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Wealth inequality, intergenerational transfers and family background

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Abstract

We estimate the contribution of intergenerational transfers (inheritances and gifts) and family background to wealth inequality in four OECD countries: France, Spain, Great Britain and the U.S. We compare the observed wealth distribution with a non-parametric counterfactual distribution where all differences in wealth associated with intergenerational transfers and family background are removed. Despite the diversity of the countries analysed, we find similar patterns. The combined contribution of intergenerational transfers and family background to wealth inequality is sizeable in the four countries, ranging from 36% in Great Britain to 49% in the U.S. When interactions between the two factors are accounted for, and the Shapley value decomposition is used to fully disentangle the contribution of each factor based on its marginal contribution, intergenerational transfers account for between 26% in Great Britain to 36% of wealth inequality in France, with family background ranging from 9% in France to 17% in the U.S.

JEL classification: D31, D63, I24

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1. Introduction

Data availability has kept the study of wealth inequality one step behind the study of income inequality. Only in recent years, some ─mainly administrative─ databases have begun to be exploited,[2] and several studies have retrospectively measured the evolution of wealth inequality in developed countries, finding a common increasing trend since the 1980s in the U.S. and in the major economies of Western Europe (Davies et al., 2017; Saez and Zucman, 2016; Zucman, 2019). Simultaneously, the link between wealth and well-being is being revisited, and some advantages derived from a higher level of wealth ─and not only income─ are now being explicitly acknowledged.[3]

Over the same period, the share of inheritance and gifts (intergenerational transfers) in aggregate wealth has also been found to increase in these countries (Alvaredo et al., 2017; Piketty and Zucman, 2015), which suggests a positive link between wealth inequality and intergenerational transfers. However, the literature on the nature of the relationship between inheritance and wealth inequality gives mixed messages on whether inheritances are best seen as reducing wealth inequality rather than contributing to it, with findings varying with the analytical approach employed.

This in turn reflects the fact that different approaches employed in the literature are actually asking rather different questions, entailing different counterfactual reference points. For example, studies focused on the change in beneficiaries' wealth (such as Boserup et al., 2016, using tax records for Denmark and Elinder et al., 2018, for Sweden) find that inheritances serve to reduce relative inequality in the wealth distribution. A similar conclusion is reached by studies, such as Crawford et al. (2016), that estimate the wealth households have generated from the inheritance receipts they report and, after subtracting that from total current wealth, find that inequality in this 'non-transfer wealth' is higher than observed wealth inequality. In both cases, the result reflects the fact that inheritances are more important relative to (pre-receipt) wealth for recipients lower down the wealth distribution than for those towards the

[2] Global statistics on wealth inequality and on the accumulated share of wealth owned by the top 1% of the world's population (Alvaredo and García-Peñalosa, 2018; Davies, Lluberas, and Shorrocks 2017) have had considerable impact among the general public.

[3] In the classic discussion about the relative or the absolute nature of subjective well-being, scholars have traditionally used income as the proxy for fulfilment of material needs (Veenhoven, 1991; Diener et al., 1993). Hochman and Skopek (2013) show that there is a subjective well-being premium for wealthier individuals, even within rich countries like Germany or Israel. Also, Johnson (2014) highlights the importance that family wealth has in the U.S. educational system, providing access to better schools located in more expensive neighbourhoods or to funding for higher education.

top; the implicit counterfactual is in effect if there were no inheritances and all wealth was 'non-transfer' wealth.

Seen through a different lens, however, the fact that inheritances go predominantly to richer households and that households who do not receive inheritances have lower levels of wealth can be seen as disequalising. This is brought out if one instead adopts as counterfactual a world in which inheritances are more evenly spread across the (pre-transfer) wealth distribution. Thus, Feiveson and Sabelhaus (2018), for example, compare the existing distribution with one where all the wealth attributable to intergenerational transfers is distributed equally across the population. Whereas the top 10% of U.S. families actually had 73% of total wealth, in that counterfactual they would only have had 57% - illustrating how shifting the reference point can dramatically affect the conclusions reached.

One can make a similar point about studies of the relationship between parental wealth and offspring's wealth level or rank in the wealth distribution. Adermon et al. (2018), for example, find that at least half of the measured parent-child wealth correlation is explained by bequests and gifts. Fessler and Schürz (2018) conclude that having received an inheritance at any point in the past lifts a household an average of 14 percentiles in the wealth distribution. These are in effect taking as reference point a world in which parental wealth has no implications for the wealth of offspring; the observed relationship, framed against that, may readily be regarded as strong and (implicitly or explicitly) inequitable.

Here we employ a distinct though related approach to assessing the relationship between intergenerational transfers and wealth outcomes in which the counterfactual is made clear and explicit from the outset. This entails analysing the entire distribution of wealth conditional on the different levels of inheritance received. If inheritances are not connected with differences in wealth, the distribution of wealth across the groups we distinguish (non-receivers, small inheritances-receivers, large-inheritance receivers) should be identical or at least very similar.[4] In contrast, the more these group distributions depart from each other, the more these differences in the overall wealth distribution are connected with differences in intergenerational transfers received.[5]

[4] This would happen if the inheritances were assigned randomly, for example.

[5] Although our analysis considers the aggregate of inheritances and inter-vivos family gifts throughout, for simplicity we will often refer to intergenerational transfers as inheritances in the text. For a detailed description of the split between inheritances and gifts in the countries analysed see Nolan et al. (2020).

These differences in wealth between inheritance-level groups could be caused, in principle, by other factors that are correlated with inheritances like age, gender, household size or family background. Indeed, the latter has been shown to be one key factor explaining inequality in terms of income (Hufe et al., 2017; Lerman, 1996). To avoid this problem, we control first by age, gender and household size, and then we characterize the association of intergenerational transfers and family background levels with the wealth distribution. In particular, our approach and data sources −with information about parental occupation/education− allows us to decompose the combined effect of intergenerational transfers and family background into their marginal effects and the effect due to their interaction.

In essence, our method groups households into different categories or 'groups' according to the intergenerational transfers received and their family background. As noted, the distribution of wealth is independent of the factors under consideration if the wealth distribution is the same across groups. But, if that is not the case, then intergenerational transfers and family background would have an influence on the final distribution of wealth and, therefore, on wealth inequality. Exploiting this idea, we construct a static counterfactual wealth distribution that assigns the same level of wealth to all households in the same rank across groups. Our analysis delivers an apples-to-apples comparison, filtering out differences in wealth attributable to intergenerational transfers and family characteristics, but it does not provide causality implications, which would need to account for dynamic behavioural responses. By comparing that counterfactual distribution of wealth with the observed one, we can measure the share of total wealth inequality that is associated with differences in intergenerational transfers received and family background.[6]

As pointed out above, in our analysis we must first isolate the influence of demographic factors like age, gender and the composition of the household. Bover (2010) and Salas-Rojo and Rodríguez (2021) have shown that a considerable part of the differences in wealth inequality between countries can be explained by those factors. Since our observed distribution of wealth already includes the receipt of inheritances, the adjustment also implicitly takes into account their connection with the demographic characteristics. To adjust for the effect of household size, we use an equivalence scale and, to adjust for age and gender,

[6] As we will expound in Section 2, this approach is inspired in the ex-post approach of the inequality of opportunity literature (see, among others, Roemer, 1998; Rodríguez, 2008; and Checchi and Peragine, 2010).

we regress household wealth on age, gender and their cross effects to obtain an age-gender adjusted wealth distribution.

Second, we need to calculate the counterfactual wealth distribution, estimating the expected wealth conditional to the quantile that the household occupies in its group distribution. The contribution of intergenerational transfers and family background to the final distribution of wealth is null if observed wealth coincides with the counterfactual wealth value for all households. In principle, the counterfactual wealth distribution can be approximated either by parametric or non-parametric estimation. In distributions where values and quantiles do not follow a specific functional form, like wealth, the non-parametric approach is preferred. Among the existing non-parametric methods, we adopt the Nadaraya-Watson estimator which, besides being one of the most commonly used smoothers, is also asymptotically bi-stochastic (Lasso de la Vega et al., 2019). This last property guarantees that our measure is positive if there is any contribution to wealth inequality.

Our empirical exercise takes advantage of a set of household surveys that gather information about wealth, inheritances, gifts and family background for recent years: The Survey of Consumer Finances (SCF) for the U.S., the Wealth and Assets Survey (WAS) for Britain and the Household Finance and Consumption Survey (HFCS) for France and Spain. The four economies under consideration are rich OECD members but have significant differences in their taxation of wealth and intergenerational transfers, which helps us to obtain results that are robust to the national fiscal system.[7]

Combined, inheritance and family background's contribution to wealth inequality (according to the mean logarithmic deviation, MLD) amounts to almost one half in the U.S., Spain and France (49%, 47%, 45% respectively) and to more than one third in Britain (36%). Our findings show that intergenerational transfers contribute up to 40% of total wealth inequality in France and Spain, 37% in the U.S. and 31% in Britain. These values are still substantial when the interaction with family background is netted out and we only consider the marginal

[7] The U.S. and Great Britain do not tax wealth directly, whereas France and Spain are among the very few countries still having a tax on wealth (OECD, 2018), which represents around 0.5% of government revenue in both countries. As for inheritance and gift taxation, Spain has a progressive tax with a maximum rate of 34%, but with different regional exemptions and reductions that have in practice eliminated the tax in some geographical areas. In France, the inheritance tax is progressive with a minimum rate of 5% and a maximum tax rate of 45% (60% beyond the 4th degree of relationship), with different gift allowances of up to 160,000 euros depending on the relationship involved. Great Britain has a flat inheritance rate of 40% with an allowance of £325,000 and an additional allowance for transfer of the family home. Gifts transferred seven years prior to the death of the donor are exempt. In the U.S., inheritance tax has a 40% maximum rate with a recently raised exclusion amount (free of tax allowance) of $11.4 million (around $5 million until 2017).

contribution of intergenerational transfers: 31% for France, 27% for the U.S., 26% for Spain, and 22% for Britain. Similarly, and although the marginal influence of family background is clearly smaller than that of transfers (between 4% and 12%), having parents with different family background in terms of educational of occupational levels relates to a sizable share of wealth differences.

When we apply the Shapley value decomposition (Shapley, 1953) to fully disentangle the combined contribution between the two factors, inheritances contribution to wealth inequality is 36% in France, 33% in Spain, 32% in the U.S. and 26% in Britain, while the contribution of family background is 9%, 14%, 17% and 10%, respectively.

Our findings are consistent with both the increase in aggregate inherited wealth and the increase in wealth inequality seen in the last decades and can help to reflect on the fiscal treatment of wealth and intergenerational transfers. A direct wealth tax is only present now in a handful of countries. Taxes on inheritances and gifts, while still in place in many OECD countries, have recently been abolished in some of them, and their role in tax systems is tending to becoming marginal (Drometer et al., 2018). It is worth noting that wealth taxation can have more than normative implications, and existing empirical evidence indicates that inequality of wealth and inequality of opportunities are harmful for economic growth (Marrero and Rodríguez, 2012 and 2013; Bagchi and Svejnar, 2015; Bradbury and Triest, 2017). Thus, the design of a fiscal system that treats wealth accumulation and transfers properly is not only a matter of fairness, but also of efficiency.

The rest of the paper is structured as follows. In Section 2 we present the non-parametric method that we use to estimate the impact of transfers and family background on wealth inequality. Section 3 describes the four databases being employed and the main choices and adjustments made with respect to the variables for the study. The main results are presented in Section 4. Finally, Section 5 concludes.

2. Estimation approach

In this section, we develop the methodology to estimate the importance of intergenerational transfers and family background in wealth inequality. Inspired on the recent literature on inequality of opportunity (Roemer, 1998; Fleurbaey, 2008; Roemer and Trannoy, 2016), our method constructs an alternative smoothed wealth distribution that allows us to contrast if the inheritances received and the family background have any influence on the distribution of wealth.[8] Among all existing methods, we believe our methodology allows us to measure the contribution -both individual and combined- of intergenerational transfers and family background to total wealth inequality in an intuitive way, by using an additive decomposable inequality index to compare the dispersion of the original wealth distribution and that of the counterfactual.

The first step of this approach consists in partitioning the population into a set of mutually exclusive and exhaustive groups, where all individuals in each group share the same set of characteristics (intergenerational transfers received and family background). Then, within each group, we order (or rank) each household by their wealth and compare the households within the same rank across groups. If intergenerational transfers and family background were two irrelevant characteristics for the distribution of wealth, households with different characteristics but in the same rank should have the same wealth. Otherwise, these characteristics have an influence on the distribution of wealth and, consequently, on wealth inequality. In fact, the greater the dispersion of wealth across groups at each rank, the higher the importance of transfers and family background in determining wealth inequality.

To measure such dispersion, we consider the expected wealth conditional to the rank of the household as our counterfactual wealth distribution. In this counterfactual, households belonging to different groups, but having the same order within each group, will have the same estimated expected wealth and there is no dispersion. Thus, the more the observed household wealth distribution differs from this counterfactual, the more important inheritances and socioeconomic background are for wealth and wealth inequality. Let us express this in formal terms.

For a population of households of size N, a wealth distribution is represented by a vector $Y = (Y_1, Y_2, \dots, Y_N)$ where Y_i is the wealth of the i-th household. Then, the population is divided into M exhaustive and mutually exclusive groups, $\prod = \{G_1, \dots, G_M\}$, such that all households belonging to the same group G_m share the same characteristics (intergenerational transfers

[8] The literature on inequality of opportunity considers that individual outcomes are a function of factors beyond individual's responsibility –circumstances– and personal efforts. Because individuals are only responsible for their own efforts, equality of opportunity requires outcomes to be a function only of individual efforts and, therefore, independent of individual circumstances. Thus, according to the ex-post approach (Roemer, 1998; Rodríguez, 2008; and Checchi and Peragine, 2010), there is equality of opportunity if all individuals who exert the same effort obtain the same outcome. However, since the distribution of effort is not observed, it is common to apply Roemer's pragmatic approach: two individuals of different groups (types) have tried equally hard (have exerted the same degree of effort) if they occupy the same rank of their respective group distributions.

received and family background), and $G_1 \cup G_2 \cup \dots \cup G_M = \{1, \dots, N\}$ and $G_r \cap G_s = \emptyset, \forall r \neq s$.

Let $Z_i = E[Y_i | q_{im}]$ be the expected wealth of household i conditional to the rank (quantile) q_i that it occupies in its group m –in vector notation $Z = (Z_1, Z_2, \dots, Z_N)$. The contribution of inheritances and family background to the explanation of the observed distribution of wealth is zero if $Y_i = Z_i$ for all $i = 1, 2, \dots, N$. Otherwise, the higher the distance between the distribution of Y and the distribution of Z, the more correlated intergenerational transfers and family background are with wealth inequality.

But, how to proxy the distribution Z? In principle, the distribution of Z can be approximated either by a parametric or a non-parametric approach. Because the non-parametric procedure is not restricted by the assumption of a particular functional form, we consider this approach more convenient for our statistical analysis. Therefore, we proxy the distribution of Z using the following non-parametric smoother:

$$\hat{Z}(q) = \sum_{i=1}^{N} W_i(q) Y_i, \tag{1}$$

where $W_i(\mathrm{q})$ represents the set of weights, which are nonnegative, sum one and downwardly weight the Y_i's if the corresponding quantile q_{im} value is far from a given value q. Among the proposals in the literature, we follow Lasso de la Vega et al. (2019) and use the classic Nadaraya–Watson estimator (Nadaraya 1964; Watson 1964).[9] The Nadaraya–Watson weights are as follows:

$$W_i^{NW}(\mathrm{q}) = \frac{K_h(\mathrm{q} - q_{im})}{\sum_{i=1}^{N} K_h(\mathrm{q} - q_{im})}, \tag{2}$$

where K_h is a continuous, positive and symmetric kernel function which integrates to one, like the Gaussian function, which is the kernel used in our application. The shape of the kernel weights is determined by *K*, whereas the size of the weights is parameterized by the bandwidth h.[10] Thus, the bandwidth determines which households are considered in the same comparable rank to obtain the benchmark value at each point. In our application, the

[9] Other non-parametric smoothers could be used. However, the Priestley and Chao (1972) and Gasser and Muller (1984) smoothers have more severe boundary bias problems than does the Nadaraya–Watson smoother (Wand and Jones, 1995). The local linear smoother, on the other hand, optimizes the minimax risk criterion (Fan, 1993) but uses negative weights which, in our case, are difficult to interpret.

[10] The kernel function with bandwidth $h > 0$ is defined as $K_h(s) = \frac{1}{h} K\left(\frac{s}{h}\right)$, which has support [-∞, ∞] for the Gaussian kernel. For consistency, the smoothing parameter $h \to 0$ and $nh \to \infty$ as the sample size $n \to \infty$ (see Wand and Jones 1995). To account for population weights, we have used in the empirical application the 'npksum' function in the R 'np' package (Hayfield and Racine, 2008). We are grateful for technical advice to Jean Opsomer and, in particular, to Luc Clair and Jeffrey Racine for their valuable help.

bandwidth is chosen in each estimation to minimize the Mean Integrated Squared Error (MISE) using the method of cross-validation.

Instead of a bandwidth, we could consider a discretional fixed and exclusive interval, such as the percentile or the decile, to compare households. However, this approach would have three shortcomings. First, it implicitly assumes that the dispersion of wealth among households belonging to the same group and rank is irrelevant and, therefore, the potential information (dispersion) that it contains is ignored. Second, because exclusive intervals are non-overlapping, close equals that are in different intervals (e.g., deciles) are considered to be different for the estimation, despite the fact that they may be closer than other observations in the same interval. Third, the crucial decision about the size of the intervals is left to the discretion of the researcher.

Our approach tackles these three problems. First, the dispersion of wealth among households belonging to the same group and rank is considered relevant and provides information for the estimates: more distant observations are weighted less than closer ones. Second, the use of overlapping intervals avoids artificial discontinuities in the classification of close equals. Third, instead of using an ad-hoc subjective value for the bandwidth, the application of a statistical criterion like the MISE permits to optimize the choice of width of the rank interval used in the estimation.[11]

An additional important property of our methodology is that the Nadaraya–Watson estimator is asymptotically bi-stochastic (Lasso de la Vega et al., 2019). This property implies that, for sufficiently large samples, the Lorenz curve of $\hat{Z}$ always dominates (or at least be equal to) the Lorenz curve of Y (Dasgupta et al., 1973; Rodríguez et al., 2005). Consequently, for any inequality index $I(\cdot)$ consistent with the Lorenz curve, the use of the Nadaraya–Watson estimator guarantees that the estimated dispersion between the observed distribution Y and the smoothed distribution $\hat{Z}$ is non-negative, i.e., $I(Y) - I(\hat{Z}) \geq 0$, as long as the set of characteristics considered (intergenerational transfers and family background) contribute to wealth inequality.

[11] The optimization process thus provides a different bandwidth for each estimation. For example, when estimating the smoothed distribution of wealth in the U.S. using the distribution conditioned to the different family backgrounds, the bandwidth (our overlapping interval) is 0.00510, which is slightly above half a percentile (the rank range goes from 0 to 1). For the smoothed wealth distribution in the U.S. using the distribution of wealth conditioned to inheritances the optimal bandwidth is 0.00502, almost exactly half a percentile. Meanwhile, when the smoother is derived from the wealth distribution conditioned to both family background and inheritances, the optimal bandwidth obtained for the U.S. sample is 0.02076 (two percentiles). In Great Britain, for example, whose sample has more observations than the U.S., the values for the bandwidth in these three estimations are 0.0014, 0.0017 and 0.0036, respectively.

The final step of the approach consists in selecting an inequality index to measure the dispersion between Y and $\hat{Z}$. Among all the inequality indices consistent with the Lorenz curve, we propose the use of the Mean Log Deviation (MLD). In the literature on wealth inequality, the use of other measures is more popular; the MLD, however, presents two main advantages for our analysis. First, the MLD is the only inequality index that is additively decomposable into a between-group and a within-group component (Bourguignon, 1979; Shorrocks, 1980) and has a path-independent decomposition (Foster and Shneyerov, 2000). Second, it is the only measure that respects both the principle of transfers -the cornerstone of the literature on inequality measurement- and the principle of monotonicity in distance (Cowell and Flachaire, 2018).[12]

Taking advantage of the first property of the MLD and ranking households according to their position in their group (using the approach commented above), the MLD index (T) can be exactly decomposed into a between (BE) and a within (WI) ranks inequality components as follows:

$$T(Y) = T^{BE}(Y) + T^{WI}(Y). \tag{3}$$

The between-rank component is directly calculated by applying the MLD to the non-parametric smoothed distribution $\hat{Z}$, $T^{BE}(Y) = T_0(\hat{Z})$, which is free of the influence of intergenerational transfers and family background. Hence, the second term, $T^{WI}(Y) = T_0(Y) - T_0(\hat{Z})$, captures the extent of wealth inequality within each rank. Precisely, this component is the part of total wealth inequality that is associated to differences in intergenerational transfers and family background. Thus, when $T^{WI}(Y) = 0$, inheritances and family background are irrelevant for wealth inequality: households at the same rank but from different groups obtain the same wealth, i.e., $T_0(Y) = T_0(\hat{Z})$. On the other hand, the greater the differences in wealth among households from different groups within the same rank, the greater the extent to which wealth inequality is associated with intergenerational transfers and family background.

[12] Some standard inequality measures like the Gini coefficient and the Theil index can be written as ratios, where the denominator is the mean. As a result, when wealth moves away from equality, both the numerator and denominator can change in the same direction and such inequality measures may decrease (instead of increase) in some cases. This undesirable behaviour is not shared by inequality indices whose denominator is the median, but these other indices do not fulfil the principle of transfers. Only the MLD satisfies both principles, transfers and monotonicity in distance, simultaneously.

3. Data: wealth, intergenerational transfers and family background

Information linking intergenerational transfers and wealth is still scarce. At the macroeconomic level, the capitalisation of capital income and the application of mortality multipliers to inheritance tax flows allow to reconstruct the share of inherited wealth for the economy as a whole in an historic perspective (Alvaredo et al., 2017; Piketty et al., 2015). In some selected countries, administrative microdata with sufficient information has allowed researchers to study the impact of transfers on inequality (Boserup et al., 2016; Elinder et al., 2018), as we discussed above. Recently, some finance household surveys have started to include information on intergenerational transfers in addition to income and wealth. While surveys may raise concerns about the ability to capture the tails of the distribution and inaccurate reporting of inheritances and gifts, these potential biases are not exclusive to them. Administrative datasets present also some biases caused by tax evasion and the truncation of the wealth distribution at the lower tail, since taxpayers in that part of the distribution are not obligated to file a tax return. More importantly for our purposes, tax records do not usually include information about the family background of individuals. Thus, we opt here to exploit household surveys, which, for a selected set of countries and waves, contain comparable information not only about household wealth and an ample set of demographic variables, but also about family background and past wealth transfers received.

We present next a set of household surveys for four OECD countries (France, Spain, the U.S. and Great Britain), comprising the information required to analyse the contribution of family background (parental occupation or education) and intergenerational transfers (inheritances and gifts) as sources of wealth inequality.

3.1 – Wealth information from Household Finance Surveys

We use the latest available wave of the Survey of Consumer Finances for the U.S. (SCF, collected in 2016 and published in late 2017), the Household Finance and Consumption Survey for Spain and France (HFCS, Wave 2, which was published in late 2016, but collected the data in 2011/2012 for Spain and 2014/2015 for France), and the third wave of Great Britain's Wealth and Assets Survey (WAS), which collected data in 2010/2012. We have complemented WAS Wave 3 with information from Waves 1 and 2 in order to obtain the total amount of transfers (for reasons explained below). For comparability, all the amounts have been converted to USD dollars at 2016 prices.

The household is the unit of analysis in the SCF and HFCS surveys for wealth and transfers. For the WAS, transfers are collected at the individual level and are aggregated here to the household level. The measure of household wealth has been chosen to be homogeneous across the surveys used. Thus, wealth includes all net worth (real and financial assets net of liabilities) and excludes rights of pension wealth in all countries. Survey sampling may not fully capture the upper tail of the wealth distribution, but statistical offices try to minimize the bias by oversampling the wealthier households. In particular, the SCF is considered the gold standard in this respect, and its results in terms of wealth concentration ─even at the top 1%─ are comparable to those obtained from tax data (Bricker et al., 2016). In Europe, the HFCS also incorporates oversampling of the upper part of the distribution in many cases. In fact, Spain and France are the countries with the highest effective oversampling rate of the top 10% households of the wealth distribution (234% and 132%, respectively) in Europe. Great Britain's WAS also applies an oversampling strategy, where addresses from wealthier postcodes are 2.5 or 3 times more likely to be sampled.[13]

Compared with administrative sources, the household wealth surveys used present comparable information, though somewhat lower levels of wealth concentration at the top of the distribution. In France, the wealth share measured through the capitalization methods for the top 10% is about 55% (Garbinti et al., 2018), while our top 10% share is 49.7% (see column 1 in Table 1). For the U.S., the top 10% of the distribution in our data has 80.5% of the wealth, a comparable share to what Saez and Zucman (2016) obtained using capitalized income tax records. Estimations derived on tax data find a share of wealth for the top 10% in the UK slightly above 50% (Alvaredo et al., 2016 and 2018), while we show, for our WAS sample, a figure of 44.2%. Finally, for Spain, Martínez-Toledano (2017) finds a top 10% wealth share of 56.5% in 2013 using administrative datasets, while our sample's top 10% share is 46.4%.

An important issue in the measurement of wealth inequality is the treatment of negative and zero wealth values. The methodology described in Section 2 focuses on the MLD inequality index. The main limitation of using this inequality index is that it only deals with positive values, consequently, we must transform or exclude non-positive observations from our

[13] See Bricker et al. (2016) for the SCF, the HFCS Document UDB5 (Country Surveys Metadata Information) and the WAS User Guide for more detailed information on oversampling and other data collection procedures. All descriptive measures and calculations presented here use the corresponding weights for each country dataset.

study. Instead of altering the data by assigning a very small positive value to non-positive observations, we have opted for the clearer option of excluding them from the sample.

The exclusion of non-positive values might raise concerns about the potential bias of wealth inequality estimates, especially if those excluded households received different inheritances and gifts than the rest of the households in the distribution. However, we believe that this is not a major concern in our application for two main reasons. First, the weighted share of observations excluded is very small in France and Spain (2.5% and 3.2%), although higher in Britain (9.0%) and the U.S. (10.4%). To test for the effect of these differences in our results, we run a robustness analysis in which we drop the lowest first decile of observations in the wealth distribution of France, Spain and Britain datasets, in order to make all countries' subsets qualitatively comparable to the one of the U.S. (which loses the first decile of the observations due to having non-positive wealth). As expected, when dropping those observations, the estimated contribution of inheritances to inequality decreases in these three countries (Table A3 in Appendix), and the U.S. becomes in fact the country with the highest contribution of inheritances to inequality in all our metrics (see Table 5). We observe therefore that the unavoidable exclusion of non-positive wealth observations in our analysis downward biases our estimates of inheritances' contribution to wealth inequality, and that bias is greater in the countries where that share of non-positive wealth households is larger (Great Britain and the US).

Second, a detailed exploration of our data reveals that households with zero or negative wealth are less likely than households with positive wealth to have received transfers and especially, large transfers (over the 75th percentile of the inheritance distribution). Households with non-positive wealth are also less likely to have received an inheritance than the subset of positive wealth households with lower wealth, in all countries except in France, where their probability of receipt is quite similar (see Table 2). Again, the possible bias in our estimates caused by the omission of non-positive wealth households would point to our estimates of the contribution of transfers to wealth inequality being underestimated.

3.2 – Intergenerational transfers and family background

The wealth transfers variable we construct includes both inheritances and gifts ever received by the household. Since the respondents provide the year in which the inheritance and gift was received, all values from past inheritances and gifts have been homogenised and updated to the current value of money in each country at the time of the survey, using historical inflation rates.[14] In SCF and HFCS, respondents provide the gross value of inheritances and gifts received, while in WAS it is the net value that is sought. For consistency, we have recovered ─prior to inflation updating─ the gross value of inheritances and gifts received in the WAS for Britain, using the tax parameters in place at the time of receipt.[15]

The HFCS survey reports the current gross value of the three main inheritances or gifts received, in addition to the main residence whenever this has been inherited. The WAS survey, in its first wave (Wave 1, 2008), asks for inheritances ever received. However, in subsequent waves, the survey asks for inheritances received in the last two years. Thus, in order to compute the total amount of inheritances for each household, we have used a cross-wave sample of surviving households in Waves 1, 2 and 3, for which we have all the inheritances ever received by these households. In WAS, gifts are reported in a separate question and, unfortunately, the survey only asks about recently received gifts in all its Waves (even Wave 1), so we only have gifts received in the previous six years, which implies a modest underestimation of total intergenerational transfers for Britain (as discussed in detail in Nolan et al., 2020). Another distinctive specificity of the WAS survey is the high number of missing observations ─not imputed by the statistical office─ especially in Wave 1. Missing inheritance amount observations, in which the respondents have answered that they *had* received such inheritances, have been imputed.[16] In the other surveys (SCF and HFCS), the statistical offices impute the missing values with a multiple imputation method[17]. Our

[14] Past inheritances may have provided returns to the household and thus have increased their current value but could also have been consumed overtime. Capitalising and discounting -with some assumptions- could attempt to address this issue, but to avoid discretionary decisions we have decided to limit the adjustment to updating the current value of money.

[15] The tax on intergenerational transfers in the UK has been historically very progressive, with a top marginal rate for bequests (estate duty and capital transfer tax) between 75% and 85% in all years between 1949 and 1983. Then, it has decreased gradually until the current flat 40% inheritance tax was established in 1988 (see Scheve and Stasavage, 2012, for a comprehensive review of the evolution of these rates in the UK and other countries).

[16] The missing observations were apparently due to a coding error occurred during the survey field work. Many respondents who answered positively to having received an inheritance do not have the amount of those inheritances registered in the data. We imputed this 20% of the values for the first and second "Past inheritances" observations (obtained 5 years before the survey or earlier) and 70% of the values of the less frequent first and second "recent inheritances" (obtained within 5 years before the survey) in the first WAS Wave. This problem did not occur for the "recent inheritances" question in WAS subsequent waves, that we also aggregated (see for details Nolan et al., 2020). The variables used for imputation were age, number of inheritances received, ownership status of main residence and expectation of reception of future inheritance, using the multiple imputation method, the "Predictive Mean Matching" method and the R 'MICE package' (van Buuren, 2007). For each imputed missing observation, 5 plausible values were obtained. We use all of them to obtain estimates and standard errors combining bootstrap and multiple imputation, as we do with the other two surveys used.

[17] For the U.S., 26% of the intergenerational transfers observations were imputed by the statistical office, while this figure is 20% in Spain. No observations are flagged as imputed in the French dataset by the data provider.

estimates and standard errors consider the multiple imputations (MI) of the datasets combined with bootstrapping, following the MI Boot method proposed by Schomaker and Heumann (2018), which performs well in their Monte Carlo simulations.

Before we classify transfers into categories, a few preliminary things must be considered. First, only inheritances above a minimum value have some economic impact in the household, therefore, the category of households with “no inheritances” is actually households not receiving any inheritance above 5000 U.S. dollars at 2016 prices. Second, because three countries have information about whether the household expects to receive a significant inheritance in the future, Spain being the exception, we have used this information to divide the households that have not received an inheritance into the categories of “not received and not expecting” and “not received but expecting”.[18] Three, we have taken the quantiles 0.25, 0.50 and 0.75 of the equivalent inheritance distributions as thresholds (they are described in Table 3). As a result, we have classified intergenerational transfers into six categories: ‘not received and not expecting’, ‘not received but expecting’, ‘low inheritance’, ‘mid-low inheritance’, ‘mid-high inheritance’, and ‘high inheritance’ for the U.S., Britain and France, and five categories for Spain, including ‘not received’, ‘low inheritance’, ‘mid-low inheritance’, ‘mid-high inheritance’, and ‘high inheritance’.

To measure family background, we use the parental information for the household head.[19] The surveys provide information about parental occupational categories for France and Spain, and parental educational achievement categories for Britain and the U.S. For the occupational category in France (based on the French Occupational classification) and the educational category in Britain, we use the father’s information (no such information is available about the head’s mother). In Spain we also use the occupational category (based on the ISCO-08 broad two-digit groups) of the father, except in the cases where this information is missing and can be replaced with the mother’s occupation. In the U.S., we use the highest educational level, which is easier to ordinally categorise than occupation, of either mother or

[18] Great Britain and U.S. datasets include a reported expected amount. However, the HFCS only has a dummy variable on whether there is a substantial inheritance expected. We have therefore used this dichotomic distinction, excluding expected inheritances in Britain and the U.S. under 10.000 USD to account only for “substantial” expected amounts.

[19] We have considered as household head the household’s reference person, which is the person with the highest income (or age in case of equal income) and responsible for the household finances. This is the criteria used in HFCS and WAS. The SCF considers by default the man as the household head, for historical backward consistency. However, it does provide a variable informing whether this role has been reversed for the interview response. Using this variable, we have been able to reassign the role of head when the respondent (who we assume is the one in charge of the household finances) is a female.

father. The distribution of observations per parental occupational/educational category is shown in Table 2.

For homogeneity, we have grouped family background in four categories in all countries. In France, we group occupational codes in: *i*) manual and agricultural workers, *ii*) employees and clerical staff, *iii*) trade/craft and middle range professionals; and *iv*) managers and high professionals.[20] For Spain, the grouping is: *i*) elementary occupations, machine operators and fishery/agriculture; *ii*) mid-level professionals, technicians and craftsmen; *iii*) administration and sales employees; *iv*) managers and high professionals. In Britain, the information about parental education is collapsed in these four groups: *i*) parents who did not go to school; *ii*) parents who left school before or at the age of 16; *iii*) parents who left school at the age of 17 or 18 or who obtained other qualifications after leaving school; *iv*) parents who gained a university or higher degree. In the U.S., the four educational categories refer to the household head's best educated parent and include: *i*) did not finish 12th grade; *ii*) finished 12th grade (completed secondary education); *iii*) obtained further qualifications after leaving high school (some college or associate degree); and *iv*) obtained a bachelor's degree or above.

3.3. The household size, age structure and gender gap

In order to isolate the role of transfers, family background and their interaction in shaping wealth inequality, we need to control by certain demographic factors, such as family size and household head's age and gender, that have been recently shown to be connected to the distribution of wealth (Bover, 2010; Salas-Rojo and Rodríguez, 2021), as pointed out by earlier literature (Atkinson, 1971; Pestieau, 1984).

Household size is likely to be correlated with inheritance receipt, since smaller households with a single adult have lower chances of receiving an inheritance than bigger households with more adults. In a more indirect way, household size's connection with family background and the household's head age and gender could also correlate with inheritances and wealth. Households with a female and/or younger head can have a different average size than those with a male and/or older head. To tackle the direct and indirect influence of household size on inheritance and wealth, we equivalize both wealth and intergenerational

[20] Although in the HFCS all countries must report the occupational categories following the ISCO-08 classification, it seems that the French data kept the coding of their original national survey.

transfers in each country analysed.[21] Unfortunately, using equivalence scales is not enough to account for differences in wealth inequality across countries associated with household structure (Bover, 2010). Indeed, a descriptive analysis of the wealth-age pattern reveals that, even after equivalising, age and gender still have a clear connection with wealth.

The equivalised wealth profile by age and gender for our four countries is shown in Figure A1 (see Appendix). Each point represents the rolling mean wealth at each age, using 9-year centred intervals. In general, for the four countries analysed, we observe a growing trend of mean wealth up to the interval of 60-65 years old. Then, it decreases slightly for the rest of the age range in France, and more significantly in Spain and Britain. The U.S. shows a steadier pattern between the age of 60 and 75, after which we observe a further increase but only for male households. Moreover, although the share of female household heads is similar in all countries ─ranging from 35% in France to 43% in the US─ female and male head households show different age-wealth profiles in all countries.

In our main specification we include all observations in which the head of the household is between 35 and 80 years old. To avoid the possible confounding effect of age and gender with the variables targeted in our analysis (wealth, intergenerational transfers and family background), we perform the following adjustment to the equivalised wealth series: we regress household wealth in logarithms on age (centred at age 65), gender and their cross effects,

$$ln\,(W_i) = \alpha + \delta F_i + \sum_{n=1}^{4} \beta_n (A_i - 65)^n + \sum_{n=1}^{4} \gamma_n F_i (A_i - 65)^n + \varepsilon_i, \qquad (4)$$

where F_i is a dummy variable that takes the value 1 when the household head is female and A_i is the age of the household head. Note that this specification permits to control for a wealth-age structure that is non-linear (Solon, 1992; Palomino et al., 2018). Likewise, it is widely known that the wealth distribution is more skewed to the right than income. Given the generally observed accumulation of wealth at the right tail of the distribution, we apply the natural logarithmic transformation to wealth data.[22]

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[21] Our equivalence scale $E = 1 + \sqrt{Number\ of\ adults - 1}$ focuses on the number of adults (members more likely to receive an inheritance) and takes into account that after the second adult (potential spouse), the rest of adult members (adult siblings, uncles, parents, older sons) are less likely to be permanent members of the household. Nevertheless, results do not change significantly if the square root of the number of people in the household is used instead (results are available upon request).

[22] The estimated OLS coefficients are shown in Table A1 (see Appendix). Note that the significance of the squared and even cubic terms in some cases (for the U.S.) indicate that the wealth-age structure is non-linear, as highlighted in Figure A1 (see appendix). We also perform our adjustment in the alternative subsample of households aged between 50 and 80 years old only, and then obtain all our estimates for that

The adjusted wealth by age and gender, W_i^{adj}, is calculated as:

$$ln\ (W_i^{adj}) = ln\ (W_i) - \hat{\delta} F_i - \sum_{n=1}^{4} \hat{\beta}_n (A_i - 65)^n - \sum_{n=1}^{4} \hat{\gamma}_n F_i (A_i - 65)^n, \qquad (5)$$

where the hat indicates the OLS estimations. The adjusted wealth represents the wealth of a male household head 65 years old. This age and gender adjusted variable is the wealth measure used from this point onwards.

4. Results

In this section, we show the results for the contributions of intergenerational transfers and family background to wealth inequality. First, we show the gross contribution of these two factors to wealth inequality when they are considered individually and jointly. For that, we directly estimate between- and within-group inequality from Equations (1)-(3), using each factor separately or taking them simultaneously to define the groups.

At this point, we must note that each gross individual contribution can include potential interactions with the other factor. Indeed, the sum of the two individual gross effects is higher than the joint contribution, revealing that both factors are positively correlated. Thus, to isolate the partial correlation between both factors, we propose a simple decomposition analysis (see below), which allows us to disentangle the combined effect of intergenerational transfers and family background into their marginal net effects plus the effect due to their interaction. Alternatively, we apply the Shapley value decomposition (Shapley, 1953), which is the only decomposition method that solves the tension between marginality and additivity (Chantreuil and Trannoy, 2013; see also Shorrocks, 2013; and Rodríguez, 2004). In our case, because we have only two characteristics, intergenerational transfers and family background, the Shapley value attributes half of the interaction to each marginal effect. As we show below, both approaches yield similar results.

For intergenerational transfers, graphical representation of the different groups (Figure 1) shows a clear connection with wealth. Here transfer groups are capturing not only their direct effect on wealth, but also the effect of any other factor correlated with them (except age, gender and household size). The figure shows that households that have received the greatest transfers (in the top quartile of the transfer distribution) dominate the wealth distribution in

subsample as a robustness check (Table A2 in Appendix). As mentioned above, we are only using positive values as required by the MLD inequality index.

terms of the first stochastic dominance (Rothschild and Stiglitz, 1970) of the rest of households at any other group in the four countries analysed.[23] Thus, the difference between this group and the rest of the groups is especially wide in the U.S., followed by Spain and France, while it is not so pronounced in Great Britain.

The dominance across the rest of transfer categories is not so clear, with their distributions closer to each other in all four countries, except for France, where the households with mid-high intergenerational transfers have a wider gap over the small-transfers group at all rank positions of the distribution. Households with no transfer are usually at the bottom of the wealth level at the lower rank. However, the distributions cross with the low or mid-low transfer types at the highest rank position in Spain and France, and especially in the U.S., where the top quartile of the households receiving no transfer (and not expecting to receive) may have higher wealth than the top quartile of households receiving low or mid-low transfer.

To measure the gross contribution of inheritances on wealth inequality, we subtract from the original wealth distribution inequality, $T(Y)$, the inequality of the smoothed distribution (counterfactual), $T_I^S(Y)$, where the differences in wealth across groups by inheritances have been removed (Table 4). Recall that $T(Y) - T_I^S(Y)$ is actually the within-rank term $T^{WI}(Y)$ in equation (3). In all cases, $T(Y)$ shows a higher value than $T_I^S(Y)$, and the gross share of inequality associated with intergenerational transfers is given by $Sh_I^G = (T(Y) - T_I^S(Y))/T(Y)$ (Table 5). Using the MLD index, we find that intergenerational transfers in France, Spain and the U.S. have a significant gross contribution to overall wealth inequality of around 40% (40.5%, 39.7% and 37.1%, respectively), while the share is slightly lower in Great Britain (30.6%), but still amounting to almost one third of the original inequality.

How does these contributions compare with the gross contributions of family background? As with transfers, the graphical representation (Figure 2) shows that there exists an evident connection between family background and wealth. In all countries, the group with the best background (first-stochastically) dominates the rest of the groups having, therefore, the highest wealth at all quantiles. For instance, in Figure 2 we see for France that households whose head's parents were "managers and professionals" have higher wealth than the rest of the groups, followed by the "trade, craft and middle professional" parental occupation, who

[23] Recall that given two distributions *F* and *G*, *F* dominates *G* according to the first stochastic dominance, if and only if, $F(x) \leq G(x)$ for all $x \in [0, \infty)$. In this case, the households in distribution *F* benefit from a higher level of welfare than those in distribution *G* according to any generic wealth-dependant welfare function that is additive, symmetric and non-decreasing.

in turn also have a wealth advantage over equivalently ranked households at the two other groups (employees and manual workers parents). In Spain, we observe that households with parents in managerial occupations dominate the other three groups, with a relevant wealth gap that starts early at the lower rank of their respective wealth distributions. In Britain, households with higher parental education have greater wealth than those who left school earlier. The parental education difference is visually greater in the U.S., where households in which the head's parents completed tertiary education show a higher wealth at all points of the ranked distribution. In contrast, households whose parents did not finish secondary school display a significant negative differential in wealth compared with the rest of the groups.

To quantify the gross contribution of family background to wealth inequality, we now subtract from the inequality of the original distribution of wealth, $T(Y)$, the inequality of a new smoothed distribution, which we denote as $T_F^S(Y)$. In this case, the non-parametric smoother eliminates differences in wealth associated with the family background (and any other factor correlated with it, other than age, gender and household size) at each percentile. As for intergenerational transfers, $T_F^S(Y)$ is lower than $T(Y)$ in all countries according to the MLD index (Table 4), and now the estimated gross share, $Sh_F^G = (T_w(Y) - T_F^S(Y))/T(Y)$, is 22.2% and 20.6% for the U.S. and Spain, respectively, which are the greatest among the four countries analysed consistently with the visual inspection of Figure 2; in France and Britain, the contributions are 14.1% and 14.5%, respectively (Table 5).

As found in other studies (Cowell et al., 2019), we find that family background does have a relevant impact on wealth inequality. Still, when put in perspective, the gross contribution of intergenerational transfers to wealth inequality is around twice that of family background in all countries. However, since parental background is measured using a single crude variable (parental occupation or education) with limited granularity, the role of this factor might be underestimated in our case.

Our next comparison is between the overall wealth distribution (adjusted by household size, gender and age) and the smoothed wealth distribution built considering simultaneously both intergenerational transfers and family background. The population is now partitioned in 24 groups (6 inheritances categories multiplied by 4 family background categories) and ─as detailed in Section 2─ the counterfactual distribution is calculated to remove differences in wealth associated with the combined effect of both characteristics (recall that for Spain we use only 20 groups because there are only 5 inheritance categories). Then, we subtract from $T(Y)$ the resultant smoothed distribution for the 24 groups, which we denote by $T_{I+F}^S(Y)$, and calculate the share of the combined effect: $Sh^C_{I+F} = (T(Y) - T^S_{I+F}(Y))/T(Y)$. This combined contribution gets close to 50% in the U.S. (48.8%) and Spain (46.9%), being just a slightly lower in France (44.6%) and 36.3% in Britain (Table 5).

As commented above, as both factors are not independent, we find that, in all countries, the joint combined contribution Sh^C_{I+F} is smaller than the addition $Sh^G_I + Sh^G_F$ (Table 5). The difference between the combined and the two individual gross shares is precisely the share explained by the interaction between both factors: $Sh^{INT}_{I+F} = (Sh^G_I + Sh^G_F) - Sh^C_{I+F}$. We find that the interaction effect is relevant in the four countries under analysis: 10.0% in France, 13.4% in Spain, 8.8% in Britain and 10.5% in the U.S. (Table 5).[24]

Likewise, we can obtain the marginal contribution, Sh^M, that each characteristic has to the joint contribution, once the gross contribution of the other characteristic —that includes their interaction— has been taken into account, so that $Sh^M_I = Sh^C_{I+F} - Sh^G_F$ and $Sh^M_F = Sh^C_{I+F} - Sh^G_I$.

Then, we can fully decompose the combined effect of intergenerational transfers and family background into their marginal (or net) effects and their interactions, i.e., $Sh^C_{I+F} = Sh^M_I + Sh^M_F + Sh^{INT}_{I+F}$, where Sh^M_I and Sh^M_F denote the respective marginal effects of each factor, which are given by:

$$Sh^M_I = Sh^G_I - Sh^{INT}_{I+F} \tag{6}$$

$$Sh^M_F = Sh^G_F - Sh^{INT}_{I+F}. \tag{7}$$

We find that the marginal contribution of inheritances is relevant in all cases, being 30.5% for France, 26.3% for Spain, 21.8% for Britain, and 26.6% for the U.S. The net share of total wealth inequality contributed by family background results in a far lower estimate in the four countries: 4.1% for France, 7.2% for Spain, 5.7% for Britain, and 11.7% for the U.S. (see Table 5),

We additionally apply the Shapley value decomposition (Shapley, 1953) to fully assign the total combined contribution of both characteristics to each of them. Having only two possible orders in which inheritances and family background can come into play, the Shapley value for each characteristic is obtained as the average between the gross contribution share to total

[24] The interacted effect would be larger if inheritances were associated with other unobserved family background characteristics not proxied by our broad categories of education and occupation, which could in turn lower the marginal contribution of intergenerational transfers.

wealth inequality (where the characteristic is accounted for first) and the marginal share (where the characteristic is considered after the other one):

$$Sh_I^{SHAPLEY} = (Sh_I^G + Sh_I^M)/2, \quad (8)$$

$$Sh_F^{SHAPLEY} = (Sh_F^G + Sh_F^M)/2. \quad (9)$$

The Shapley contribution of inheritances to wealth inequality is around one third for France (35.5%), Spain (33.0%) and the U.S. (31.8%), and more than one quarter for Great Britain (26.2%). The Shapley contribution of family background is around one tenth of wealth inequality for France and Britain (9.1% and 10.1%) and slightly higher for Spain (13.9%) and the U.S. (16.9%), the only country where that contribution reaches more than half of the transfers contribution.[25]

Finally, we have run two robustness checks to address possible biases that could happen due to data selection. Even though we have adjusted for age prior to our analysis to control for the possible relation of wealth and inheritances receipt with the life cycle (recall Section 3), we have replicated our analysis with a subsample of only the households in which the head is between 50 and 80 years old (our original sample included heads between 35 and 80 years old). Our results for this selection, which are shown in Table A2 (see Appendix), are very similar to our main data choice, with a slight increase in the contribution of both inheritances and family background in all metrics (gross, marginal and Shapley value). It is noticeable that using this more restricted age sample puts Britain more in line with the other three countries.

The second robustness check aligns the sample of all countries in the lower tail of the wealth distribution. As said, the use of the MLD index requires only positive values so we have to exclude households with non-positive wealth. While this adjustment excludes a very small percent of households in France or Spain, it excludes a significant share in Britain and, especially, in the U.S., where around the 10% of the observations are discarded. Thus, excluding the lowest 10% of the wealth distribution in all countries (whether wealth is positive, zero or negative) gives an equivalently homogeneous sub-sample of the wealth distribution for all four countries. The results of this analysis are in Table A3 (see Appendix)

[25] Note again that we use parental occupation categories for Spain and France, while parental education is used for Britain and the U.S. This has to be considered when comparing the results, although we find that there is no clear pattern of consistent bias driven by the parental background variable used. While the greatest contribution -using the Shapley value- is found for the U.S. (using education), we also find that the background contribution in Spain (using occupation) is the second greatest, with a similar magnitude.

and show the decrease of the contribution of family background and, especially, of intergenerational transfers for France and Spain. Now, in all metrics, Spain is the country with the lowest contribution of intergenerational transfers to wealth inequality (23.9% according to the Shapley value) instead of Britain (25.1%), and it is the U.S. the country with the highest contribution (31.8%) instead of France (28.3%).

5. Concluding remarks

Research to date on the relationship between inheritance and wealth inequality gives mixed messages on whether inheritances are best seen as reducing wealth inequality rather than contributing to it, with findings varying with the analytical approach employed. This reflects the fact that different approaches employed in the literature are actually asking rather different questions, entailing different counterfactual reference points. In this paper, in contrast with previous approaches, we have assessed the relationship between intergenerational transfers, family background and wealth by analysing the entire distribution of wealth conditional on the different levels of family background and inheritance received. If these two individual characteristics were not related with observed differences in total wealth, the distribution of wealth across the groups we have constructed should have been very similar. We found that, on the contrary, these distributions were quite different, and the association of parental background and especially inheritances with wealth inequality was sizeable. While not to be interpreted in a causal fashion, these descriptive associations are of major substantive interest.

We analysed the contribution of intergenerational transfers and family background to wealth inequality in four rich countries. We applied a non-parametric estimation to obtain a counterfactual distribution in which differences in household wealth associated with these two characteristics are removed across the whole distribution. After also controlling for household size and household head's age and gender, we found a sizeable contribution of inheritances and gifts to wealth inequality in all four countries, ranging between 31% and 41% in gross terms and between 22% and 31% after netting out the interaction with family background.

Our findings also show that the role of inheritances and gifts in all countries is roughly twice that of family background, which is associated with between 14% and 22% of wealth inequality in gross terms and between 4% and 12% in net terms. The interactive contribution of both factors ranges between 10% and 15%, so that the combined total contribution of inheritances and parental background approaches half of overall wealth inequality in three of the four countries analysed and is, in all cases, significantly greater than one-third. When fully decomposing the total combined effect ─including their interaction─ between the two characteristics using the Shapley value decomposition, inheritances account for between 26% and 36% of total wealth inequality, while family background accounts for between 9% and 17%.

These results demonstrate the value of the innovative analytical approach we have employed to assess the role of intergenerational wealth transfers and family background in overall wealth inequality, which adds a different perspective to the existing literature and are thus of considerable significance from methodological, empirical and normative perspectives.

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1. Tables and Figures

Table 1. Descriptive statistics.

France. Monetary measures in 2016 USD.

	Full Sample	Sample aged 35 -80	Sample aged 35 -80, positive wealth	Sample aged 35 -80, positive equivalent wealth and equivalent inheritance	Sample aged 35 -80, positive age-gender adjusted equivalent wealth and equivalent inheritance
Observations	11648	9459	9235	9235	9235
Share of inheritance recipients	31.9%	35.9%	36.1%	36.1%	36.1%
Average age	53.3	55.9	56.0	56.0	56.0
Average age of recipients	56.9	58.0	58.1	58.1	58.1
Average wealth	250730	292039	300234	174607	268565
Average inheritance (among recipients)	182696	182657	184052	117670	117670
Wealth MLD Index	NA	NA	1.12	1.07	1.05
Bottom 50% Wealth Share	6.3%	8.5%	9.4%	9.9%	9.8%
Top 20% Wealth Share	67.1%	64.1%	63.3%	62.6%	63.9%
Top 10% Wealth Share	49.7%	47.3%	46.7%	45.9%	46.9%

Spain. Monetary measures in 2016 USD.

	Full Sample	Sample aged 35 -80	Sample aged 35 -80, positive wealth	Sample aged 35 -80, positive equivalent wealth and equivalent inheritance	Sample aged 35 -80, positive age-gender adjusted equivalent wealth and equivalent inheritance
Observations	5949	5189	5065	5065	5065
Share of inheritance recipients	28.8%	29.8%	30.6%	30.6%	30.6%
Average age	53.8	54.8	55.1	55.1	55.1
Average age of recipients	58.4	58.8	58.9	58.9	58.9
Average wealth	309123	339289	351049	184116	285154
Average inheritance (among recipients)	270275	263738	264788	143382	143382
Wealth MLD Index	NA	NA	0.84	0.83	0.77
Bottom 50% Wealth Share	11.7%	12.7%	13.8%	13.6%	14.5%
Top 20% Wealth Share	62.1%	61.4%	60.1%	59.9%	57.9%
Top 10% Wealth Share	46.4%	45.8%	45.1%	44.2%	41.7%

Great Britain. Monetary measures in 2016 USD.

	Full Sample	Sample aged 35 -80	Sample aged 35 -80, positive wealth	Sample aged 35 -80, positive equivalent wealth and equivalent inheritance	Sample aged 35 -80, positive age-gender adjusted equivalent wealth and equivalent inheritance
Observations	12782	10916	10223	10223	10223
Share of inheritance recipients	31.7%	32.6%	34.4%	34.4%	34.4%
Average age	55.3	55.5	56.0	56.0	56.0
Average age of recipients	56.8	57.3	57.6	57.6	57.6
Average wealth	331241	361884	398934	224759	361253
Average inheritance (among recipients)	203194	209497	214183	125129	125129
Wealth MLD Index	NA	NA	1.06	1.05	1.02
Bottom 50% Wealth Share	7.8%	9.4%	12.7%	12.3%	12.4%
Top 20% Wealth Share	62.6%	61.1%	58.2%	58.4%	59.2%
Top 10% Wealth Share	44.2%	43.0%	40.9%	41.1%	41.9%

United States. Monetary measures in 2016 USD.

	Full Sample	Sample aged 35 -80	Sample aged 35 -80, positive wealth	Sample aged 35 -80, positive equivalent wealth and equivalent inheritance	Sample aged 35 -80, positive age-gender adjusted equivalent wealth and equivalent inheritance
Observations	6248	4914	4487	4487	4487
Share of inheritance recipients	17.9%	20.2%	21.6%	21.6%	21.6%
Average age	51.0	55.5	56.2	56.2	56.2
Average age of recipients	58.0	59.8	60.2	60.2	60.2
Average wealth	559456	681174	763109	409749	645725
Average inheritance (among recipients)	393532	401819	415404	251837	251837
Wealth MLD Index	NA	NA	2.07	2.04	1.84
Bottom 50% Wealth Share	0.6%	1.5%	2.8%	2.8%	3.6%
Top 20% Wealth Share	90.2%	88.7%	86.8%	86.4%	83.8%
Top 10% Wealth Share	80.7%	78.9%	77.0%	76.2%	72.2%

Notes: For each country and data subsample criteria: observations, share of households receiving any substantial intergenerational transfer (over 5000 USD in 2016 prices), average age of the household head (overall and within recipient households), average household wealth, average inheritance (for recipients), wealth inequality (MLD) and measures of wealth concentration (bottom 50% and top 20% and top 10% shares). All measures weighted using population weights and calculated using all multiple imputed values in the surveys.

Table 2. Negative wealth and inheritances.

	Share with zero or negative wealth		Share receiving inheritance			Share receiving large inheritance		
	Unweighted	Weighted	Household with positive wealth	Households with positive wealth (bottom half)	Households with zero or negative wealth	Household with positive wealth	Households with positive wealth (bottom half)	Households with zero or negative wealth
France	2.37%	2.53%	36.14%	21.02%	24.93%	13.88%	4.02%	5.24%
Spain	2.39%	3.16%	30.63%	21.30%	4.94%	13.88%	5.57%	1.07%
UK	6.35%	9.01%	34.41%	21.87%	13.80%	13.90%	5.29%	2.92%
US	8.69%	10.36%	21.64%	12.10%	7.81%	8.52%	1.59%	1.23%

Notes: Share of households with zero or negative wealth in each country (columns 1-2). Share of each group of households (all with positive wealth, bottom half of those with positive wealth or households with zero or negative wealth) that receive a transfer (columns 3-5) or a large transfer that is above the 75th percentile of the intergenerational transfers distribution (columns 6-9). All measures weighted using population weights (except first column) and calculated using all multiple imputed values in the surveys.

Table 3. Inheritances amount and parental occupation.

	France	Spain	Great Britain	United States
Inheritance amount at the 25th percentile	15795	25338	16262	23309
Inheritance amount at the median	39379	58634	42241	59756
Inheritance amount at the 75th percentile	105615	127345	108056	145949
Share of non-recipients expecting an inheritance	30.2%	NA	31.6%	9.8%
Share with low parental occupation/education level	48.7%	45.3%	4.6%	23.4%
Share with mid-low parental occupation/education level	19.3%	29.7%	64.8%	35.5%
Share with mid-high parental occupation/education level	18.0%	14.6%	24.9%	14.9%
Share with high parental occupation/education level	14.0%	10.4%	5.8%	26.2%
Share of women household heads	37.4%	43.2%	36.8%	51.3%

Notes: Values of inheritances at the 25th, 50th and 75th percentiles (cut-off points for inheritance groups) in rows 1-3. Share of non-recipients reporting expecting a substantial intergenerational transfer (row 4). In rows 5-8, share of households in which the head has low, mid-low, mid-high or high level or parental family background (occupation for France and Spain; education for Great Britain and the United States). See Section 3 for a detailed explanation of these categories. In row 9, share of female household heads. Again, see Section 3 and Footnote 17 for the U.S. case. All measures weighted using population weights and calculated using all multiple imputed values of the surveys. Sample used is aged between 35 and 80, excluding non-positive wealth and before adjusting by age, gender and household size (fourth column of Table 1).

Table 4. Inequality of wealth and smoothed wealth distributions.

			France	Spain	Great Britain	United States
Original Adjusted Wealth Distribution	T	Estimate	1.047	0.756	1.022	1.841
		Standard Error	(0.033)	(0.040)	(0.022)	(0.045)
		C.I. (Low - High)	(0.975 - 1.119)	(0.670 - 0.843)	(0.976 - 1.069)	(1.745 - 1.937)
Inheritance Smoothed	T_I^S	Estimate	0.623	0.456	0.710	1.158
		Standard Error	(0.033)	(0.032)	(0.026)	(0.058)
		C.I. (Low - High)	(0.552 - 0.693)	(0.388 - 0.524)	(0.654 - 0.765)	(1.033 - 1.284)
Family Background Smoothed	T_F^S	Estimate	0.899	0.601	0.874	1.433
		Standard Error	(0.036)	(0.046)	(0.024)	(0.048)
		C.I. (Low - High)	(0.822 - 0.976)	(0.503 - 0.699)	(0.822 - 0.926)	(1.329 - 1.537)
Inheritance and Family Background Smoothed	T_{I+F}^S	Estimate	0.580	0.402	0.651	0.943
		Standard Error	(0.028)	(0.028)	(0.021)	(0.043)
		C.I. (Low - High)	(0.520 - 0.640)	(0.341- 0.462)	(0.605 - 0.697)	(0.850 - 1.036)

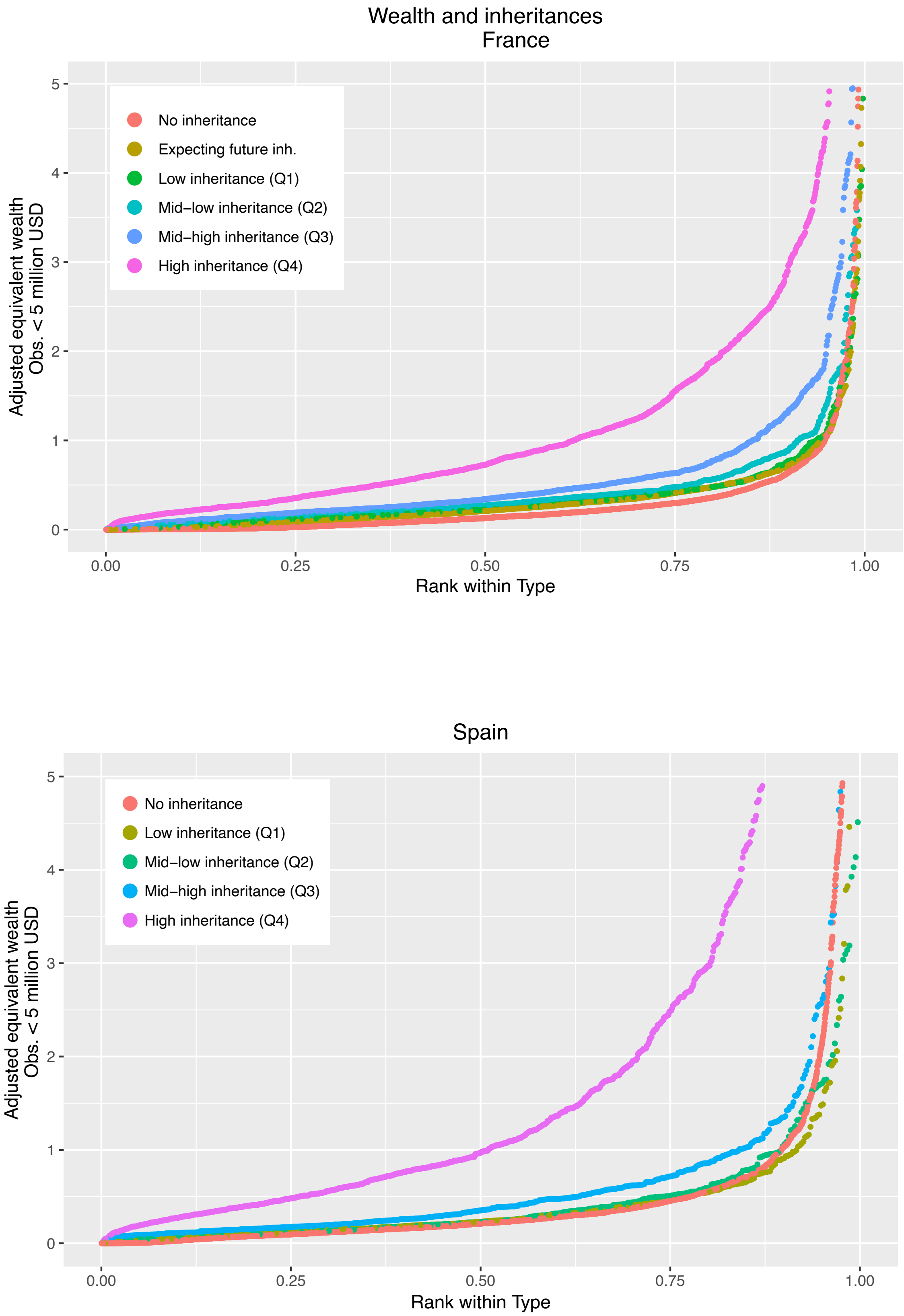
Notes: Inequality (measured by the MLD Index) of the original adjusted wealth distribution (row 1) and of the different smoothed counterfactual distributions in which differences in wealth associated with inheritances (row 2), family background (row 3) or both (row 4) have been removed. See Section 2 for details on the smoothing procedure. All measures weighted using population weights. Standard errors and confidence intervals calculated using bootstrap (100 reps) and multiple imputation (MI Boot method as proposed in by Schomaker and Heumann, 2018). Sample used is aged between 35 and 80, excluding non-positive wealth observations and adjusting by age, gender and household size (fifth column of Table 1)

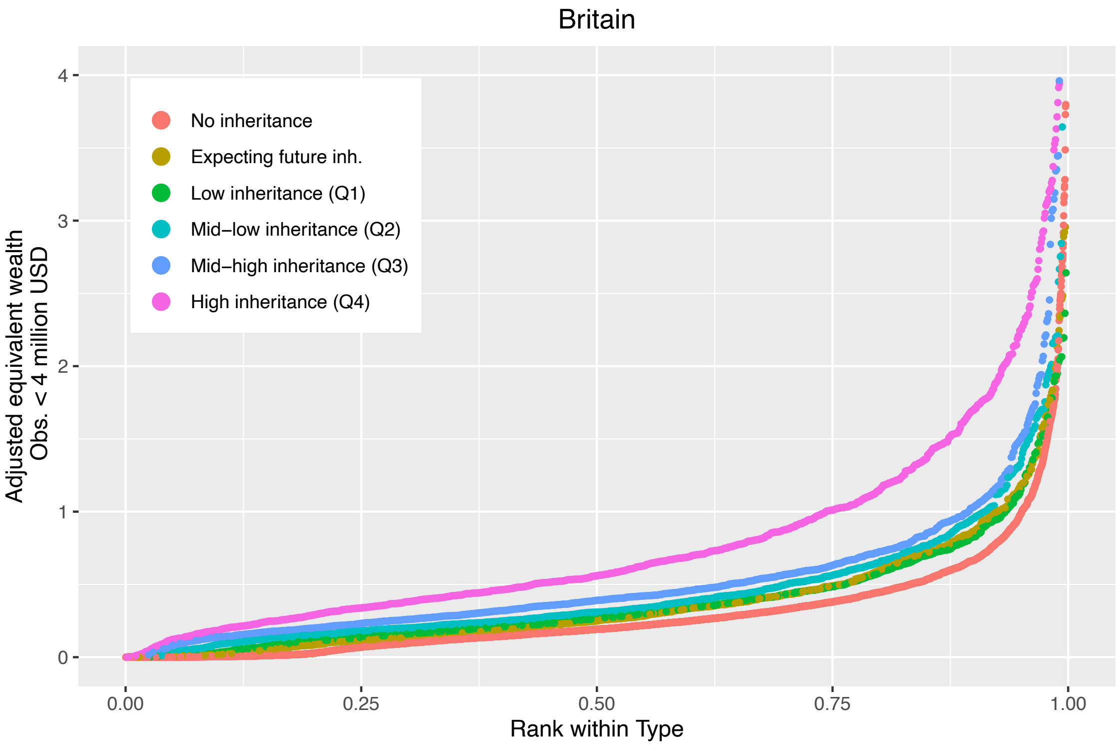
Table 5. Contributions to total wealth inequality of inheritances and family background (%).

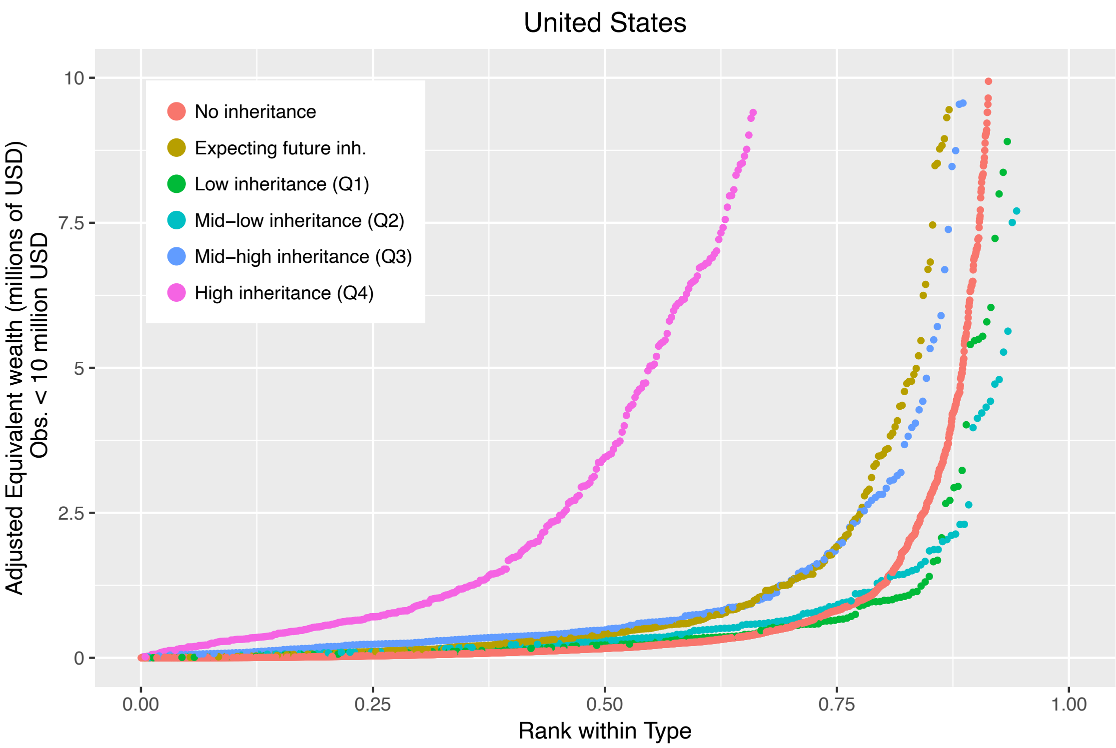
			France	**Spain**	**Great Britain**	**United States**
Gross Inheritance Contribution	Sh_I^G	Estimate	40.5%	39.7%	30.6%	37.1%
		Standard Error	(1.8%)	(2.9%)	(2.3%)	(2.9%)
		C.I. (Low - High)	(36.6% - 44.5%)	(33.5% - 46.0%)	(25.7% - 35.5%)	(30.9% - 43.3%)
Gross Family Background Contribution	Sh_F^G	Estimate	14.1%	20.6%	14.5%	22.2%
		Standard Error	(1.3%)	(4.1%)	(1.6%)	(1.8%)
		C.I. (Low - High)	(11.2% - 17.0%)	(11.7% - 29.5%)	(11.1% - 17.9%)	(18.3% - 26.0%)
Combined Inheritance and Family Background Contribution	Sh_{I+F}^J	Estimate	44.6%	46.9%	36.3%	48.8%
		Standard Error	(1.5%)	(2.6%)	(1.8%)	(2.1%)
		C.I. (Low - High)	(41.4% - 47.8%)	(41.3% - 52.5%)	(32.3% - 40.3%)	(44.1% - 53.4%)
Interacted Contribution	$Sh_{I+F}^{INT.} = Sh_I^G + Sh_F^G - Sh_{I+F}^J$	Estimate	10.0%	13.4%	8.8%	10.5%
		Standard Error	(1.8%)	(4.4%)	(1.6%)	(2.8%)
		C.I. (Low - High)	(6.1% - 14.0%)	(3.9% - 23.0%)	(5.4% - 12.2%)	(4.5% - 16.5%)
Marginal Inheritance Contribution	$Sh_I^M = Sh_{I+F}^J - Sh_F^G$	Estimate	30.5%	26.3%	21.8%	26.6%
		Standard Error	(1.5%)	(4.4%)	(2.0%)	(2.1%)
		C.I. (Low - High)	(27.3% - 33.7%)	(16.9%- 35.7%)	(17.4% - 26.1%)	(22.1% - 31.1%)
Marginal Family Background Contribution	$Sh_F^M = Sh_{I+F}^J - Sh_I^G$	Estimate	4.1%	7.2%	5.7%	11.7%
		Standard Error	(1.1%)	(2.2%)	(0.9%)	(2.5%)
		C.I. (Low - High)	(1.6% - 6.5%)	(2.4% -12.0%)	(3.7% - 7.7.%)	(6.2% - 7.1%)
Shapley Inheritance Contribution	$Sh_I^{SHAPLEY}$	Estimate	35.5%	33.0%	26.2%	31.8%
		Standard Error	(1.4%)	(3.0%)	(2.0%)	(2.1%)
		C.I. (Low - High)	(32.5% -38.5%)	(26.6% - 39.4%)	(21.9% - 30.5%)	(27.3% - 36.4%)
Shapley Family Background Contribution	$Sh_F^{SHAPLEY}$	Estimate	9.1%	13.9%	10.1%	16.9%
		Standard Error	(0.9%)	(2.5%	(1.0%	(1.7%)
		C.I. (Low - High)	(7.3% - 10.9%)	(8.6% - 19.2%)	(7.9% - 12.3%)	(13.3% - 20.6%)

Notes: Gross contribution of each characteristic to wealth inequality (rows 1-2) and of both characteristics combined (row 3) based on comparing the original adjusted wealth inequality and the inequality of the counterfactual wealth distributions. Interacted contribution to wealth inequality of both characteristics (row 4) and marginal contribution of each of them (rows 5 and 6) based on our methodology (see Section 2). Rows 6 and 7 show the contribution of each characteristic using the Shapley value decomposition. All measures weighted using population weights. Standard errors and confidence intervals calculated using bootstrap (100 reps) and multiple imputation (MI Boot method as proposed in by Schomaker and Heumann, 2018). Sample used is aged between 35 and 80, excluding non-positive wealth observations and adjusting by age, gender and household size (fifth column of Table 1)

Figure 1. Wealth and inheritances received.

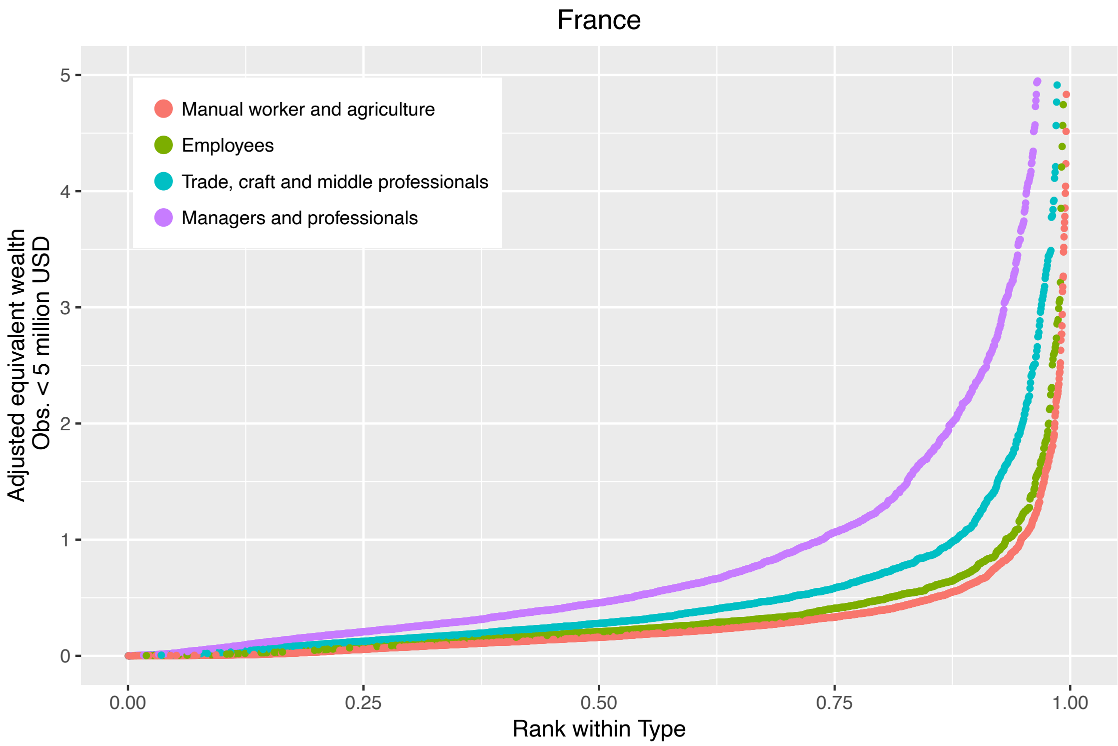


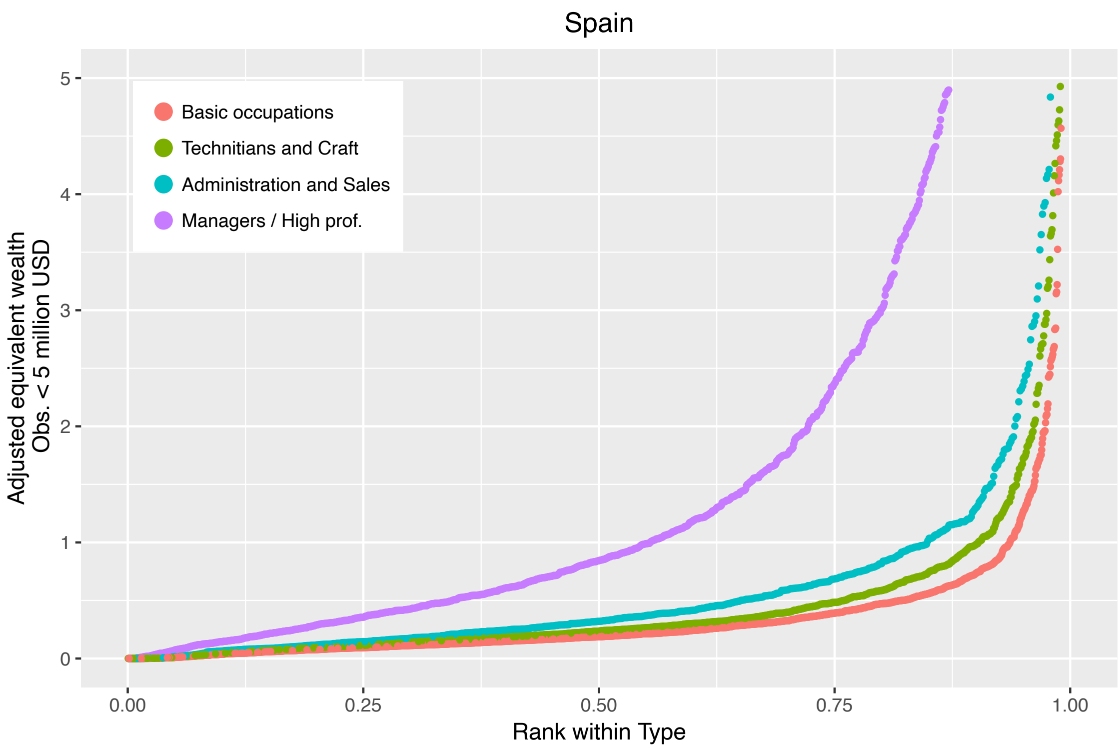


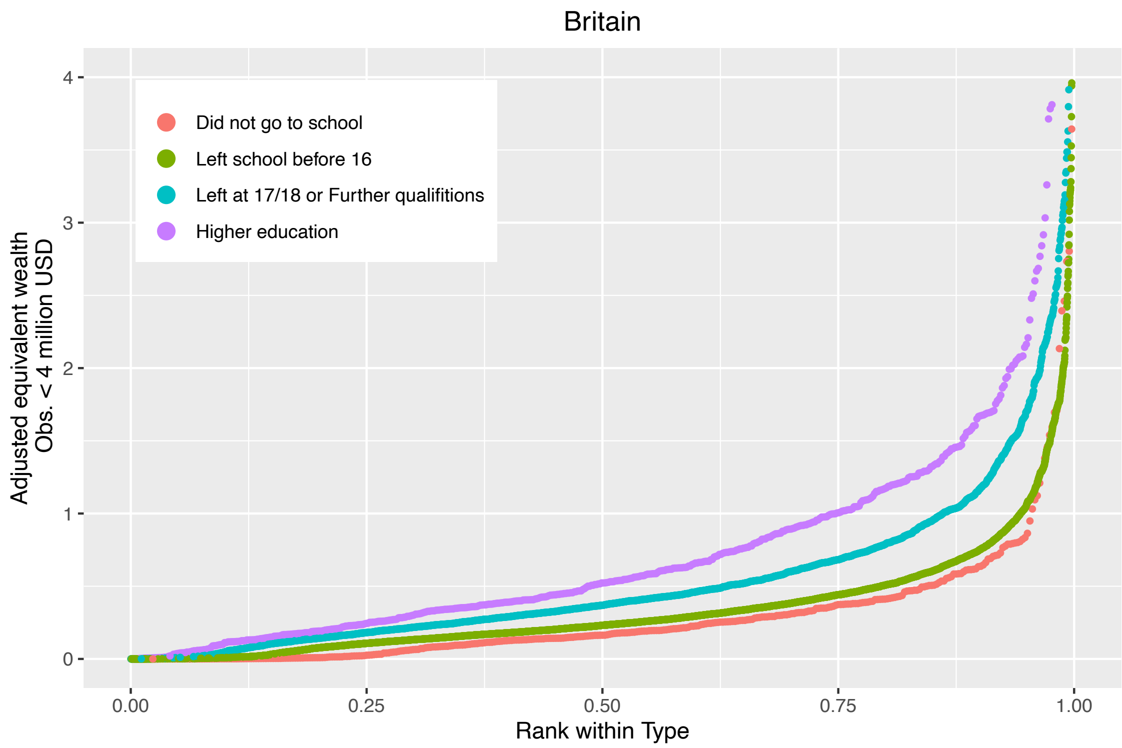


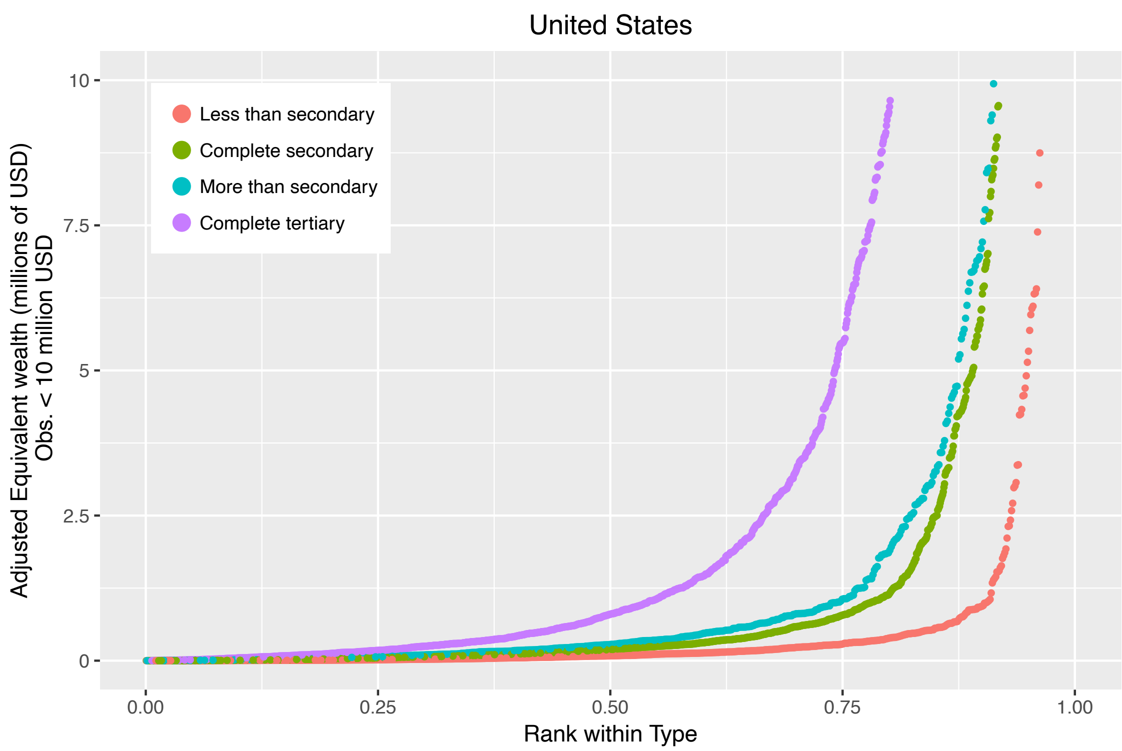
Notes: Wealth distributions of each inheritance group (according to the inheritance size) when ranked according to their within-group wealth. Sample used is aged between 35 and 80, excluding non-positive wealth observations and adjusting by age, gender and household size.

Figure 2. Wealth and parental background.









Notes: Wealth distributions of each family background group (occupational or educational level) when ranked according to their within-group wealth. Sample used is aged between 35 and 80, excluding non-positive wealth observations and adjusting by age, gender and household size.

Appendix A.

Table A1. OLS regression coefficients of log wealth on age and gender variables.

	France			*Spain*		
	Estimate	*S.E.*	*p*	*Estimate*	*S.E.*	*p*
α (Intercept)	11.454	0.041	<0.001	11.81	0.055	<0.001
β_1(Age difference)	0.021	0.007	0.003	0.018	0.009	0.042
β_1 (Age difference)^2	-0.001	0.000	0.028	-0.002	0.000	<0.001
β_1 (Age difference)^3	0.000	0.000	0.675	0.000	0.000	0.635
β_1 (Age difference)^4	0.000	0.000	0.986	0.000	0.000	0.74
δ (Female dummy)	-0.244	0.067	<0.001	-0.342	0.086	<0.001
γ_1 (Interaction female-age difference)	0.033	0.011	0.004	0.004	0.013	0.785
γ_2 (Interaction female-age difference)^2	-0.001	0.001	0.03	0.001	0.001	0.076
γ_3 (Interaction female-age difference)^3	0.000	0.000	0.006	0.000	0.000	0.371
γ_4 (Interaction female-age difference)^4	0.000	0.000	0.081	0.000	0.000	0.087
Observations		9235			5066	
R2		0.049			0.05	
R^2 adjusted		0.048			0.049	

	Britain			*US*		
	Estimate	*S.E.*	*p*	*Estimate*	*S.E.*	*p*
α (Intercept)	11.775	0.045	<0.001	11.537	0.079	<0.001
β_1(Age difference)	-0.002	0.007	0.821	-0.001	0.013	0.925
β_1 (Age difference)^2	-0.002	0.000	<0.001	0.000	0.001	0.869
β_1 (Age difference)^3	0.000	0.000	0.263	0.000	0.000	0.009
β_1 (Age difference)^4	0.000	0.000	0.102	0.000	0.000	0.015
δ (Female dummy)	-0.318	0.075	<0.001	-0.692	0.111	<0.001
γ_1 (Interaction female-age difference)	-0.002	0.012	0.878	0.042	0.019	0.026
γ_2 (Interaction female-age difference)^2	-0.001	0.001	0.235	0.001	0.001	0.553
γ_3 (Interaction female-age difference)^3	0.000	0.000	0.369	0.000	0.000	0.030
γ_4 (Interaction female-age difference)^4	0.000	0.000	0.199	0.000	0.000	0.024
Observations		10218			4486	
R2		0.045			0.064	
R^2 adjusted		0.044			0.062	

Notes: Coefficients of the regression used to adjust wealth by age and gender prior to our main analysis:

$\ln(W_i) = \alpha + \delta F_i + \sum_{n=1}^{4} \beta_n (A_i - 65)^n + \sum_{n=1}^{4} \gamma_n F_i (A_i - 65)^n + \varepsilon_i$

We finally retain the adjusted value as by: $\ln(W_i^{adj}) = \ln(W_i) - \hat{\delta} F_i - \sum_{n=1}^{4} \hat{\beta}_n (A_i - 65)^n - \sum_{n=1}^{4} \hat{\gamma}_n F_i (A_i - 65)^n$

Details and comments on the coefficients in Section 3.

Table A2. Inequality of distributions and contributions of inheritances and family background to total wealth inequality (%) for the 50-80 years old sample.

A)

			France	**Spain**	**Great Britain**	**United States**
Original Adjusted Wealth Distribution	T	Estimate	0.989	0.753	0.949	1.857
		Standard Error	(0.028)	(0.046)	(0.021)	(0.048)
		C.I. (Low - High)	(0.928 - 1.050)	(0.655 - 0.852)	(0.904 – 0.995)	(1.754 - 1.959)
Inheritance Smoothed	T_I^S	Estimate	0.564	0.450	0.606	1.115
		Standard Error	(0.021)	(0.038)	(0.026)	(0.049)
		C.I. (Low - High)	(0.520 - 0.608)	(0.369 - 0.532)	(0.549 - 0.662)	(1.009 - 1.221)
Family Background Smoothed	T_F^S	Estimate	0.799	0.588	0.784	1.369
		Standard Error	(0.029)	(0.045)	(0.028)	(0.055)
		C.I. (Low - High)	(0.736 - 0.862)	(0.491 - 0.684)	(0.723 - 0.844)	(1.251 - 1.487)
Inheritance and Family Background Smoothed	T_{I+F}^S	Estimate	0.520	0.377	0.552	0.873
		Standard Error	(0.021)	(0.034)	(0.024)	(0.049)
		C.I. (Low - High)	(0.475 - 0.566)	(0.304- 0.451)	(0.501 - 0.603)	(0.767 – 0.978)

Notes: Inequality (measured by the MLD Index) of the original adjusted wealth distribution (row 1) and of the different smoothed counterfactual distributions in which differences in wealth associated with inheritances (row 2), family background (row 3) or both (row 4) have been removed. See Section 2 for details on the smoothing procedure. All measures weighted using population weights. Standard errors and confidence intervals calculated using bootstrap and multiple imputation (MI Boot method as proposed in Schomaker and Heumann, 2018). Sample used is aged between 50 and 80, excluding non-positive wealth observations and adjusting by age, gender and household size.

B)

			France	Spain	Great Britain	United States
Gross Inheritance Contribution	Sh_I^G	Estimate	43.0%	40.2%	36.2%	39.9%
		Standard Error	(1.6%)	(3.3%)	(2.1%)	(2.5%)
		C.I. (Low - High)	(39.5% - 46.4%)	(33.2% - 47.3%)	(31.7% - 40.8%)	(34.5% - 45.4%)
Gross Family Background Contribution	Sh_F^G	Estimate	19.2%	22.0%	17.4%	26.3%
		Standard Error	(1.9%)	(3.1%)	(2.4%)	(2.2%)
		C.I. (Low - High)	(15.0% - 23.4%)	(15.3% - 28.7%)	(12.3% - 22.6%)	(21.6% - 30.9%)
Combined Inheritance and Family Background Contribution	Sh_{I+F}^C	Estimate	47.4%	49.9%	41.8%	53.0%
		Standard Error	(1.7%)	(3.1%)	(2.0%)	(2.5%)
		C.I. (Low - High)	(43.6% - 51.1%)	(43.2% - 56.6%)	(37.6% - 46.1%)	(47.6% - 58.4%)
Interacted Contribution	$Sh_{I+F}^{INT.} = Sh_I^G + Sh_F^G - Sh_{I+F}^C$	Estimate	14.8%	12.3%	11.8%	13.2%
		Standard Error	(1.6%)	(4.7%)	(2.2%)	(2.5%)
		C.I. (Low - High)	(11.3% - 18.2%)	(2.2% - 22.4%)	(7.0% - 16.6%)	(7.7% - 18.7%)
Marginal Inheritance Contribution	$Sh_I^M = Sh_{I+F}^C - Sh_F^G$	Estimate	28.2%	27.9%	24.4%	26.7%
		Standard Error	(1.9%)	(3.7%)	(2.8%)	(2.9%)
		C.I. (Low - High)	(24.2% - 32.2%)	(20.0%- 35.9%)	(18.4% - 30.4%)	(20.5% - 33.0%)
Marginal Family Background Contribution	$Sh_F^M = Sh_{I+F}^C - Sh_I^G$	Estimate	4.4%	9.7%	5.6%	13.1%
		Standard Error	(0.9%)	(3.8%)	(0.9%)	(2.2%)
		C.I. (Low - High)	(2.6% - 6.6%)	(1.6% -17.8%)	(3.6% - 7.7.%)	(8.4% - 17.7%)
Shapley Inheritance Contribution	$Sh_I^{SHAPLEY}$	Estimate	35.6%	34.1%	30.3%	33.3%
		Standard Error	(1.5%)	(2.6%)	(2.2%)	(2.4%)
		C.I. (Low - High)	(32.2% -38.9%)	(28.5% - 39.6%)	(25.6% - 35.1%)	(28.1% - 38.5%)
Shapley Family Background Contribution	$Sh_F^{SHAPLEY}$	Estimate	11.8%	15.9%	11.5%	19.7%
		Standard Error	(1.3%)	(2.5%)	(1.4%)	(1.7%)
		C.I. (Low - High)	(9.1% - 14.6%)	(10.4% - 21.3%)	(8.4% - 14.6%)	(15.9% - 23.4%)

Notes: Gross contribution of each characteristic to wealth inequality (rows 1-2) and of both characteristics combined (row 3) based on comparing the original adjusted wealth inequality and the inequality of the counterfactual wealth distributions. Interacted contribution to wealth inequality of both characteristics (row 4) and marginal contribution of each of them (rows 5 and 6) based on our methodology (see Section 2). Rows 6 and 7 show the contribution of each characteristic using the Shapley value decomposition. All measures weighted using population weights. Standard errors and confidence intervals calculated using bootstrap and multiple imputation (MI Boot method as proposed in by Schomaker and Heumann, 2018), Sample used is aged between 50 and 80, excluding non-positive wealth and adjusting by age, gender and household size.

Table A3. Inequality of distributions and contributions of inheritances and family background to total wealth inequality (%). Samples exclude observations in the first decile of the wealth distribution for France, Spain and Great Britain to be comparable with the sample for the U.S. when non-positive wealth observations are excluded.

A)

			France	Spain	Great Britain	United States
Original Adjusted Wealth Distribution	T	Estimate	0.816	0.534	0.957	1.841
		Standard Error	0.033	0.029	0.020	(0.045)
		C.I. (Low - High)	(0.745 – 0.888)	(0.471 – 0.597)	(0.976 – 0.999)	(1.745 - 1.937)
Inheritance Smoothed	T_I^S	Estimate	0.559	0.387	0.685	1.158
		Standard Error	0.033	0.027	0.026	(0.058)
		C.I. (Low - High)	(0.488 - 0.630)	(0.330 - 0.444)	(0.630 - 0.740)	(1.033 - 1.284)
Family Background Smoothed	T_F^S	Estimate	0.726	0.445	0.842	1.433
		Standard Error	0.035	0.031	0.019	(0.048)
		C.I. (Low - High)	(0.649 - 0.802)	(0.379 - 0.512)	(0.800 - 0.884)	(1.329 - 1.537)
Inheritance and Family Background Smoothed	T_{I+F}^S	Estimate	0.521	0.337	0.634	0.943
		Standard Error	0.028	0.023	0.022	(0.043)
		C.I. (Low - High)	(0.460 - 0.582)	(0.287- 0.387	(0.587 - 0.681)	(0.850 - 1.036)

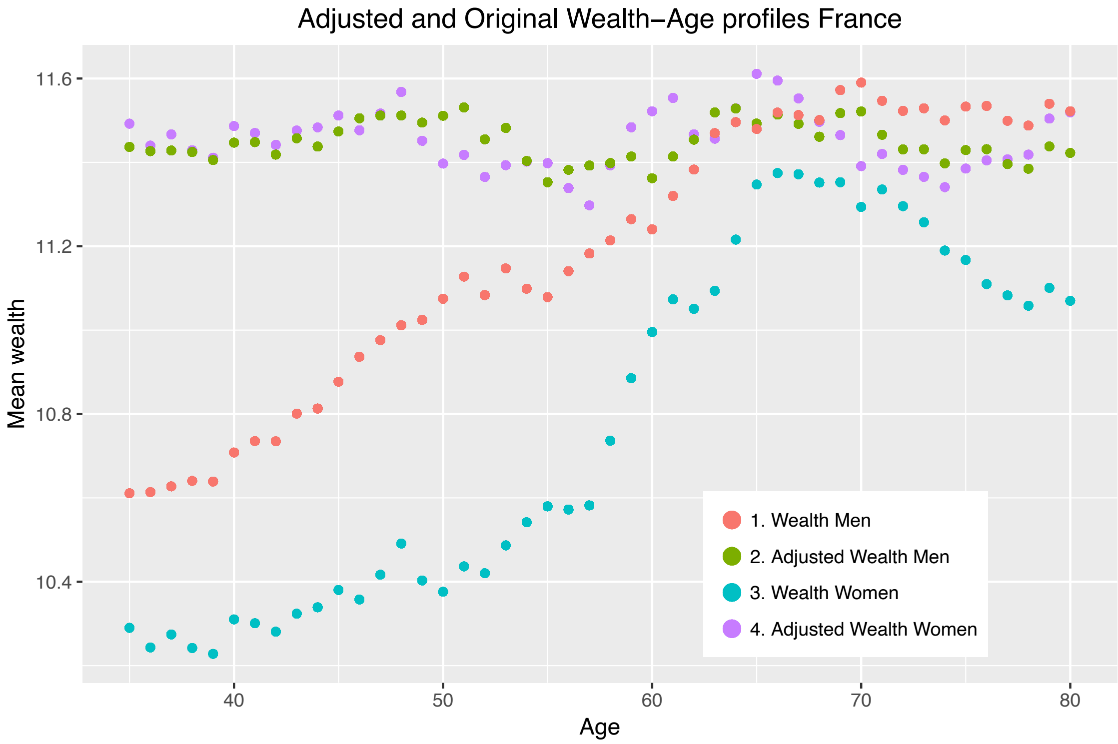
Notes: Inequality (measured by the MLD Index) of the original adjusted wealth distribution (row 1) and of the different smoothed counterfactual distributions in which differences in wealth associated with inheritances (row 2), family background (row 3) or both (row 4) have been removed. See Section 2 for details on the smoothing procedure All measures weighted using population weights. Standard errors and confidence intervals calculated using bootstrap and multiple imputation (MI Boot method as proposed in by Schomaker and Heumann, 2018) Sample used is aged between 35 and 80, excluding non-positive wealth observations in the U.S. and the lowest 10% of the wealth distribution observations in the other three countries, adjusting by age, gender and household size.

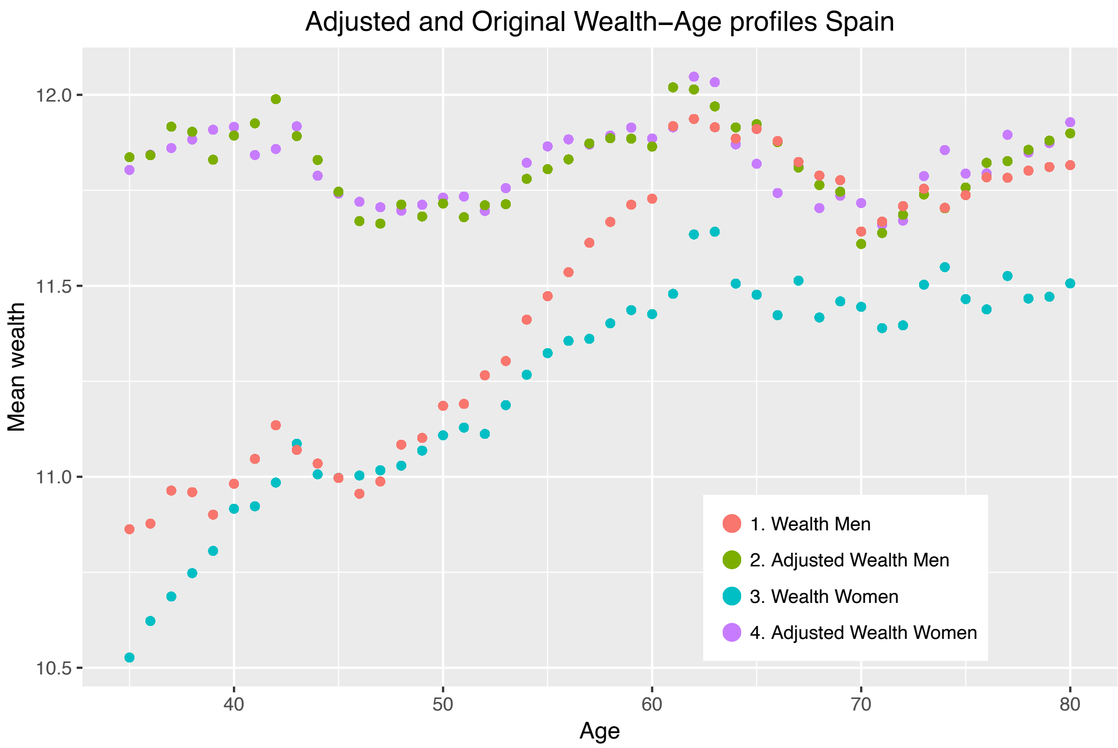
B)

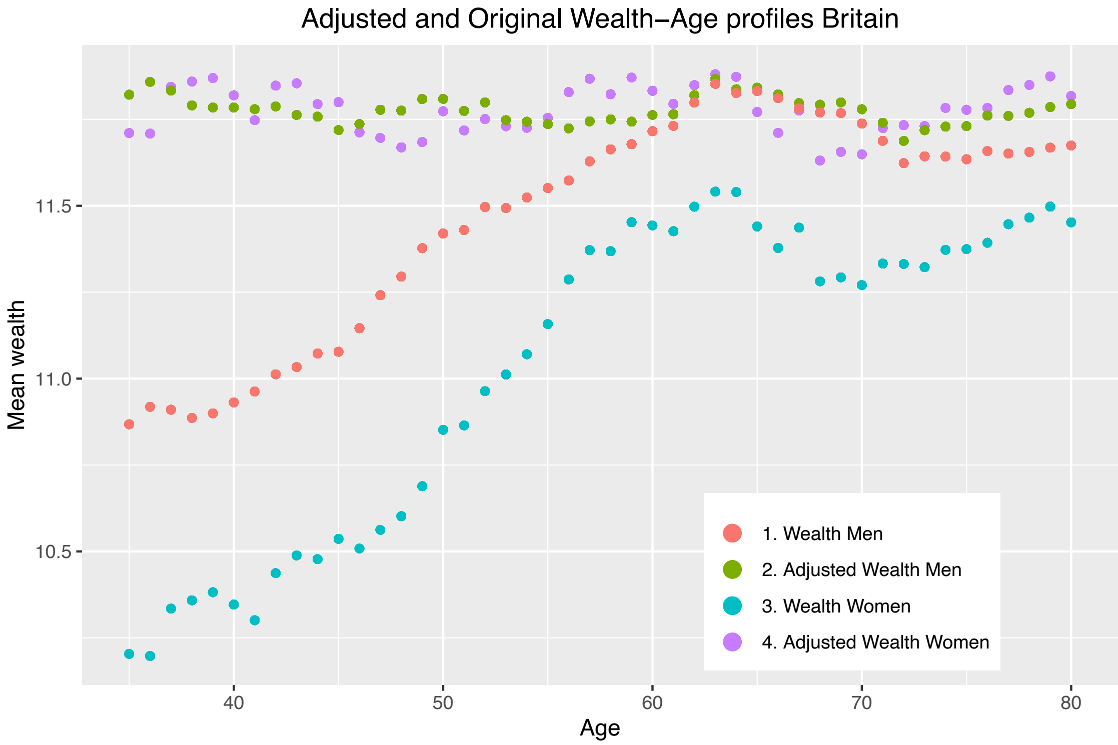
			France	Spain	Great Britain	United States
Gross Inheritance Contribution	Sh_I^G	Estimate	31.5%	27.6%	28.4%	37.1%
		Standard Error	(1.7%)	(2.6%)	(2.1%)	(2.9%)
		C.I. (Low - High)	(27.8% - 35.3%)	(22.0% - 33.0%)	(23.9% - 33.0%)	(30.9%35.5%3%)
Gross Family Background Contribution	Sh_F^G	Estimate	11.1%	16.6%	12.0%	22.2%
		Standard Error	(1.2%	(2.1%)	(1.3%)	(1.8%)
		C.I. (Low - High)	(8.6% - 13.6%)	(12.2% - 21.1%)	(9.1% - 14.8%)	(18.3% - 26.0%)
Combined Inheritance and Family Background Contribution	Sh_{I+F}^C	Estimate	36.2%	36.8%	33.8%	48.8%
		Standard Error	(1.4%	(2.7%)	(1.8%)	(2.1%)
		C.I. (Low - High)	(33.2% - 39.1%)	(30.9% - 42.7%)	(29.9% - 37.6%)	(44.1% - 53.4%)
Interacted Contribution	$Sh_{I+F}^{INT} = Sh_I^G + Sh_F^G - Sh_{I+F}^C$	Estimate	6.5%	7.4%	6.7%	10.5%
		Standard Error	(1.6%)	(2.8%)	(1.4%)	(2.8%)
		C.I. (Low - High)	(3.1% - 9.8%)	(1.3% - 13.5%)	(3.7% - 9.6%)	(4.5% - 16.5%)
Marginal Inheritance Contribution	$Sh_I^M = Sh_{I+F}^C - Sh_F^G$	Estimate	25.1%	20.2%	21.8%	26.6%
		Standard Error	(0.9%)	(3.0%)	(1.9%)	(2.1%)
		C.I. (Low - High)	(23.3% - 27.1%)	(13.7%- 26.6%)	(17.7% - 25.9%)	(22.1% - 31.1%)
Marginal Family Background Contribution	$Sh_F^M = Sh_{I+F}^C - Sh_I^G$	Estimate	4.6%	9.3%	5.3%	11.7%
		Standard Error	(1.1%)	(2.6%)	(1.0%)	(2.5%)
		C.I. (Low - High)	(2.3% - 6.9%)	(3.7% -14.8%)	(3.2% - 7.4%)	(6.2% - 7.1%)
Shapley Inheritance Contribution	$Sh_I^{SHAPLEY}$	Estimate	28.3%	23.9%	25.1%	31.8%
		Standard Error	(1.2%)	(2.4%)	(1.9%)	(2.1%)
		C.I. (Low - High)	(25.8% -30.8%)	(18.7% - 29.1%)	(21.0% - 29.2%)	(27.3% - 36.4%)
Shapley Family Background Contribution	$Sh_F^{SHAPLEY}$	Estimate	7.9%	13.0%	8.6%	16.9%
		Standard Error	(0.8%	(1.9%	(0.9%	(1.7%)
		C.I. (Low - High)	(6.2% - 9.6%)	(9.0% - 16.9%)	(6.6% - 10.7%)	(13.3% - 20.6%)

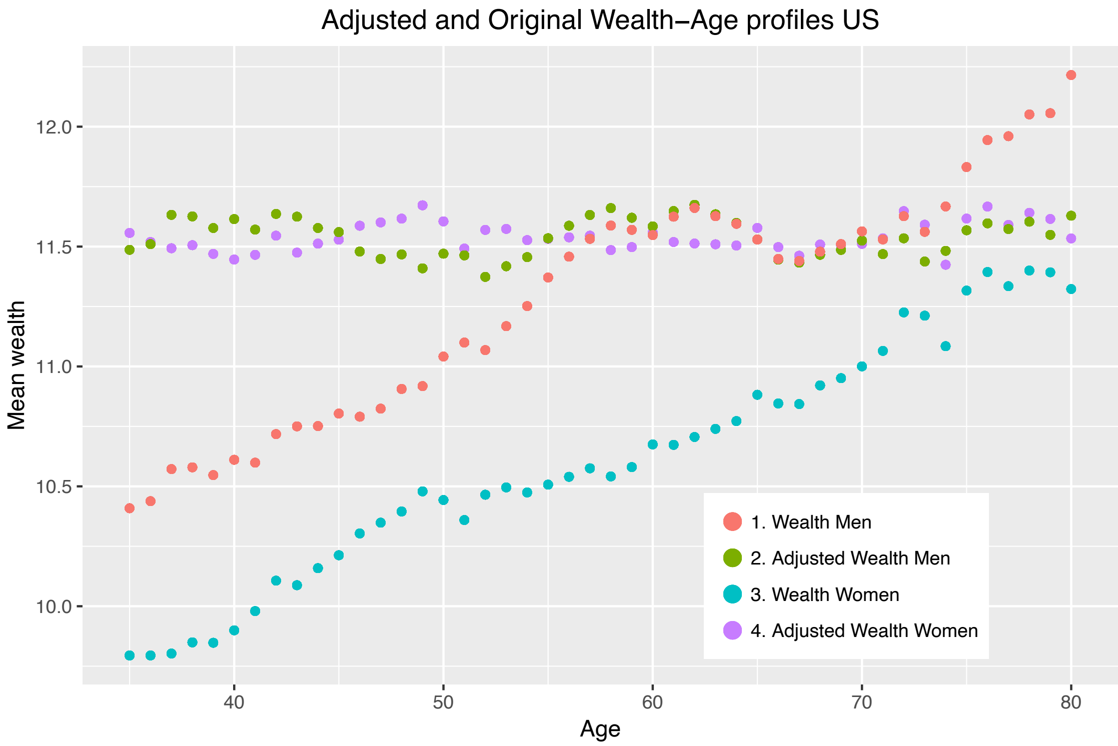
Notes: Gross contribution of each characteristic to wealth inequality (rows 1-2) and of both characteristics combined (row 3) based on comparing the original adjusted wealth inequality and the inequality of the counterfactual wealth distributions. Interacted contribution to wealth inequality of both characteristics (row 4) and marginal contribution of each of them (rows 5 and 6) based on our methodology (see Section 2). Rows 6 and 7 show the contribution of each characteristic using the Shapley value decomposition. All measures weighted using population weights. Standard errors and confidence intervals calculated using bootstrap and multiple imputation (MI Boot method as proposed in by Schomaker and Heumann, 2018), Sample used is aged between 35 and 80, excluding non-positive wealth observations in the U.S. and the lowest 10% of the wealth distribution observations in the other three countries, adjusting by age, gender and household size.

Figure A1. Age wealth profile by gender of the household head.
(rolling mean over 9 years centred intervals)









Notes: Original and age-gender adjusted wealth distributions, by gender, in each of the countries analysed. Values represent the moving rolling average across 9 years of age. Details of the adjustment in Section 3.