37	28.02
Share with mid parental occupational class (%)	62.34	62.07
Share with low parental occupational class (%)	10.28	9.91
Share receiving inheritance (%)	33.77	37.71
Age (Mean)	61.01	72.01
Age (Standard Deviation)	14.26	7.36

Table 2: Net Wealth Descriptive Statistics - Euros (rounded to the unit)

	Sample over 30 years old	Sample over 60 years old
Mean	1 317 590	1 560 973
SD	4 850 618	4 944 354
q10	56 733	84 893
q25	150 526	186 889
q50	336 457	443 145
q75	883 566	1 118 776
q90	2 193 514	2 770 527

Table 3: Regular Income Descriptive Statistics - Euros (rounded to the unit)

	Sample over 30 years old	Sample over 60 years old
Mean	71 336	69 851
SD	289 936	297 680
q10	9 234	8 400
q25	16 392	14 000
q50	30 800	27 010
q75	60 071	56 000
q90	119 070	113 278

Table 4: Inheritances Descriptive Statistics - Euros (rounded to the unit)

	Sample over 30 years old	Sample over 60 years old
Mean	415 996	262 179
SD	2 501 372	924 025
q10	3 543	4 874
q25	17 000	18 030
q50	80 000	90 076
q75	217 450	240 405
q90	510 974	500 000

Figure 1: Distribution of Wealth and Income for each type (6 types) conditioned to rank within type ('effort')

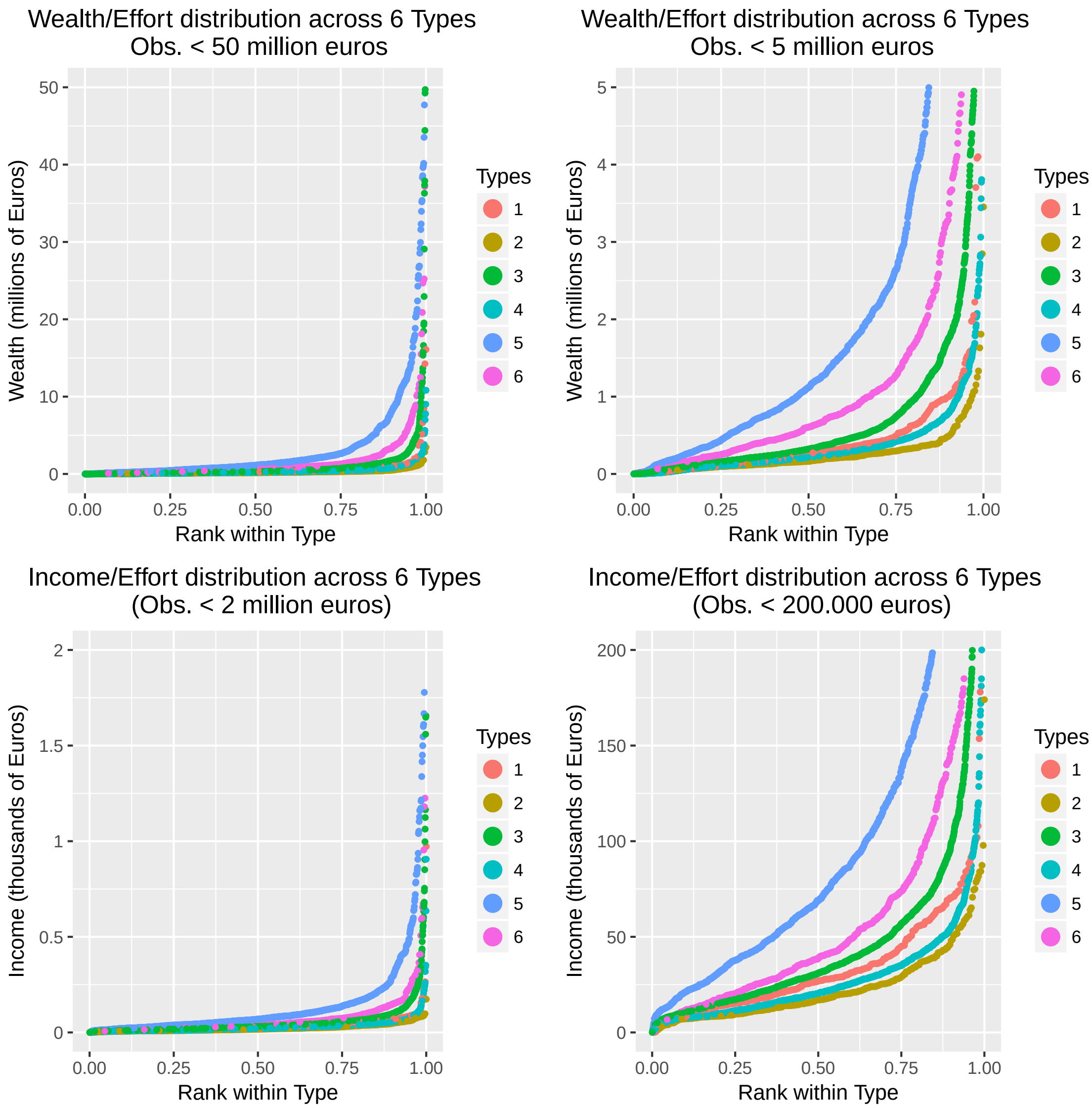

Figure 1: Type 1: Men with low parental occupation; Type 2: Women with low parental occupation; Type 3: Men with mid parental occupation; Type 4: Women with mid parental occupation; Type 5: Men with high parental occupation; Type 6: Women with parental occupation. Database: Household heads 30 years old or older.

Figure 2: Non Parametric Regression Ex-Post Smoothing vs Discreet Tranches Ex-Post Methods

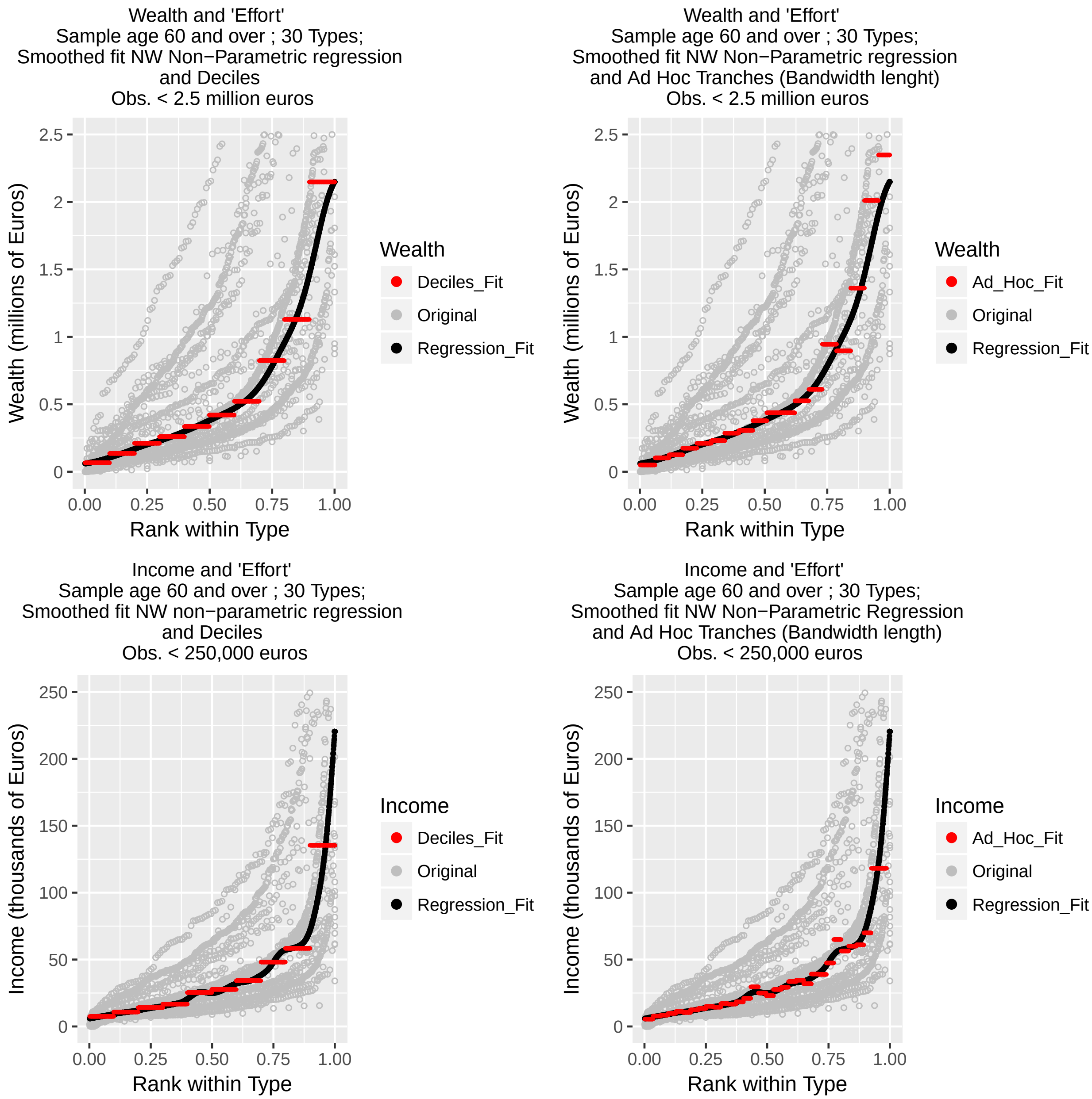

Figure 2

Table 5: Inequality, IE and IO in Wealth - Non Parametric Regression - Different Data Choices and Indices

	Inequality			IE			IO		
	Theil-0	Atkinson (1)	Gini	Theil-0	Atkinson (1)	Gini	Theil-0	Atkinson (1)	Gini
6 Types	0.691	0.499	0.553	0.541	0.418	0.493	0.149	0.081	0.060
12 Types	0.691	0.499	0.553	0.491	0.388	0.487	0.200	0.111	0.066
30 Types	0.691	0.499	0.553	0.428	0.348	0.475	0.263	0.151	0.078
6 Types >60	0.669	0.488	0.555	0.485	0.384	0.482	0.184	0.104	0.073
12 Types >60	0.669	0.488	0.555	0.447	0.361	0.478	0.221	0.127	0.078
30 Types > 60	0.669	0.488	0.555	0.341	0.289	0.446	0.328	0.199	0.109

Table 6: IO Share in Wealth - Non Parametric Regression - Different Data Choices and Indices

	IO Ratio (%)		
	Theil-0	Atkinson (1)	Gini
6 Types	21.63	16.19	10.93
12 Types	28.93	22.22	11.97
30 Types	38.09	30.24	14.17
6 Types >60	27.55	21.26	13.16
12 Types >60	33.11	26.04	13.99
30 Types > 60	48.97	40.71	19.65

Table 7: Inequality, IE and IO in Income - Non Parametric Regression - Different Data Choices and Indices

	Inequality			IE			IO		
	Theil-0	Atkinson (1)	Gini	Theil-0	Atkinson (1)	Gini	Theil-0	Atkinson (1)	Gini
6 Types	0.386	0.320	0.459	0.295	0.256	0.409	0.091	0.065	0.050
12 Types	0.386	0.320	0.459	0.294	0.255	0.408	0.092	0.065	0.050
30 Types	0.386	0.320	0.459	0.291	0.252	0.407	0.095	0.068	0.052
6 Types >60	0.433	0.351	0.497	0.321	0.275	0.438	0.112	0.077	0.058
12 Types >60	0.433	0.351	0.497	0.314	0.269	0.433	0.119	0.082	0.064
30 Types > 60	0.433	0.351	0.497	0.288	0.250	0.418	0.145	0.101	0.078

Table 8: IO Share in Income - Non Parametric Regression - Different Data Choices and Indices

	IO Ratio (%)		
	Theil-0	Atkinson (1)	Gini
6 Types	23.56	20.21	10.84
12 Types	23.75	20.38	10.94
30 Types	24.66	21.20	11.24
6 Types >60	25.77	21.79	11.78
12 Types >60	27.53	23.37	12.86
30 Types > 60	33.46	28.77	15.80

Table 9: Inequality, IE and IO in Wealth - Regressogram Method - Deciles - Different Data Choices and Indices

	Inequality			IE			IO		
	Theil-0	Atkinson (1)	Gini	Theil-0	Atkinson (1)	Gini	Theil-0	Atkinson (1)	Gini
6 Types	0.691	0.499	0.553	0.477	0.379	0.487	0.214	0.120	0.066
12 Types	0.691	0.499	0.553	0.458	0.367	0.482	0.233	0.131	0.072
30 Types	0.691	0.499	0.553	0.420	0.343	0.473	0.271	0.156	0.080
6 Types >60	0.669	0.488	0.555	0.415	0.339	0.476	0.254	0.148	0.080
12 Types >60	0.669	0.488	0.555	0.412	0.338	0.473	0.256	0.150	0.082
30 Types > 60	0.669	0.488	0.555	0.375	0.313	0.458	0.294	0.175	0.098

Table 10: IO Share in Wealth - Regressogram Method - Deciles - Different Data Choices and Indices

	IO Ratio (%)		
	Theil-0	Atkinson (1)	Gini
6 Types	31.01	24.00	12.02
12 Types	33.71	26.35	12.95
30 Types	39.23	31.27	14.54
6 Types >60	38.00	30.39	14.35
12 Types >60	38.34	30.71	14.84
30 Types > 60	43.89	35.84	17.58

Table 11: Inequality, IE and IO in Income - Regressogram Method - Deciles - Different Data Choices and Indices

	Inequality			IE			IO		
	Theil-0	Atkinson (1)	Gini	Theil-0	Atkinson (1)	Gini	Theil-0	Atkinson (1)	Gini
6 Types	0.384	0.319	0.458	0.286	0.249	0.405	0.098	0.070	0.053
12 Types	0.384	0.319	0.458	0.287	0.249	0.405	0.098	0.070	0.053
30 Types	0.384	0.319	0.458	0.285	0.248	0.404	0.099	0.071	0.054
6 Types >60	0.432	0.351	0.496	0.315	0.270	0.434	0.117	0.081	0.062
12 Types >60	0.432	0.351	0.496	0.311	0.268	0.432	0.121	0.083	0.064
30 Types > 60	0.432	0.351	0.496	0.301	0.260	0.424	0.131	0.091	0.072

Table 12: IO Share in Income - Regressogram Method - Deciles - Different Data Choices and Indices

	IO Ratio (%)		
	Theil-0	Atkinson (1)	Gini
6 Types	25.50	21.97	11.48
12 Types	25.43	21.91	11.51
30 Types	25.77	22.22	11.73
6 Types >60	27.17	23.05	12.53
12 Types >60	27.93	23.73	13.00
30 Types > 60	30.36	25.94	14.49

Table 13: Inequality, IE and IO in Wealth - Regressogram Method - Bandwidth Tranche - Different Data Choices and Indices

	Inequality			IE			IO		
	Theil-0	Atkinson (1)	Gini	Theil-0	Atkinson (1)	Gini	Theil-0	Atkinson (1)	Gini
6 Types	0.691	0.499	0.553	0.557	0.427	0.498	0.134	0.072	0.055
12 Types	0.691	0.499	0.553	0.514	0.402	0.494	0.177	0.097	0.059
30 Types	0.691	0.499	0.553	0.439	0.355	0.480	0.252	0.144	0.074
6 Types >60	0.669	0.488	0.555	0.508	0.398	0.490	0.161	0.089	0.066
12 Types >60	0.669	0.488	0.555	0.479	0.381	0.486	0.189	0.107	0.069
30 Types > 60	0.669	0.488	0.555	0.384	0.319	0.462	0.285	0.169	0.093

Table 14: IO Share in Wealth - Regressogram Method - Bandwidth Tranche - Different Data Choices and Indices

	IO Ratio (%)		
	Theil-0	Atkinson (1)	Gini
6 Types	19.37	14.39	9.91
12 Types	25.67	19.49	10.69
30 Types	36.45	28.77	13.32
6 Types >60	24.06	18.34	11.84
12 Types >60	28.33	21.91	12.51
30 Types > 60	42.55	34.59	16.77

Table 15: Inequality, IE and IO in Income - Regressogram Method - Bandwidth Tranche - Different Data Choices and Indices

	Inequality			IE			IO		
	Theil-0	Atkinson (1)	Gini	Theil-0	Atkinson (1)	Gini	Theil-0	Atkinson (1)	Gini
6 Types	0.384	0.319	0.458	0.306	0.263	0.413	0.079	0.056	0.045
12 Types	0.384	0.319	0.458	0.304	0.262	0.412	0.081	0.057	0.045
30 Types	0.384	0.319	0.458	0.299	0.259	0.410	0.085	0.061	0.047
6 Types >60	0.432	0.351	0.496	0.335	0.285	0.446	0.097	0.066	0.050
12 Types >60	0.432	0.351	0.496	0.334	0.284	0.445	0.098	0.067	0.051
30 Types > 60	0.432	0.351	0.496	0.316	0.271	0.434	0.116	0.080	0.062

Table 16: IO Share in Income - Regressogram Method - Bandwidth Tranche - Different Data Choices and Indices

	IO Ratio (%)		
	Theil-0	Atkinson (1)	Gini
6 Types	20.44	17.43	9.73
12 Types	21.00	17.94	9.93
30 Types	22.18	18.99	10.29
6 Types >60	22.49	18.88	10.15
12 Types >60	22.62	19.00	10.36
30 Types > 60	26.86	22.77	12.56

Figure 3: Distribution of Wealth and Income conditioned to rank within type ('effort'). Men with mid-level parental occupation. Types obtained by amount of inheritance.

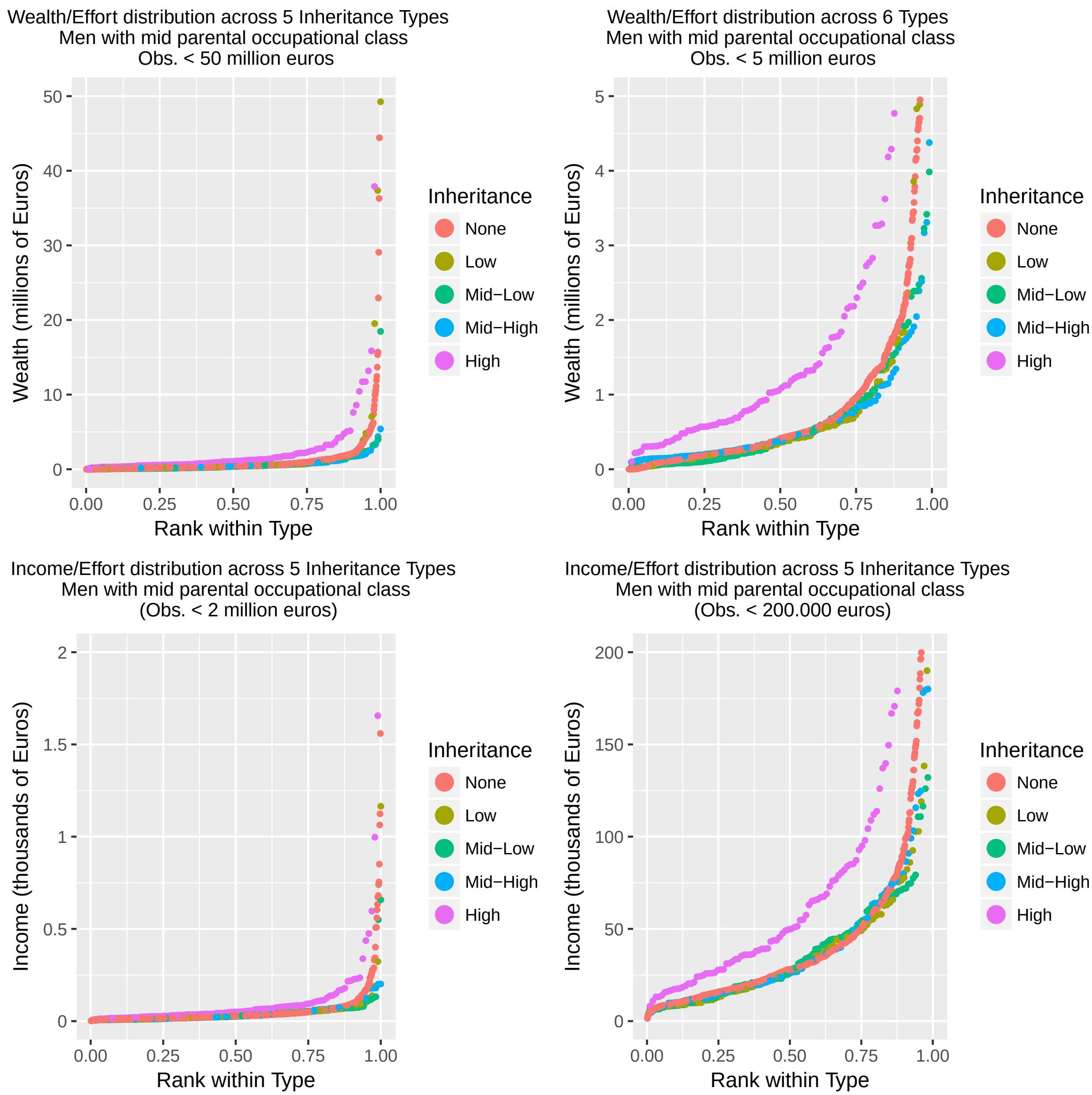

Figure 3: The inheritance thresholds to create the 5 inheritance types are the quartiles (q25, q50 and q75) of the inheritances distribution (see Table 4)

Figure 4: Distribution of Wealth and Income conditioned to rank within type ('effort'). Men with high-level parental occupation. Types obtained by amount of inheritance.

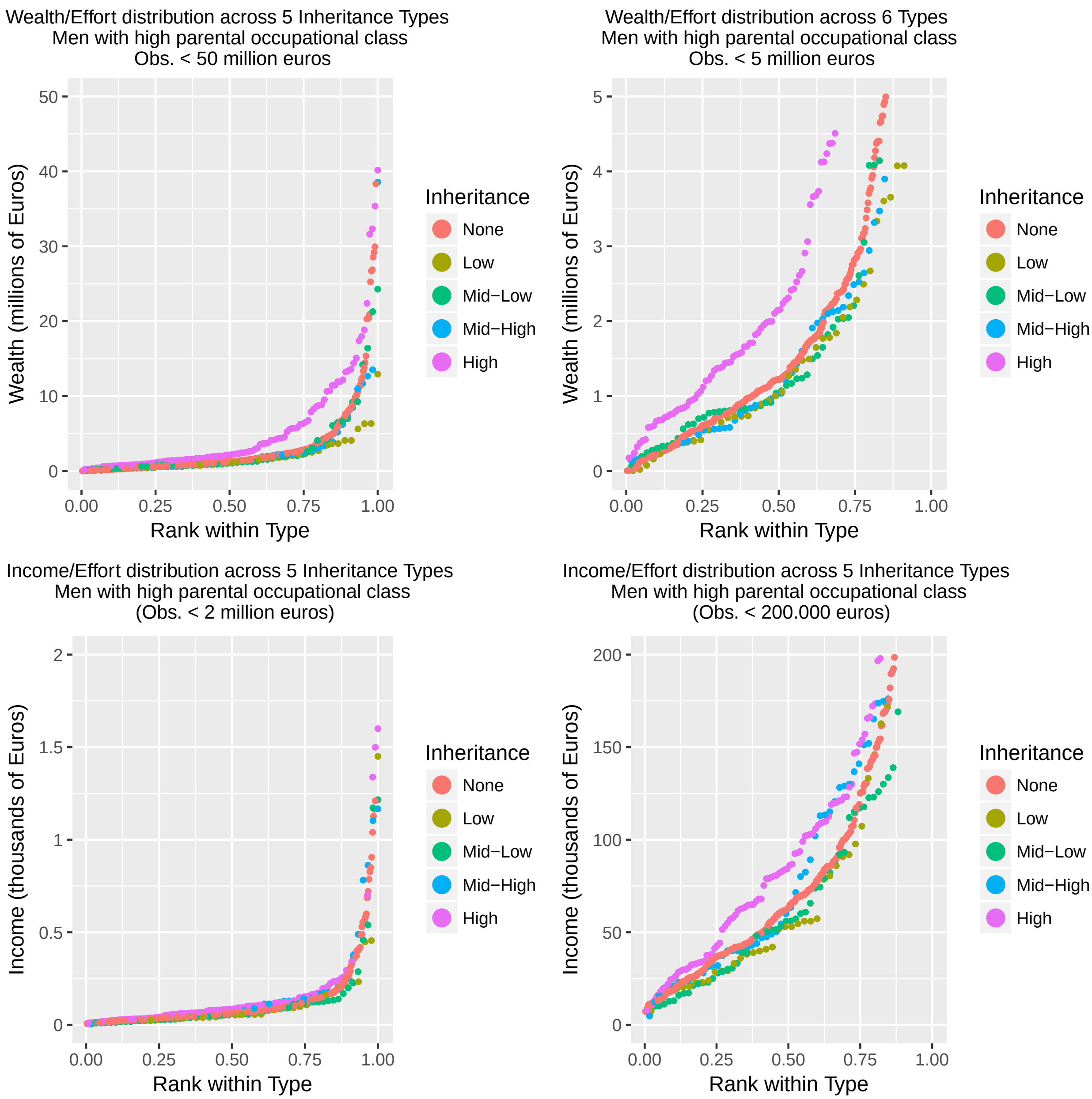

Figure 4: The inheritance thresholds to create the 5 inheritance types are the quartiles (q25, q50 and q75) of the inheritances distribution (see Table 4)