Society for the Study of Economic Inequality

Working Paper Series

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ECINEQ WP 2019 - 506

ECINEQ 2019 - 506
September 2019

www.ecineq.org

The distribution of wealth in the U.S. and Spain: the role of socio-economic factors*

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Abstract

The literature has typically found that socio-economic factors (age, education, income, labor status, household structure) are irrelevant to explain the large cross-country disparities in wealth. As a result, institutions and other unobserved factors have received all the credit. Here, we propose to focus on one type of wealth inequality, the part of overall wealth inequality that is explained by parental background and inheritances (inequality of opportunity -IO- in wealth). By means of a counterfactual decomposition method (DiNardo et al., 1996), we show that imposing the distribution of socio-economic factors in the U.S. (2016) into Spain (2014) has little effect on overall wealth inequality. However, socio-economic factors play an important role when wealth IO is considered. Moreover, the Shapley decomposition shows that the distribution of age, education and income in the U.S. contribute to increase wealth IO in the counterfactual, whereas the opposite happens with the distribution of labor status and household structure. These results are robust to different types of wealth (total, financial or real state), inequality indices (MLD or Gini coefficient), IO measures (absolute or relative) and samples (total or above 55 years).

Keywords: wealth inequality, socio-economic factors, inequality of opportunity in wealth, United States, Spain.

JEL Classification: C81, D31, D63.

*We acknowledge comments and suggestions from the participants at the XXII Encuentro de Economía Aplicada (Cartagena, Spain) and ICAE Seminar at Universidad Complutense de Madrid. This paper has received financial support from the Ministerio de Economía y Competitividad of Spain under project ECO2016-76506-C4-1-R and Comunidad de Madrid (Spain) under project S2015/HUM-3416-DEPOPORCM. The contribution of Amaia Palencia, Alberto Palacios and Pablo de la Vega is also acknowledged. All views and any remaining errors or omissions are our sole responsibility.

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1. Introduction

Recent studies on wealth inequality have found that the bottom third of the wealth distribution is asset-poor, middle class' wealth is mostly composed by real estates, whilst for the upper tail the main component of their portfolios is financial assets, which are considered to be the main source of the increase in wealth inequality during the last decades (Demirgüc-Kunt and Levine, 2009; Gennaioli et al., 2014; Badarinza et al., 2016).[2] The sources of wealth differences between countries have been more elusive to find. The comparison between the U.S. and some European countries has shown that socio-economic factors like education, labor status, household structure or income are not relevant to explain the differences in wealth inequality (Christelis et al., 2013; Sierminska and Doorley, 2017; Cowell et al., 2018a). The consistent large cross-country disparities are then attributed to institutions and other latent factors. But why socio-economic factors do not seem to account for differences in wealth across countries?

The main proposal in the literature to deal with this issue is the analysis of wealth by percentiles. The idea is that current analysis is hiding differences at the tails of the distribution, which somehow compensate each other provoking small changes in the measurement of overall wealth inequality (Bover, 2010; Cowell et al., 2018a). However, the results obtained by this literature are not conclusive, as they do not coincide on the role and relevance of the covariates analyzed. For example, Bover (2010) highlights the importance of household characteristics, while Cowell et al. (2018a) finds it rather small when income or education are considered. Moreover, the use of percentiles to propose policies that overturn the dynamics of wealth inequality is limited. Here, we explore a different avenue. Perhaps, it is not a matter of the position that individuals occupy at the wealth distribution, but of the type of wealth inequality under consideration. For example, Cobb-Clark and Hildebrand (2006) show how difficult is for Mexican Americans to climb the ladder of the wealth distribution. Our proposal is to estimate the importance of socio-economic factors for that part of total wealth inequality that is explained by parental background and received inheritances.

According to the literature on inequality of opportunity, certain outcomes like wealth (income, utility, health) are actually a composite measure of two types of variables. In the first group, we find individual *circumstances*, factors beyond individual's control like

[2] Wealthier households are also more educated and up to 40% of retirement wealth inequality is attributed to financial knowledge (Lusardi et al., 2017).

socio-economic background, race, or health endowments. In the second group, we have individual *efforts*, factors within individual's control like occupational choice or number of hours worked (Roemer, 1998; Van de Gaer, 1993; Fleurbeay, 2008). Then, overall outcome inequality is the combination of two inequalities: inequality of opportunity (IO), due to different circumstances, and inequality of effort (IE). The IO literature considers that any society concerned with fairness should minimize the IO component as the distribution of circumstances is morally arbitrary.[3]

The IO literature has traditionally focused on income (Bourguignon et al., 2007; Ferreira and Gignoux, 2011; Marrero and Rodríguez, 2011), although it has been applied to health at some extent in the last years (Trannoy et al., 2010; Bricard et al., 2013; Carrieri, 2018). However, this interest on IO has not yet been expanded to wealth inequality probably due to the lack of appropriate data. An empirical analysis of IO requires not only comparable measures of individual wealth, but also individual circumstances or social origins to be measured in a comparable and homogeneous way. Unfortunately, there are few databases with this information and, even then, the number of circumstances tends to be limited. Only two contributions can be highlighted: Palomino et al. (2019) where the level of IO in wealth (according to parental background and bequests) is compared for the U.K., the U.S., France and Spain, and Song et al. (2018) where IO in wealth is analyzed for China.

Taking advantage of this literature we first estimate overall wealth inequality and wealth IO for financial, real estates and total gross wealth in the U.S. (2016) and Spain (2014). Because we are mainly focused on the intergenerational transmission of wealth and the DFL methodology is data consuming, we consider parental background and inheritances as our circumstances. Then, by means of the DiNardo-Fortin-Lemieux (DFL) counterfactual decomposition (DiNardo et al., 1996), we estimate the explanatory power of socio-economic factors (age, education, income, labor status and household structure) for overall wealth inequality and wealth IO.

Consistent with previous literature, the results for overall wealth inequality show that differences between the U.S. and Spain have to be attributed to institutions and other unobserved variables because socio-economic factors only explain around 10% of total dispersion in wealth. However, when we consider the part of total wealth inequality

[3] Recently, it has been proposed that IO is also relevant for growth. In an empirical application for the U.S. states, Marrero and Rodríguez (2013) found that IO has a negative effect on future economic growth. Later, Marrero et al. (2016) observed that the negative effect of IO on growth for the U.S. states is mainly concentrated in the low percentiles of the distribution.

explained by parental background and bequests, it is found that socio-economic factors actually play a remarkable role for explaining differences between the two countries. This result is robust to the inequality index (MLD or Gini coefficient), the IO approach (absolute or relative), the type of wealth (total, financial or real estate) and the sample (total sample or individuals above 55 years old) under consideration. Then, we estimate the effect of each socio-economic factor separately by applying the Shapley value decomposition. In general, it is observed that age, education and the income distribution of the U.S. significantly increase IO in wealth for Spain, whereas the labor status and household structure of the U.S. decrease it.

These results are relevant for several reasons. First, they confirm that the distribution of wealth is not independent from individual circumstances. In particular, we observe that the part of total wealth inequality that is explained by family background and inheritances is important in the U.S. and Spain. Second, despite that socio-economic factors seem to be unimportant for overall wealth inequality, it is clear from our results that this is not the case for the part of wealth that is explained by the previous circumstances, i.e., the type of wealth inequality that is considered is relevant. Third, the results obtained for wealth disparities between the U.S. and Spain have shown that the effects of socio-economic factors work through two important channels: education and labor status. On the one hand, the U.S. educational distribution, when imposed to Spain, increases IO. This fact may be caused by the joint effect of a higher wage premium of education (Crivellaro, 2016) and a larger access to secondary and tertiary education in the U.S.. On the other hand, the significantly smaller unemployment rate in the U.S. seem to provide many more opportunities to acquire wealth to their citizens. In sum, we suggest that the IO approach adopt here can be helpful to unmask wealth differences across countries.

The remainder of the article is structured as follows. Section 2 explains the methods used to measure IO and the DiNardo et al. (1996) counterfactual decomposition. Section 3 describes the database, clarifies the variables under consideration and comments on their main statistics. Section 4 presents our main findings for overall wealth inequality and IO in wealth, whilst Section 5 includes some concluding remarks.

2. Methods

The literature on IO has shown that parental background is one of the most important circumstances determining individual outcomes (Chechi and Peragine, 2010; Ferreira and Gignoux, 2011; Marrero and Rodríguez, 2011 and 2012). Likewise, inheritances have been found to affect the distribution of wealth in a significant way (Wolff and Gittleman, 2014; Palomino et al., 2019). Unfortunately, race, which has been shown to be important for the accumulation of wealth in the U.S. (Cobb-Clark and Hildebrand, 2006; Thompson and Suarez, 2015), is not available for Spain. Then, because the DFL method is data consuming (types must contain enough observations to launch the necessary logits, see below) and we are mainly focused on the intergenerational transmission of wealth, we consider parental background and bequests as our circumstances.[4]

Based on these two variables, we first estimate the level of IO in the U.S. and Spain. Among the IO indices existing in the literature, we adopt the ex-ante parametric IO index proposed in Ferreira and Gignoux (2011). We have leaned toward this method because it is the most popular approach (Marrero and Rodríguez, 2012; Brunori et al., 2018) so the interested reader can put our results in perspective. For robustness, we have also applied the method proposed by Bjorklund et al. (2012) which takes into account the possible correlation between effort and opportunities, although the results did not vary significantly. In addition, we implemented the correction proposed by Niehues and Peichl (2014) but, same as Brunori et al. (2018, footnote 11), we did not find significant differences with respect to the canonical model results.[5]

Consider a finite population of discrete individuals indexed by $i \in \{1, \ldots, N\}$, the individual wealth, w_i, is assumed to be a function of the set of circumstances, C_i, that the individual faces and the amount of effort, e_i, such that $w_i = f(C_i, e_i)$. Circumstances are exogenous because they cannot be affected by individual decisions, but effort is assumed to be influenced, among other factors, by circumstances. Consequently, individual wealth can be rewritten as $w_i = f(C_i, e_i(C_i))$. Population then is divided into T mutually exclusive and exhaustive types where all the individuals in the same type t have the same circumstances. As a result, there is equality of opportunity in the economy if the distribution of wealth across types is the same. Accordingly, given wealth distributions

[4] We also considered gender as a circumstance. Unfortunately, the necessary logit estimations of the DiNardo et al. (1996) methodology were not accurate.

[5] Results are available from the authors upon request.

by types, first and second order stochastic dominance by types could be contrasted. However, the stochastic dominance criterion is partial and incomplete, since the distribution functions can cross (Atkinson, 1970). The alternative approach considered by the literature has been to use a particular moment of said distributions, in particular, the average. Thus, let $\bar{w} = (\bar{w}^1, \dots, \bar{w}^T)$ be the T-dimensional vector of average wealth for the various types. A necessary though not sufficient condition to be equality of opportunity is that the elements of vector $\bar{w}$ be equal. Consequently, IO can be defined as $I(\bar{w})$, where I is a specific inequality measure.

Among the available inequality indices, our first choice is the mean logarithmic deviation (MLD), because it is additively decomposable (Bourguignon, 1979; Cowell, 1980; Shorrocks, 1980) and has a path-independent decomposition (Foster and Shneyerov, 2000).[6] For a wealth distribution w, the MLD index can be exactly decomposed as follows:

$$MLD(w) = MLD(\bar{w}) + \sum_{t=1}^{T} p_t MLD(w^t), \tag{1}$$

where w^t is the wealth distribution of type t and p_t is the population share of type t. The between-group inequality index, $MLD(\bar{w})$, is by construction an absolute measure of IO. A relative version of this index is:

$$IO^{Rel} = \frac{MLD(\bar{w})}{MLD(w)}. \tag{2}$$

Despite that the Gini coefficient (G) is not an additively decomposable index, it has also been used in the literature to measure inequality of opportunity (Lefranc et al., 2008; Rodríguez, 2008; Brunori et al., 2019). For robustness, we will replicate our analysis for the Gini coefficient by using $G(\bar{w})$ as our alternative measure of absolute IO and $\frac{G(\bar{w})}{G(w)}$ as our alternative index of relative IO.

Following Bourguignon et al. (2007) and Ferreira and Gignoux (2011), we estimate the between-group component parametrically with a regression where the dependent variable is the natural logarithm of wealth.[7] Our independent variables are parental qualification

[6] The path-independent property implies that the result of the decomposition is independent of the component that is eliminated first, the within-group inequality or the between-group inequality. Because the MLD cannot deal with zeros by definition we have added 1 dollar to all wealth observations in the sample.

[7] The use of the natural logarithm is especially useful for the measurement of IO in wealth because it smooths the effect of outliers in the upper tail of the distribution of wealth.

(education or occupation) and bequests received. The log-linear equation to be estimated is then the following:

$$\ln w_i = \varphi C_i + u_i, \tag{3}$$

where u_i represents effort variables, but also unobserved circumstances and random variables, such as luck.[8] The dispersion within types is removed by approximating individual wealth with the fitted value $\hat{w}_i = \exp(\hat{\varphi} C_i)$. Then, applying the MLD (or Gini) to the vector $\hat{w}$ gives us the parametric estimate of IO which reflects the wealth disparities between individuals as if they had received the mean wealth of their type.

Once we have obtained the part of total wealth inequality explained by parental background and inheritances for the US and Spain, we perform a counterfactual analysis based on the decomposition method proposed by DiNardo et al. (1996).[9] The main idea of this procedure consists on estimating which part of the differences between the wealth distributions of our two countries is explained by socio-economic variables, and which part is attributable to cross-country unobservable variables. This methodology has been previously used to analyze race wealth inequality (Cobb-Clark and Hildebrand, 2006), gender wealth gaps (Sierminska et al., 2008; Anastasiade and Tillé, 2017), job polarization (Autor, 2019), occupational segregation (Gradín, 2013; Gradín et al., 2015), and wealth differences across countries (Cowell et al., 2018a and 2018b). Ours is the first attempt, as far as we are aware, to apply this approach to explain IO differences across countries.

Consider two countries A and B and one objective variable, w, which is wealth (financial, real states or total) in our case. Also consider the vector of socio-economic factors z that determine the distribution of w in a given economy.[10] Then, the cumulated wealth distribution in country A, given its own characteristics represented by z, is:

$$\int F(w|z, A)\, dF(z|A). \tag{4}$$

We define a counterfactual country in which we keep the wealth distribution of country A but impose the distribution of the socio-economic factors in country B as follows:

$$\int F(w|z, A)\, dF(z|B). \tag{5}$$

[8] See Lefranc et al. (2009) for an explicit consideration of luck in the measurement of IO.

[9] A complete description of this methodology can be found in Fortin et al. (2011).

[10] When referring to the array z we use the terms “socio-economic factors” and “covariates” without distinction from now on.

This expression can be obtained from equation (4) by multiplying the latter by a reweighting factor Ψ:

$$\int F(w|z,A)\Psi\, dF(z|A), \tag{6}$$

where $\Psi = \frac{dF(z|B)}{dF(z|A)}$. Therefore, to generate the counterfactual in (5) we simply need to modify the sample weights of country A to represent the existing socio-economic structure in country B. The reweighting factor Ψ is derived by using the Bayes rule:

$$\Psi = \frac{dF(z|B)}{dF(z|A)} = \frac{\frac{P(B|z)*P(z)}{P(B)}}{\frac{P(A|z)*P(z)}{P(A)}} = \frac{P(B|z)}{P(A|z)} \cdot \frac{P(A)}{P(B)}. \tag{7}$$

The left-side part of the last ratio in equation (7) is a *belonging ratio*. It is calculated with a logit where the dependent variable, which is a binary variable that takes 1 if the observation belongs to country B (or A), is regressed against the covariates defined in vector z. In our case, these variables will be age (a), attained education (e), income (y), labor status (l) and household structure (h). The right-side part of the last ratio in equation (7) is a *population ratio* which controls for the different relative size of both countries.

In addition, we can be interested in studying the separate effect of each socio-economic factor. To do this, we follow the procedure first developed by Cobb-Clark and Hildebrand (2006). Consider the actual distribution of wealth in country A to be:

$$C^A = \int F(w|a,e,y,l,h,A)\, dF(a|e,y,l,h,A)\, dF(e|y,l,h,A)\, dF(y|l,h,A)$$
$$dF(l|h,A)\, dF(h|A). \tag{8}$$

The first term is the conditional wealth distribution given our vector z. The second term represents the conditional age expectation given the other socio-economic factors. Similarly, the rest of terms collect the conditional expectations of education, income, labor status and household structure, respectively.

Given equation (8), we define a new set of counterfactuals. By imposing the age distribution of country B into country A, we have

$$C^1 = \int F(w|a,e,y,l,h,A)\, dF(a|e,y,l,h,B)\, dF(e|y,l,h,A)\, dF(y|l,h,A)$$
$$dF(l|h,A)\, dF(h|A), \tag{9}$$

where the difference between the equations (8) and (9) determines the effect of age. Likewise, we can also define a counterfactual C^2 for which we impose the distributions of age and education attainment of country B into country A. The difference $C^1 - C^2$ will give us the effect of education attainment. In the same manner, we can calculate C^3, C^4 and C^5 by subsequently adding the effects of income, labor status and household structure. In the end, we find that the whole difference between countries A and B can be decomposed in the following way:

$$C^A - C^B = [C^A - C^1] + [C^1 - C^2] + [C^2 - C^3] + [C^3 - C^4] + [C^4 - C^5] + [C^5 - C^B]. \tag{10}$$

This equation gives us the effect of each socio-economic factor separately. In addition, the last term collects all the effects that are not explained by the set of covariates, i.e., the differences attributed to institutions and other unobservable (or omitted) factors. Unfortunately, equation (8) is just one possible combination of the socio-economic factors because there are up to 120 possibilities (the number of permutations of 5 covariates is 5!). We do not have preference for any of them, so we have to apply the Shapley value. By assuming that all possible combinations of factors have the same probability, the Shapley value calculates the contribution of each socio-economic factor as the average of all its possible contributions.[11]

In our analysis we consider the United States as the country of reference, so we plug its socio-economic factor distribution into Spain. Of course, the imposition of the Spanish covariates into the U.S. economy would provide the reverse results. According to this procedure, the *actual difference* between the inequality of wealth in Spain and the U.S. is decomposed into two components. First, the *compositional effect* which measures the difference between the inequality of wealth in Spain and the counterfactual. A negative compositional effect will indicate that the counterfactual generated after imposing the U.S. characteristics is bigger than the actual inequality of wealth in Spain, and vice versa. Second, a *residual* (explained by institutional and other unobservable factors) which measures the difference between the counterfactual and the value of inequality of wealth

[11] The Shapley value is the only decomposition method that solves the tension between marginality and consistency (Chantreuil and Trannoy, 2013). See also, Sastre and Trannoy (2002), Rodríguez (2004) and Shorrocks (2013).

in the U.S.. This analysis is applied not only to the absolute wealth IO indices but also to the relative ones.

3. Databases: the U.S. (2016) and Spain (2014)

Our databases are the *Survey of Consumer Finances* (SCF) for the U.S. (2016) published by the Federal Reserve and the *Survey of Household Finances* (EFF) for Spain (2014) published by the Central Bank of Spain. To compensate for the large skewness of the wealth distribution, both surveys oversample the households at the upper tail of the wealth distribution. This characteristic does not bias our results because both the Federal Reserve and the Central Bank of Spain provide the appropriate sample weights (Bover, 2008). Furthermore, both surveys include up to five imputations, performed to avoid missing data and non-response biases.[12]

To make these databases fully comparable, all wealth measures should be in the same currency. Accordingly, our results are presented in U.S. dollars of 2016. Equally important is the fact that despite being quite similar, the two databases under consideration diverge in the definition of some variables. Since the level of disaggregation of the SCF is higher for the variables under analysis, we adapt this survey to the definitions provided by the Central Bank of Spain. As a result, our statistics for the U.S. are slightly different from the values reported in the SCF.

We have chosen these two economies for two main reasons. First, the SCF and the EFF are arguably the most complete databases of wealth. The SCF and the EFF are published every three years since 1983 and 2002, respectively, while the first wave of the Eurosystem's Household Finance and Consumption Survey (HFCS) was released in April 2013. Both surveys oversample the upper tail of the wealth distribution since the first wave and provide a complete set of sociodemographic variables. In addition, the SCF and the EFF contain information about inheritances and parental qualification (parental education in the SCF and parental occupation in the EFF) which are fundamental variables for analyzing the level of IO due to the intergenerational transmission of wealth. Second, the literature has consistently studied the similitudes and differences between both countries. For instance, U.S. households have been found to be less reluctant to

[12] Because there is no particular preference for any given imputation, we average the values of the five imputations.

invest in finances, whereas Spanish households have shown a clear preference for real estate assets (Azpitarte, 2012). Financial markets are more developed in the U.S. as they present a more flexible regulation and a wider array of products to be acquired (Mendoza et al, 2009). Also, both countries have exhibited important differences in their demographic structures which is reflected in life cycle decisions such as when to leave the parental household (Bover, 2010).

Our unit of analysis is the head of the household for who we observe individual circumstances and wealth. As said in the previous section, two individual circumstances are considered: parental qualification and inheritances. The EFF has traditionally provided information about the parental occupation of the respondent. On the contrary, the 2016 wave is the first occasion when the SCF has published a similar variable, parental education. To make them comparable, we must think about them as proxies for parental qualification. To this end, we take the National Classification of Occupations in Spain to create three qualification categories: low, medium and high. As for the SCF, because there are four categories (illiterate, primary, secondary and tertiary education), we match our two databases by merging the first two categories of parental education. Then, our final variable (parental qualification) is defined as the highest qualification achieved by any of the two parents.

With respect to the second individual circumstance, inheritances, we follow Palomino et al. (2019) who claim that receiving an inheritance is not as relevant for IO as the quantity received. Accordingly, we divide the total population into two groups: individuals whose bequest is null or less than $75,000 (which is approximately equivalent to the sixth decile of the bequest distribution in Spain) and individuals who inherited that quantity or more. This division implicitly implies that bequests below $75,000 are irrelevant for individual opportunities. When dividing the total population into types, we were restricted by the size of the types since they must contain enough observations to run the logits of the DFL methodology. This definition is the one that showed the types with most equal size. Nonetheless, we adopted alternative definitions, but the results were quite similar.[13]

Hence, we are left with six different types: three groups from parental qualification times two groups from inheritances. The OECD (2018) claims that in most western countries people start receiving bequests at the age of 55 due to the life-cycle. Then, our results

[13] The results are available from the authors upon request.

might be biased by those individuals from wealthy families who are too young to have received a bequest. To account for this, we replicate our analysis for individuals above 55 years.

The size of the samples and the summary statistics of the circumstances used to define the types are presented in Table 1. It is first observed that, in our main sample, the proportion of individuals with at least one parent highly qualified is similar in both countries, although differences are significant for the intermediate and low qualifications. In particular, the U.S. shows more individuals with parents intermediately qualified, while there is a higher share of low educated parents in Spain. With respect to individual bequests, around 9% of the U.S. sample have inherited more than $75000, whereas this value in Spain scales up to 14%. For the subsample, individuals over 55 years, we find that parents are less educated and, as expected, that the proportion of individuals who report to have inherited is higher. According to our data, 14.5% and 18% of people received a bequest bigger than $75,000 in the U.S. and Spain, respectively.

[PLACE TABLE 1 HERE]

Following Cowell et al. (2018a) we considered five variables to explain the wealth differences between the U.S. and Spain. These variables are standard in the literature on wealth inequality as the set of socio-economic and demographic variables that coincide across surveys is limited. The first variable is *age* which controls for life cycle dynamics. For the total sample we selected household heads between 25 and 74 years old and, following Pfeffer and Killewald (2016), we stablished ranges of 10 years.[14] Second, we use *education attainment* which is divided into three categories: illiterates and primary education, secondary education (high school and professional formation) and tertiary education (graduate and postgraduate). Third, the variable *income* which is categorized by deciles. Four, *labor status* which has three categories: workers (employed and self-employed), unemployed, and others (mainly retired or disabled citizens). Unfortunately, we could not refine this variable due to the different definitions provided by the two surveys. Finally, the *household structure* that combines two dichotomous variables: to be single or married, and to have kids living in the household or not. The share of each

[14] We performed a sensitivity analysis for different ranges, but our findings were similar. The results are available from the authors upon request.

covariate is also presented in Table 1 with the exception of income, which is described in Table 2.

The proportion of educated people is significantly higher in the U.S. than in Spain, where one third of the sample is low educated. In both countries the bulk of the surveyed population lies on the intermediate education group, although it represents 62.24% of the sample in the U.S., while it is 41.09% of the sample in Spain. The labor status reflects that in 2015, when the U.S. survey was collected, unemployment was significantly lower than in Spain in 2013. Note that these values do not necessarily coincide with the observed values for those years since the SCF and EFF do not try to be representative of the U.S. and Spanish labor markets. The marital status is similar in both economies, although there are less surveyed households with kids in Spain. For the subsample of individuals above 55 years old, there is a clear changing pattern on the educational profile. Now, low educated individuals are predominant: almost 40% in the U.S. and 52% in Spain. The working status is also different because most observations are now in the "other" category (retired and disabled people). Finally, the share of married individuals is smaller since the probability of being widowed is higher, and the proportion of household heads with kids is obviously lower.

Finally, in our analysis we dissect three different gross wealth concepts.[15] *Financial wealth* is composed by deposits, listed and unlisted shares, stocks, bonds, fixed income securities, mutual funds, insurances and pension schemes. *Real estate wealth* is composed by the aggregated value of real estate properties, such as offices, houses, garages and so on. *Gross total wealth* is just the sum of both, financial and real estate wealth. Table 2 presents the summary statistics of wealth and income variables. Real estate assets constitute the lion's share in both portfolios, but country differences are clear: they represent around 67% in the U.S., while this value is 80% for Spain. The high values of standard deviations reflect the large (right) skewness of the wealth distributions, which is confirmed by the MLD and Gini coefficients. Unsurprisingly, the distribution of wealth in the U.S. is more unequal than in Spain, particularly in real estate wealth. Likewise, income levels are also considerably lower and more equally distributed in Spain.

[15] We have also performed a complete analysis for several types of debt. However, the exact economic interpretation of having opportunities to acquire debt is difficult to grasp. For this reason, we only focus on gross wealth, although the results for debt are available from the authors upon request.

Individuals above 55 show similar patterns, although they possess more wealth and income on average and across percentiles. Inequality in both countries remains similar.

[PLACE TABLE 2 HERE]

4. Results

The overall inequality of gross wealth is presented in Table 3. We first show the MLD of the three wealth definitions for Spain, the U.S. and the counterfactual. Then, we display the actual difference, the compositional effect and the residual, in absolute and relative terms. Finally, we present the Shapley decomposition of the compositional effect by socio-economic factors. To determine whether the changes are statistically significant we have estimated standard errors by bootstrapping, using the replication weights provided by both surveys to avoid the bias caused by different sample sizes. As other authors have acknowledged in previous studies, it is necessary to remark that the DFL approach is just an accounting methodology, so we do not provide any causal explanation.

Overall inequality of the counterfactuals is similar to the actual values for Spain. In fact, the confidence intervals partly overlap for the three wealth definitions, so they can be thought as being statistically equivalent. This implies that imposing the U.S. covariate distribution into Spain does not meaningfully alter its wealth inequality. As a result, the differences on wealth distribution between the two countries are basically attributed to their particular institutions and other non-observed factors. This fact is highlighted by the compositional effect in relative terms which represents only around 10% of the actual difference across wealth definitions. In the Appendix, the results for the Gini coefficient in Table A1 confirm the robustness of this finding. Moreover, the bottom part of Table 3 and Table A1 in the Appendix replicate this analysis for the subsample of those above 55 years old, reaching the same conclusions. This result is consistent with the previous literature where household characteristics do not explain differences in wealth inequality across countries (Christelis et al., 2013; Sierminska and Doorley, 2017; Cowell et al., 2018a).

To understand which are the main socio-economic factors that explain the compositional effect, we apply the Shapley value decomposition. For total gross wealth, it is observed that the educational and labor status structures in the U.S. cause a decrease in inequality when imposed into Spain. The opposite happens when age and the income distribution are the covariates imposed. Indeed, these variables seem to compensate each other. The same happens with financial gross wealth, despite age is not significant anymore. Finally, for real estate gross wealth, education also becomes no significant. Nonetheless, these results are not robust because none of these covariates statistically explain the compositional effect according to the Gini coefficient (Table A1 in the Appendix).

[PLACE TABLE 3 HERE]

In Table 4 we present the decomposition of individual opportunities to acquire wealth due to parental qualification and bequests. First, we study absolute opportunities and decompose the compositional effect to obtain the separate effect of each covariate. Then, we repeat the same analysis for relative opportunities. Imposing the U.S. socio-economic factors into Spain generates a counterfactual that presents a significant increase for the absolute case. In fact, the compositional effect represents 55%, 69% and 40% of the actual difference for total, financial and real state gross wealth, respectively. It is observed that the compositional effect is not irrelevant anymore. In opposition to our previous finding for overall wealth inequality, socio-economic factors explain a big share of disparities in individual opportunities between the two countries under consideration. Differences cannot be mainly attributed only to institutions anymore.

On the effect of the covariates, the Shapley value decomposition shows that when imposed into Spain, socio-economic factors do not have a significant effect for all types of wealth. Thus, education for total and real state gross wealth and the age and income for all types of wealth increase the absolute IO. The opposite happens with labor status for total and real state gross wealth and household structure for real state gross wealth. For relative IO, the results follow the same pattern. The relative compositional effect is quite big since the counterfactual is higher than relative IO in the U.S.. The results for the Shapley value decomposition are also similar. All the covariates show the same effect as before, although all of them are significant for total and real estate gross wealth, whereas for financial wealth, only age and income are significant. Using the Gini coefficient (Table A2 in the Appendix), we obtain similar results: both absolute and relative IO greatly increase in the counterfactual. Again, differences between Spain and the U.S. cannot be attributed only to institutions. About the covariates, they show the same effect as before, although income is now not significant for any type of wealth.

These results are consistent with previous literature in saying that the educational system and the labor market are two important channels of transmission of individual opportunities (Palomino et al., 2016; Bussolo et al., 2019), in our case for the acquisition of wealth. For total and real state gross wealth, imposing the U.S. educational distribution on Spain increases absolute and relative IO, whereas the opposite is observed for the labor status. On the one hand, the U.S. educational system may increase IO when being imposed to Spain because the wage premium of education is higher in the U.S. (Crivellaro, 2016) and the access to secondary and tertiary education in the U.S. is greater (see Table 3). On the other hand, the significantly smaller unemployment rate in the U.S. seem to provide many more opportunities to their citizens to accumulate wealth.

The population of Spain is more aged than the population of the U.S. (see Table 1) and for this reason, imposing the demography (age) of the U.S. on Spain causes an increase in the dispersion of opportunities to acquire wealth, above all, real state gross wealth. The more unequal distribution of income in the U.S. seems to translate to a more unequal distribution of opportunities to acquire wealth in Spain when the income distribution in the U.S. is imposed into Spain. Meanwhile, the structure of the households in the U.S. promotes a more equal distribution of individual opportunities for wealth.

[PLACE TABLE 4 HERE]

Table 5 is devoted to the subsample of people above 55. In this case, for both absolute and relative IO, it is observed that the compositional effect and the residual effect compensate each other. Thus, the set of socio-economic factors increases significantly the IO of the counterfactual distribution, while the opposite happens with the institutions and other unobserved factors. For this subsample is even more evident that socio-economic factors are important to explain the final inequality of wealth, despite that they seemed to be irrelevant when individual opportunities to acquire wealth were not distinguished (Table 4). When the Shapley value decomposition is applied, it is observed that age, education and income have the same effect as for the whole sample. As expected, once we restrict our study to the oldest individuals of the distribution, labor status and household structure become irrelevant for the opportunities to acquire wealth (relative IO). For the Gini coefficient (Table A3) we see that these results are maintained with only one exception: the income distribution of the U.S. when imposed to Spain decreases both absolute and relative IO in the counterfactual.

[PLACE TABLE 5 HERE]

5. Concluding remarks

This article has analyzed the explicative power of socio-economic factors for the part of total wealth inequality due to parental background and inheritances. For this task, we have focused on the distribution of wealth in the U.S. (2016) and Spain (2014). By using data from the SCF (2016) for the U.S. and the EFF (2014) for Spain, and the DFL counterfactual method, we have decomposed absolute and relative differences in wealth IO between these two countries. Disparities are attributed to a set of socio-economic characteristics, while the residual condenses the role of institutions and other non-observed factors. Later, by means of the Shapley value decomposition, we analyze the effect of each covariate separately.

Our results for overall wealth inequality are consistent with the literature, they show that the imposition of the U.S. covariates into Spain does not significantly change its overall wealth inequality. Consequently, most differences between both countries are attributed to the residual (institutions). On the contrary, when analyzing wealth IO we get the opposite result because the U.S. socio-economic factors cause a great change in wealth IO for the counterfactual of Spain. These effects are robust to different concepts of IO (absolute and relative), different inequality indices (MLD and Gini coefficient) and different samples (total sample and individuals above 55 years old). It seems, therefore, that analyzing wealth IO, instead of overall wealth inequality, may help to unmask the hidden effects of socio-economic factors on the distribution of wealth. By socio-economic factors, age, education attainment and income increase wealth IO, while the effect of labor status and household structure is the opposite.

These findings highlight the importance of studying the influence of socio-economic factors by types of wealth inequality. Being endowed with a certain bequest, or having more qualified parents, may significantly widen individual opportunities to accumulate wealth. By focusing on the opportunities that people have to acquire wealth, we have shown that institutions are not as important as for overall wealth inequality and that socio-economic factors play a clear and well-defined role. For example, more years of education have a potential positive effect on individual opportunities to acquire wealth in Spain. On the contrary, given the high observed unemployment rates, labor status in Spain will work most likely in the opposite direction. These results clearly call for a deeper analysis of the effects that socio-economic factors have on the accumulation of wealth.

TABLES

Table 1. Samples, circumstances and non-monetary covariates.

Total Sample	U.S.	Spain	Subsample: individuals above 55	U.S.	Spain
Number of observations	5,758	5,548	*Number of observations*	2,699	3,263
Parental qualification			*Parental qualification*		
Low	20.67	44.23	Low	27.59	44.56
Medium	51.97	34.12	Medium	53.85	36.83
High	27.36	21.65	High	18.56	18.61
Bequest			*Bequest*		
< $75,000	91.03	85.81	< $75,000	85.53	81.97
≥ $75,000	8.97	14.19	≥ $75,000	14.47	18.03
Non-monetary Covariates			*Non-monetary Covariates*		
Age (mean)	51.19	52.68	Age (mean)	65.38	66.39
Low Education	2.46	33.19	Low Education	39.49	52.10
Intermediate Education	62.24	41.09	Intermediate Education	26.11	26.11
High Educated	35.30	25.72	High Educated	34.40	21.79
Worker	62.09	47.69	Worker	36.34	20.16
Unemployed	3.57	17.06	Unemployed	1.96	8.86
Other	34.34	35.25	Other	61.70	70.98
Married	58.87	59.54	Married	55.65	54.18
With Kids	43.73	31.77	With Kids	21.59	18.02

Note: circumstance values are expressed as percentages of the sample size. Age is the mean age of each country. The rest of covariates are expressed as percentages of their respective samples. Data come from the SCF (2016) for the U.S. and the EFF (2014) for Spain.

Table 2. Wealth and income statistics.

	Mean	Sd	p10	p50	p90	MLD	Gini
Total Sample							
U.S.							
Total Assets	659,738	5295,225	0,561	147,001	1001,201	2.55	82.92
Financial	212,524	2278,716	0,251	8,001	235,001	3.42	92.49
Real Estate	447,214	4187,564	1,001	125,001	700,001	4.37	81.15
Income	104,886	467,339	15,600	55,000	176,000	0.65	59.46
Spain							
Total Assets	312,677	1181,542	3,297	174,987	601,358	1.22	60.24
Financial	60,883	519,526	0,110	8,678	117,536	2.52	83.31
Real Estate	251,794	940,662	1,098	153,785	510,786	1.98	58.60
Income	31,884	32,158	8,400	24,000	60,150	0.31	42.02
Subsample: individuals above 55							
	Mean	**Sd**	**p10**	**p50**	**p90**	**MLD**	**Gini**
U.S.							
Total Assets	987,816	6900,416	1,032	209,001	1467,001	2.22	81.64
Financial	364,187	3224,523	0,283	15,343	487,501	3.33	90.37
Real Estate	623,629	5261,138	1,001	160,001	955,001	3.28	79.96
Income	114,215	607,005	13,800	49,000	188,000	0.80	65.31
Spain							
Total Assets	419,049	1710,001	32,989	215,887	826,045	1.12	61.87
Financial	95,476	771,421	0,198	11,534	190,584	2.58	84.16
Real Estate	323,573	1352,182	15,845	178,251	636,038	1.55	59.19
Income	36,435	31,375	8,400	22,500	63,000	0.35	45.19

Note: values are expressed in thousand U.S. Dollars of 2016. The term Sd stands for Standard Deviation, while p10, p50 and p90 represent the percentiles 10, 50 and 90 of the corresponding wealth or income distribution. Data come from the SCF (2016) for the U.S. and the EFF (2014) for Spain.

Table 3. Decomposition of total wealth inequality (MLD).

Total Sample	Total Gross Wealth	Financial Gross Wealth	Real Estate Gross Wealth
Spain MLD (a)	1.22	2.52	1.98
	(0.05)	(0.08)	(0.07)
US MLD (b)	2.55	3.42	4.37
	(0.03)	(0.04)	(0.05)
Counterfactual MLD (c)	1,34	2.45	2.26
	(0.09)	(0.12)	(0.25)
Actual Difference (d = a - b)	-1.33	-0.90	-2.39
Compositional Effect (e = a - c)	-0.12	0.07	-0.28
Relative Comp. Effect (e/d · 100)	9,03 %	-7.77 %	11.71 %
Residual (f = c - b)	-1.21	-0.97	-2.11
Relative Residual (f/d · 100)	90.97 %	107.77 %	88.29 %
		Shapley Decomposition	
Age	-0,07*	-0,09	-0,08
	(0,02)	(0,03)	(0,04)
Education	0,11*	0,22*	0,05
	(0,04)	(0,05)	(0,08)
Income	-0,29*	-0,36*	-0,52*
	(0,03)	(0,03)	(0,05)
Labor	0,12*	0,23*	0,20*
	(0,03)	(0,04)	(0,07)
Household Structure	0,01	0,07	0,07
	(0,03)	(0,04)	(0,05)
	Age > 55 Subsample		
Spain MLD (a)	1,11	2,57	1,54
	(0,06)	(0,12)	(0,10)
US MLD (b)	2,24	3,35	3,33
	(0,03)	(0,04)	(0,07)
Counterfactual MLD (c)	1.21	2,49	1,60
	(0,20)	(0,22)	(0,24)
Actual Difference (d = a - b)	-1,13	-0,78	-1,79
Compositional Effect (e = a - c)	-0,10	0,08	-0,06
Relative Comp. Effect (e/d · 100)	8,84%	-10,25%	3,35%
Residual (f = c - b)	-1,03	-0,86	-1,73
Relative Residual (f/d · 100)	91,15%	110,25%	96,65%
		Shapley Decomposition	
Age	0,00	-0,00	0,01
	(0,02)	(0,03)	(0,02)
Education	-0,03	0,24*	-0,07
	(0,08)	(0,09)	(0,12)
Income	-0,11	-0,37*	-0,22*
	(0,08)	(0,08)	(0,12)
Labor	0,04	0,14	0,19*
	(0,04)	(0,07)	(0,07)
Household Structure	0,00	0,07	0,03
	(0,05)	(0,04)	(0,06)

Note: the asterisk (*) indicates that the counterfactual or the correspondent covariate is statistically significant, based on the overlapping of the confidence intervals. They are calculated with the standard errors (in parenthesis) after 50 replications with the weights provided by the EFF for Spain (2014) and the SCF for the U.S. (2016).

Table 4. Decomposition of IO in wealth (MLD, Total sample).

	Total Gross Wealth	Financial Gross Wealth	Real Estate Gross Wealth
Spain Absolute IO (a)	0,27	0,23	0,65
	(0,03)	(0,03)	(0,05)
US Absolute IO (b)	0,60	0,58	1,56
	(0,03)	(0,04)	(0,08)
Counterfactual Absolute IO (c)	0,45*	0,47*	1,01*
	(0,08)	(0,11)	(0,30)
Actual Difference (d = a - b)	-0,33	-0,35	-0,92
Compositional Effect (e = a - c)	-0,18	-0,24	-0,36
Relative Comp. Effect (e/d · 100)	54,54%	68,57%	39.13%
Residual (f = c - b)	-0,15	-0,11	-0,55
Relative Residual (f/d · 100)	45,46%	31,43%	60,87%
		Shapley Decomposition	
Age	-0,05*	-0,09*	-0,14*
	(0,02)	(0,05)	(0,04)
Education	-0,11*	-0,05	-0,31*
	(0,03)	(0,04)	(0,06)
Income	-0,11*	-0,10*	-0,19*
	(0,03)	(0,03)	(0,04)
Labor	0,06*	0,02	0,19*
	(0,02)	(0,03)	(0,05)
Household Structure	0,03	-0,02	0,09*
	(0,02)	(0,03)	(0,04)
Spain Relative IO (a)	22.34	9.22	32.73
	(1.63)	(1.94)	(1.05)
US Relative IO (b)	23.53	17.10	35.95
	(0.42)	(0.78)	(0.37)
Counterfactual Relative IO (c)	32.05*	19.14*	44.03*
	(2.87)	(3.86)	(1.41)
Actual Difference (d = a - b)	-1.19	-7.88	-3.22
Compositional Effect (e = a - c)	-9.71	-9.92	-11.30
Relative Comp. Effect (e/d · 100)	815,96%	125,88%	350.93%
Residual (f = c - b)	8.52	2.04	8.08
Relative Residual (f/d · 100)	-715,96%	-25,88%	-250,93%
		Shapley Decomposition	
Age	-4.28*	-4.11*	-6.32*
	(2.62)	(1.92)	(2.12)
Education	-5.18*	-1.63	-9.74*
	(1.57)	(1.83)	(1.10)
Income	-11.51*	-3.77*	-13.05*
	(1.31)	(1.63)	(1.10)
Labor	6.71*	-0.13	10.20*
	(1.01)	(3.11)	(0.63)
Household Structure	4.55*	-0.28	7.61*
	(1.41)	(3.53)	(0.79)

Note: the asterisk (*) indicates that the counterfactual or the correspondent covariate is statistically significant, based on the overlapping of the confidence intervals. They are calculated with the standard errors (in parenthesis) after 50 replications with the weights provided by the EFF for Spain (2014) and the SCF for the U.S. (2016).

Table 5. Decomposition of IO in wealth (MLD, Age > 55).

	Total Gross Wealth	Financial Gross Wealth	Real Estate Gross Wealth
Spain Absolute IO (a)	0,22	0,44	0,42
	(0,05)	(0,08)	(0,06)
US Absolute IO (b)	0,56	0,77	1,03
	(0,03)	(0,06)	(0,08)
Counterfactual Absolute IO (c)	0,82*	0,82*	1,39*
	(0,08)	(0,09)	(0,07)
Actual Difference (d = a - b)	-0,34	-0,33	-0,61
Compositional Effect (e = a - c)	-0,60	-0,38	-0,97
Relative Comp. Effect (e/d · 100)	176,47%	115,15%	159,01%
Residual (f = c - b)	0,26	0,05	0,36
Relative Residual (f/d · 100)	-76,47%	-15,15%	-59,01%
		Shapley Decomposition	
Age	-0,14*	-0,13	-0,22*
	(0,06)	(0,08)	(0,08)
Education	-0,13*	-0,12	-0,22*
	(0,06)	(0,08)	(0,09)
Income	-0,10	0,04	-0,19*
	(0,06)	(0,08)	(0,08)
Labor	-0,11*	-0,08	-0,15*
	(0,06)	(0,07)	(0,08)
Household Structure	-0,12*	-0,09	-0,19*
	(0,06)	(0,07)	(0,08)
Spain Relative IO (a)	19.90	17.06	27.24
	(2.82)	(2.41)	(1.90)
US Relative IO (b)	25.09	23.08	31.46
	(3.93)	(1.03)	(3.07)
Counterfactual Relative IO (c)	56.24*	32.54*	67.84*
	(3.05)	(4.26)	(1.98)
Actual Difference (d = a - b)	-5.19	-6.02	-4.22
Compositional Effect (e = a - c)	-36.34	-15.48	-40.60
Relative Comp. Effect (e/d · 100)	700,19%	257,14%	962,08%
Residual (f = c - b)	31.15	9.46	36.38
Relative Residual (f/d · 100)	-600,19%	-157,14%	-862,02%
		Shapley Decomposition	
Age	-13.67*	-6.24*	-19.19*
	(2.78)	(3.50)	(2.24)
Education	-10.46*	-4.89*	-12.13*
	(1.45)	(2.18)	(1.13)
Income	-6.18*	2.52	-9.78*
	(3.38)	(3.00)	(2.78)
Labor	-1.67	-3.29	2.48
	(2.16)	(2.48)	(1.01)
Household Structure	-4.36	-3.58	-1.98
	(2.24)	(2.35)	(1.30)

Note: the asterisk (*) indicates that the counterfactual or the correspondent covariate is statistically significant, based on the overlapping of the confidence intervals. They are calculated with the standard errors (in parenthesis) after 50 replications with the weights provided by the EFF for Spain (2014) and the SCF for the U.S. (2016).

Appendix

Table A1. Decomposition of total wealth inequality (Gini coefficient).

Total Sample	Total Gross Wealth	Financial Gross Wealth	Real Estate Gross Wealth
Spain Gini (a)	60.24	83.31	58.60
	(1.08)	(1.13)	(1.01)
US Gini (b)	82.92	92.49	81.15
	(4.34)	(0.17)	(0.52)
Counterfactual Gini (c)	61.69	82.97	60.46
	(1.15)	(1.21)	(1.19)
Actual Difference (d = a - b)	-22.68	-9.18	-22.55
Compositional Effect (e = a - c)	- 1.45	0.34	-1.86
Relative Comp. Effect (e/d · 100)	6,39%	-3,70%	8,25%
Residual (f = c - b)	-21.23	- 9.52	-20.69
Relative Residual (f/d ·100)	93,61%	103,70%	91,75%
		Shapley Decomposition	
Age	- 2.17*	-0.95	-1.72*
	(0.41)	(0.39)	(0.40)
Education	- 0.23	1.36	-0.22
	(1.02)	(0.89)	(1.23)
Income	-1.45	-2.59*	-1.65
	(0.98)	(1.05)	(1.12)
Labor	1.27	1.51	1.08
	(0.77)	(0.80)	(0.93)
Household Structure	1.13	1.01	0.65
	(0.51)	(0.42)	(0.52)
	Age > 55 Subsample		
Spain Gini (a)	61.86	84.15	59.19
	(1.47)	(1.56)	(1.46)
US Gini (b)	81.75	90.63	80.07
	(0.49)	(0.26)	(0.64)
Counterfactual Gini (c)	62.90	82.82	60.80
	(2.13)	(2.08)	(2.01)
Actual Difference (d = a - b)	-19.89	-6.48	-20.88
Compositional Effect (e = a - c)	-1.04	1.33	-1.61
Relative Comp. Effect (e/d · 100)	5,23%	-20,52%	7,71%
Residual (f = c - b)	-18.85	-7.81	-19.27
Relative Residual (f/d ·100)	94,77%	120,52%	92,29%
		Shapley Decomposition	
Age	-0.55	-0.58	-0.42
	(0.41)	(0.39)	(0.40)
Education	-0.01	2.65*	0.15
	(1.03)	(0.87)	(1.24)
Income	-1.01	-2.29	-1.76
	(0.98)	(1.06)	(1.13)
Labor	-0.48	0.27	-0.18
	(0.77)	(0.81)	(0.93)
Household Structure	1.01	1.28	0.60
	(0.51)	(0.42)	(0.52)

Note: the asterisk (*) indicates that the counterfactual or the correspondent covariate is statistically significant, based on the overlapping of the confidence intervals. They are calculated with the standard errors (in parenthesis) after 50 replications with the weights provided by the EFF for Spain (2014) and the SCF for the U.S. (2016).

Table A2. Transmission of wealth decomposition (Gini coefficient, Total sample).

	Total Gross Wealth	Financial Gross Wealth	Real Estate Growth Wealth
Spain Absolute IO (a)	28.78	36.42	26.94
	(2.24)	(2.35)	(2.01)
US Absolute IO (b)	34.30	41.44	30.89
	(1.42)	(1.94)	(1.16)
Counterfactual Absolute IO (c)	34.06*	44.50*	31.55
	(2.73)	(3.80)	(3.30)
Actual Difference (d = a - b)	-5.51	-5.02	-3.96
Compositional Effect (e = a - c)	-5.28	-8.08	-4.61
Relative Comp. Effect (e/d · 100)	95,82%	160,95%	116,41%
Residual (f = c - b)	-0.24	3.06	0.66
Relative Residual (f/d · 100)	4,18%	-60,95%	-16,41%
		Shapley Decomposition	
Age	-13.41*	-10.52*	-14.19*
	(1.69)	(3.88)	(1.74)
Education	-7.61*	-5.72	-7.96*
	(1.90)	(3.50)	(2.01)
Income	0.82	-1.77	1.26
	(1.40)	(1.69)	(1.51)
Labor	7.09*	5.15*	7.83*
	(1.49)	(2.13)	(1.64)
Household Structure	7.83*	4.78*	8.45*
	(1.35)	(1.72)	(1.54)
Spain Relative IO (a)	47.78	43.72	45.97
	(2.53)	(4.20)	(3.59)
US Relative IO (b)	41.39	44.82	38.10
	(1.47)	(2.04)	(1.78)
Counterfactual Relative IO (c)	55.01*	53.64*	52.15*
	(4.27)	(4.52)	(2.32)
Actual Difference (d = a - b)	6.40	-1.10	7.86
Compositional Effect (e = a - c)	-7.23	-9.92	-6.18
Relative Comp. Effect (e/d · 100)	-112,96%	901,18%	-78,63%
Residual (f = c - b)	13.63	8.82	14.05
Relative Residual (f/d · 100)	212,96%	-801,18%	178,63%
		Shapley Decomposition	
Age	-13.80*	-10.88*	-14.45*
	(2.85)	(3.19)	(3.03)
Education	-8.01*	-6.09	-8.32*
	(1.98)	(2.46)	(2.15)
Income	0.43	-2.14	0.95
	(1.77)	(1.83)	(1.82)
Labor	6.70*	4.78	7.53*
	(1.53)	(2.02)	(1.50)
Household Structure	7.45*	4.41	8.11*
	(1.27)	(2.16)	(1.32)

Note: the asterisk (*) indicates that the counterfactual or the correspondent covariate is statistically significant, based on the overlapping of the confidence intervals. They are calculated with the standard errors (in parenthesis) after 50 replications with the weights provided by the EFF for Spain (2014) and the SCF for the U.S. (2016).

Table A3. Transmission of wealth decomposition (Gini coefficient, Age > 55)

	Total Gross Wealth	Financial Gross Wealth	Real Estate Growth Wealth
Spain Absolute IO (a)	30.85	37.74	29.61
	(2.37)	(2.15)	(2.10)
US Absolute IO (b)	35.16	42.32	31.11
	(1.60)	(2.25)	(2.09)
Counterfactual Absolute IO (c)	37.27*	47.15*	36.03*
	(3.82)	(3.35)	(3.18)
Actual Difference (d = a-b)	-4.31	-4.58	-1.50
Compositional Effect (e = a - c)	-6.42	-9.41	-6.42
Relative Comp. Effect (e/d·100)	148,96	205,45	428,00
Residual (f = c – b)	2.11	4.83	4.92
Relative Residual (f/d·100)	-48,96	-105,45	-328,00
		Shapley Decomposition	
Age	-6.34*	-9.52*	-6.00*
	(2.14)	(4.29)	(2.01)
Education	-3.86	-4.45*	-3.89
	(2.19)	(2.14)	(1.95)
Income	7.15*	5.77	6.96*
	(2.33)	(4.53)	(2.06)
Labor	-1.11	-0.32	-1.18
	(2.07)	(2.29)	(2.07)
HH Structure	-2.26	-0.89	-2.31
	(1.99)	(2.41)	(1.82)
Spain Relative IO (a)	49.87	44.85	50.03
	(3.80)	(3.41)	(3.40)
US Relative IO (b)	43.07	46.83	38.91
	(2.00)	(2.52)	(2.67)
Counterfactual Relative IO (c)	62.33*	59.00*	61.37*
	(3.39)	(4.19)	(4.12)
Actual Difference (d = a-b)	6.81	-1.97	11.11
Compositional Effect (e = a-c)	-12.46	-14.15	-11.34
Relative Comp. Effect (e/d·100)	-182,96%	718,27%	-102,07%
Residual (f=c-b)	19.26	12.17	22.46
Relative Residual (f/d·100)	282,96%	-618,27%	202,07%
		Shapley Decomposition	
Age	-13.86*	-12.19*	-14.49*
	(3.42)	(3.74)	(3.59)
Education	-7.09	-5.84	-7.64*
	(3.53)	(2.43)	(3.23)
Income	12.39*	6.02*	14.53*
	(3.95)	(2.04)	(3.63)
Labor	-0.80	-0.73	-0.53
	(3.16)	(2.99)	(3.62)
HH Structure	-3.10	-1.41	-3.21
	(3.24)	(2.84)	(3.89)

Note: the asterisk (*) indicates that the counterfactual or the correspondent covariate is statistically significant, based on the overlapping of the confidence intervals. They are calculated with the standard errors (in parenthesis) after 50 replications with the weights provided by the EFF for Spain (2014) and the SCF for the U.S. (2016).

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