SERIEs (2021) 12:389–421
https://doi.org/10.1007/s13209-021-00232-w

ORIGINAL ARTICLE

The distribution of wealth in Spain and the USA: the role of socioeconomic factors

Pedro Salas-Rojo[1] · **Juan Gabriel Rodríguez**[2]

Received: 21 November 2020 / Accepted: 7 April 2021 / Published online: 2 June 2021

Abstract

The literature has typically found that the distribution of socioeconomic factors like education, labor status and income does not account for the remarkable wealth inequality disparities between countries. As a result, their different institutions and other latent factors receive all the credit. Here, we propose to focus on one type of wealth inequality, the inequality of opportunities (IOp) in wealth: the share of overall wealth inequality explained by circumstances like inheritances and parental education. By means of a counterfactual decomposition method, we find that imposing the distribution of socioeconomic factors of the USA into Spain has little effect on total, financial and real estate wealth inequality. On the contrary, these factors play an important role when wealth IOp is considered. A Shapley value decomposition shows that the distribution of education and labor status in the USA consistently increase wealth IOp when imposed into Spain, whereas the opposite effect is found for the distribution of income.

Keywords Wealth inequality · Socioeconomic factors · Inequality of opportunity · Spain · USA

This paper has received financial support from the Ministerio de Ciencia e Innovación (Spain) under project PID2019-104619RB-C42 and Comunidad de Madrid (Spain) under project H2019/HUM-5793-OPINBI-CM. Salas-Rojo also received financial support from Ministerio de Ciencia, Innovación y Universidades through FPU grant 17/735. We acknowledge comments and suggestions from Pablo de la Vega, Alberto Palacios, Amaia Palencia, Juan César Palomino and Daniel Walderstrom, participants at the XXII Encuentro de Economía Aplicada (Cartagena, Spain) and ICAE Seminar at Universidad Complutense de Madrid. We are particularly thankful to two anonymous referees who helped us to improve this paper. All views and any remaining errors or omissions are our sole responsibility.

✉ Pedro Salas-Rojo
pedsalas@ucm.es

Juan Gabriel Rodríguez
juangabr@ucm.es

1 ICAE and EQUALITAS, Universidad Complutense de Madrid, Madrid, Spain

2 ICAE, EQUALITAS and CEDESOG, Universidad Complutense de Madrid, Madrid, Spain

JEL codes C81 · D31 · D63

1 Introduction

Recent studies on wealth inequality have found a wide heterogeneity on the type of assets owned along the wealth distribution. While the bottom third is asset-poor and the middle-class' wealth is mostly composed by real estates, the upper tail is characterized by possessing a high quantity of financial assets, which are also considered to be the main contributors to the increase in wealth inequality observed during the last decades (Demirgüc-Kunt and Levine 2009; Gennaioli et al. 2014; Badarinza et al. 2016; Lusardi et al 2017; Anghel et al. 2018). The sources of wealth disparities among countries have been, however, more elusive to find out. The comparison between the USA and some European countries has shown that covariates like education, labor status, household structure or income distribution do not explain the large cross-country differences in wealth inequality (Christelis et al. 2013; Doorley and Sierminska 2017; Cowell et al. 2018a). Consequently, aggregate disparities have been attributed to a wide variety of institutions and other latent factors. But, why do socioeconomic factors not seem to account for wealth inequality disparities across countries? In this paper, we suggest that we should change the wealth inequality concept under consideration. In particular, we propose to study the factors that condition the opportunities of individuals to accumulate wealth.

According to the inequality of opportunity literature, certain economic outcomes such as wealth, income or health are actually a composite measure of two types of variables (Roemer 1998; Van de Gaer 1993). In the first group, we find individual circumstances, factors beyond individual's control like the inheritances received, the parental education, race, sex or health endowments. In the second group, we have individual efforts, factors under the responsibility of individuals like the occupational choice or the number of hours worked. As a result, overall inequality is the combination of two types of inequality: inequality of opportunity (IOp), the part of total inequality explained by circumstances and inequality of efforts. In this context, any society concerned with fairness should minimize the IOp component, as the distribution of circumstances is morally arbitrary (Rawls 1971; Sen 1980).[1]

The IOp literature has traditionally focused on income (Bourguignon et al 2007; Rodríguez 2008; Ferreira and Gignoux 2011; Marrero and Rodríguez 2011 2012), health (Trannoy et al. 2010; Jusot et al. 2013; Tsawe and Susuman 2020), education (Gamboa and Waltenberg 2012; Lasso de la Vega et al 2020) and happiness (Li Donni et al. 2015). However, mainly due to the lack of appropriate data, its implementation to the analysis of wealth inequality has been scarce. Only a few recent works have highlighted the role of two circumstances, the inheritances received and parental education, on the process of wealth accumulation (Adermon et al. 2018; Palomino et al. 2020; Nolan et al. 2020; Salas-Rojo and Rodríguez 2020). Following this literature, we

[1] Recently, it has been proposed that IOp is also relevant for economic efficiency. In an empirical application for the USA, Marrero and Rodríguez (2013) find that IOp has a negative effect on future economic growth. Moreover, Marrero et al. (2016) observe that the negative effect of IOp on growth for the USA is mainly concentrated in the low percentiles of the distribution.

calculate wealth IOp for total, financial and real estate in Spain (Survey of Household Finances, 2014 EFF) and the USA (the Survey of Consumer Finances, 2016 SCF) by using the inheritances received and parental education as our circumstances.

Wealth is, by definition, a stock variable accumulated over time, so it is affected by all the decisions that the individual makes during his life (De Nardi 2015). In fact, the variables of wealth surveyed at a certain moment in life by databases like the EFF and SCF summarize the aggregate result of individual past decisions about wealth. For this reason, we control for the life cycle and sex of individuals before the IOp method is applied to measure the relationship between our controlled circumstances and the distribution of wealth.

To study whether a set of covariates (income, labor status and education) explains the differences on total, financial and real estate wealth inequality and wealth IOp between Spain and the USA, we apply the DiNardo–Fortin–Lemieux (DiNardo et al. 1996, DFL from now on) decomposition method. This approach has been applied to the decomposition of overall wealth inequality (Cowell et al. 2018a, b) but, to the best of our knowledge, this is the first time that the DFL is used in the IOp framework. This method will allow us to determine whether the above covariates affect the individual opportunities to accumulate (total, financial and real estate) wealth.

After estimating overall wealth inequality and wealth IOp, we use the DFL decomposition method to impose the distribution of income, education and labor status of the USA into Spain. In this manner, we create a counterfactual country whose wealth distribution is characterized by the covariates of the former and the institutional framework of the latter. In line with the existing literature (Christelis et al. 2013; Doorley and Sierminska 2017; Cowell et al. 2018a), we find the wealth distributions of this counterfactual to be similar to those of Spain. As a result, cross-country wealth inequality disparities between Spain and the USA are not explained by the aggregate effect of the covariates. Specifically, only around 3.1% of total wealth inequality differences, 1.2% of financial wealth inequality differences and 4.4% of real estate wealth inequality differences are attributed to the set of considered covariates. A Shapley value decomposition is applied to show that while the education and labor status distributions of the USA reduce the wealth inequality of the counterfactual, the income distribution increases it, so the net effect is closed to zero. With these results at hand, we should blame—as the literature does—different institutions and other latent factors for the remaining differences in wealth inequality between both countries.

Once this is done, we focus on (total, financial and real estate) wealth IOp. First, we find that wealth IOp in the USA is always higher than in Spain, no matter the inequality index nor the wealth definition considered. After imposing the covariates distribution from the USA into Spain, we find a significant rise in wealth IOp measures in the counterfactual. The covariates now explain 20.4% of total, 76.3% of financial and 6.2% of real estate wealth IOp disparities among Spain and the USA. Opposed to the analysis for overall wealth inequality, a Shapley value decomposition shows that the education and labor status distribution of the USA increases wealth IOp in the counterfactual, while the income distribution decreases it.

To better understand these results, we focus on the relationship between circumstances and covariates. First, a higher educational persistence is observed in the counterfactual than in Spain, i.e., those who receive high inheritances and have well-educated parents are more likely to reach high education levels. Second, a similar relationship is found for labor status: having well-educated parents and receiving high inheritances increases the probability of being employed in the counterfactual than in Spain. On the contrary, income is more equally distributed in the counterfactual, particularly across those with high and intermediate parental education, equalizing the individual opportunities to accumulate wealth. Hence, it seems that the type of wealth inequality considered is relevant for the analysis of covariates.

Decomposing wealth IOp cross-country disparities with the DFL method highlights the role of socioeconomic factors as mediating variables between individual circumstances and wealth accumulation. While the IOp literature had already found bequests and parental education to explain a remarkable share of wealth disparities (Palomino et al. 2020; Salas-Rojo and Rodríguez 2020), the wealth inequality framework had signaled the strong relation between human capital or enjoying a stable labor status with higher wealth stocks (Lusardi et al 2017; Anghel et al. 2018). Our approach joins both frameworks, opening new avenues to further exploration on the transmission channels of opportunities across generations.

The reminder of the article is structured as follows. Section 2 explains the method used to estimate wealth IOp and how we perform the DFL counterfactual decomposition. Section 3 describes the database, defines the variables under consideration and comments their main statistics. In Sect. 4, we present the main findings for overall wealth inequality and wealth IOp, while Sect. 5 concludes.

2 Methods

This section is divided in two parts. First, we present the wealth IOp framework and the parametric approach employed to estimate it. After that, we explain the DFL decomposition method that we implement to analyze whether the covariates explain the cross-country differences on wealth inequality and wealth IOp.

2.1 Measuring Inequality of Opportunity

To introduce the wealth IOp framework, first consider a finite population of individuals indexed by $i\{1, \ldots, n\}$. Individuals' own wealth, w_i, is assumed to be a continuous function of the set of circumstances, C_i, and the amount of effort they exert, e_i, such that $w_i = f(C_i, e_i)$.[2] Circumstances are exogenous because they cannot be affected by individual decisions, but effort is assumed to be partially influenced by circumstances. Consequently, individuals' wealth can be rewritten as $w_i = f(C_i, e_i(C_i))$.

Population is divided into T mutually exclusive and exhaustive *types*, where all individuals belonging to type t share the same circumstances. Consequently, an economy will have equality of opportunity if the wealth distribution is independent from

[2] Because we are interested on the intergenerational transmission of opportunities to accumulate wealth, we will collect in vector C_i the inheritances received and parental education, and will adjust wealth by age and gender to control for the effect of these two other circumstances (see below).

individual circumstances.[3] Given the wealth distributions conditioned on types, first- and second-order stochastic dominance could be contrasted. However, these criteria are partial and incomplete because type distributions can cross (Atkinson 1970). An alternative approach uses a particular moment of the wealth distribution: the mean. Following the ex-ante approach (Van de Gaer 1993), we construct an n-dimensional vector $\overline{w}$ by assigning to every individual the mean wealth of her type. Disparities in vector $\overline{w}$ will be attributed to individual circumstances so IOp can be formally defined as $I(\overline{w})$, where I is an inequality measure.

Under this definition, IOp measures depend on two factors: the inequality index employed and the method of estimation of the imputed wealth vector $\overline{w}$. Our preferred results are obtained with the Gini index which is the most used inequality index in the wealth literature and has been recently applied in the IOp framework (see Brunori et al. 2019a; Cabrera et al. 2020). Nonetheless, we also apply the Mean Logarithmic Deviation (MLD) for robustness (the results are shown in "Appendix").[4]

After dividing the population into types, we estimate the imputed wealth vector $\overline{w}$ with the parametric method proposed by Bourguignon et al. (2007) and Ferreira and Gignoux (2011).[5] These authors propose the estimation of Eq. (1), where the logarithm of (total, financial and real estate) wealth is regressed on the set of observed circumstances C:

$$\ln(w_i) = \alpha + \varphi C_i + \varepsilon_i. \tag{1}$$

Then, the estimated smoothed vector $\hat{w}$ is obtained by fitting the parameters of Eq. (1):

$$\hat{w}_i = \exp\left[\hat{\alpha} + \hat{\varphi} C_i\right]. \tag{2}$$

Predicted wealth conforms the counterfactual distribution where each observation receives the expected wealth of her type, as we only control for individual circumstances. Then, applying an inequality measure, such as the Gini index or the MLD, over the new vector $\widehat{w_i}$ gives an absolute measure of IOp.

$$IOp = I(\widehat{w_i}). \tag{3}$$

[3] Formally, equality of opportunity is achieved if $\int w|t_1 d_{t_1} = \int w|t_2 d_{t_2}, \forall 1, 2|t_1 \in \mathrm{T}, t_2 \in \mathrm{T}$, where t_1 and t_2 are types belonging to the full set of types T.

[4] Traditionally, the MLD has been used in the IOp literature because it is additively decomposable and has a path-independent decomposition (Foster and Shneyerov 2000). However, here we are not particularly interested in the exact additive decomposition of the inequality index. More importantly, because vector $\overline{w}$ is a smoothed distribution of wealth, and provided that the MLD is more sensitive to extreme values, results based on this index are likely to be downward-biased (Brunori et al. 2019a). For this reason, we prefer to focus on the better-known Gini index.

[5] For robustness, we have also checked our results with the nonparametric method proposed by Checchi and Peragine (2010) and the additional adjustment methods proposed in Bjorklund et al. (2012) and Niheues and Peichl (2014). Results did not vary significantly and are available from the authors upon request. We have leaned toward the parametric method (Ferreira and Gignoux 2011) because it is the most common approach in the literature, so the resulting IOp estimates can easily be put in perspective.

Here, it is important to note that due to data limitations the relevant set of individual circumstances is always difficult to obtain, so empirical measurement of IOp has to rely on the set of observed circumstances. For this reason, IOp measures are usually considered as lower-bound estimates of the actual IOp levels (Ferreira and Gignoux 2011; Ramos and Van de Gaer 2016: Brunori et al. 2019b).

2.2 The DiNardo–Fortin–Lemieux decomposition

To estimate the effect of covariates on overall wealth inequality and wealth IOp, we follow the counterfactual decomposition method proposed by DiNardo et al. (1996). The main idea behind this procedure consists on dividing the differences between two objective distributions in two components: the first would be explained by the set of explicitly controlled variables (covariates), while the second would be a residual attributed to cross-country unobservable factors, such as institutions. This decomposition method has already been employed to analyze racial 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; Palencia-Esteban 2019) and wealth disparities across countries (Cowell et al. 2018a, b). Here, we apply this method to explain IOp differences across countries.

Consider countries A and B and one objective variable w representing any wealth definition. Moreover, consider a vector of covariates or socioeconomic factors z that determines the distribution of w in a given economy. Following Cowell et al. (2018a), the cumulative wealth distribution in A can be expressed as:

$$F(w|A) = \int_z F(w, z|A)\mathrm{d}z = \int_z F(w|z, A)\mathrm{d}F(z|A). \tag{4}$$

Now we can define a counterfactual wealth distribution that mixes the wealth distribution in country A with the socioeconomic factor distributions from country B:

$$\int_Z F(w|z, A)\mathrm{d}F(z|B) = \int_z F(w|z, A)\Psi(\mathrm{z})\mathrm{d}F(z|A). \tag{5}$$

This counterfactual is constructed after multiplying Eq. (4) by $\Psi(\mathrm{z}) = \frac{\mathrm{d}F(z|B)}{\mathrm{d}F(z|A)}$, a reweighting factor component that modifies the distribution of socioeconomic factors in A to resemble their distribution in B. By using the Bayes rule, this reweighting component can be rewritten as follows:

$$\Psi(\mathrm{z}) = \frac{\frac{f(B|z)*f(z)}{f(B)}}{\frac{f(A|z)*f(z)}{f(A)}} = \frac{f(B|z)}{f(A|z)}\frac{f(A)}{f(B)}, \tag{6}$$

where $f(\cdot)$ is a density function. The left-hand side of the last ratio in Eq. (6) is estimated with a logit model, where a dependent binary variable that takes value 1 if the observation belongs to country B (or A) is regressed against the socioeconomic factors defined in z. Likewise, the right-hand side of the last ratio controls for the different relative size of both countries.

Once it is estimated, Ψ is used to reweight individuals in country A, generating a counterfactual characterized by the wealth distribution in A conditioned on the distribution of socioeconomic factors in B, as expressed in Eq. (5). Given the higher wealth inequality levels in the USA (see data section), to simplify the exposition of our results we plug the distribution of socioeconomic factors in the USA into Spain.[6]

As previously said, the DFL method decomposes the *actual difference* between overall wealth inequality and wealth IOp in Spain and the USA in two components. First, the *compositional effect* measures the difference between the level of wealth inequality in Spain and the counterfactual. Accordingly, a positive compositional effect will indicate that overall inequality or IOp of the counterfactual is smaller than the actual level of overall inequality or IOp in Spain. Second, the *residual effect*, attributed to institutions and other unobservable latent factors, is the difference between wealth inequality or wealth IOp in the USA and the counterfactual.

So far, the DFL method describes the aggregate effect of the socioeconomic factors collected in vector z. However, we are also interested on how they contribute to the counterfactual separately. For this task, we follow the DFL method extension proposed in Cobb-Clark and Hildebrand (2006) to disentangle the compositional effect. Following the related literature (Sierminska et al. 2008; Cowell et al. 2018a), we consider three factors in vector z: the level of education (e), the income distribution (i) and the labor status (l). Thus, for countries A and B, we write the wealth distribution in the following way:

$$C^A = \int F(w|e,i,l,A)\mathrm{d}F(e|i,l,A)\mathrm{d}F(i|l,A)\mathrm{d}F(l|A) \tag{7}$$

$$C^B = \int F(w|e,i,l,B)\mathrm{d}F(e|i,l,B)\mathrm{d}F(i|l,B)\mathrm{d}F(l|B). \tag{8}$$

The first term in the right side of Eq. (7) expresses the conditional expected wealth function in A given vector $z = (e, i, l)$; the second term represents the conditional expected education distribution in A given income and labor status; the third term is the expected distribution of income conditioned on the labor status and belonging to country A; finally, the last term is the labor status distribution of country A. Equation (8) follows the same reasoning, but for country B.

Then, we can define a counterfactual by imposing, for instance, the education distribution of country B into A:

$$C^1 = \int F(w|e,i,l,A)\mathrm{d}F(e|i,l,B)\mathrm{d}F(i|l,A)\mathrm{d}F(l|A). \tag{9}$$

The wealth distribution differences between (7) and (9) are caused by the differences in education between countries A and B. Similarly, we could define the counterfactual

[6] The imposition of the same vector of socioeconomic characteristics in Spain into the USA should provide symmetric results. We have checked this possibility and have confirmed that the conclusions remain the same.

C^2 in which we impose both, the distribution of education and income of country B into A.

$$C^2 = \int F(w|e,i,l,A)dF(e|i,l,B)dF(i|l,B)dF(l|A). \tag{10}$$

The difference between C^1 and C^2 reflects the extra effect of income, as education has been previously controlled for. Likewise, we could define a counterfactual C^3 that also implements the labor status distribution of B into A.

$$C^3 = \int F(w|e,i,l,A)dF(e|i,l,B)dF(i|l,B)dF(l|B). \tag{11}$$

The distributional difference between countries A and B could hence be decomposed as follows:

$$C^A - C^B = \left[C^A - C^1\right] + \left[C^1 - C^2\right] + \left[C^2 - C^3\right] + \left[C^3 - C^B\right], \tag{12}$$

where $\left[C^A - C^1\right]$ collects the effect of education, $\left[C^1 - C^2\right]$ represents the extra effect of income, $\left[C^2 - C^3\right]$ is the extra effect of labor status and, finally, $\left[C^3 - C^B\right]$ is the residual not explained by the set of controlled covariates, i.e., the differences attributed to institutions and other unobservable or omitted factors.

To measure the contribution of each socioeconomic factor, we have assumed a particular combination of the set of covariates, but we could have measured the effect of attained education first and, later, the impact of labor status. Because in this paper we control for three different covariates (education, income and labor status), we face up to 6 possibilities (3!). Therefore, the consideration of just one combination of covariates would arbitrarily neglect other potential possibilities, which could bias our results. As we do not have well-defined preferences for any possibility, we apply the Shapley value decomposition. This method assumes that all possible combinations of covariates have the same probability to appear.[7] Thus, for each possible combination, we define the correspondent counterfactual distribution and, then, calculate overall wealth inequality and wealth IOp. Finally, we average all results to get the contribution of each socioeconomic factor.

3 Data

The data come from the 2014 wave of the Survey of Household Finances (EFF) for Spain, published by the Central Bank of Spain, and the 2016 wave of the Survey of Consumer Finances (SCF) for the USA, published by the Federal Reserve. We employ survey data because it facilitates cross-country comparisons by providing the necessary covariates which are otherwise hard to find in tax databases.

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

We chose Spain and the USA for two reasons. First, the EFF and SCF are the most comprehensive available databases for wealth, containing ample information not only on total, financial and real estate wealth, but also on inheritances and family background (parental occupation or education), two fundamental circumstances for the analysis of IOp. Second, the literature has consistently studied the similitudes and differences between both economies (Bover 2010; Azpitarte 2012). For instance, it is widely known that financial markets are more developed in the USA, presenting a more flexible regulation and a wider array of products to be acquired. This provokes that US citizens are more prone to accumulate financial wealth, while their Spanish counterparts generally prefer real estates (Ampudia 2013; Anghel et al. 2018).

Cross-country analysis with wealth data requires the implementation of several previous adjustments. First, to make monetary measures fully comparable, they must be expressed in the same currency, in our case $2011 after using the PPP adjustment provided by the Luxembourg Income Survey (LIS). Moreover, despite that their design is similar, both databases diverge in some wealth definitions. Since the SCF provides a wider level of disaggregation, we slightly adapt this survey to the definitions provided by the Central Bank of Spain.

Our unit of analysis is the household, for whom we take the correspondent wealth and income levels. However, we observe individual covariates and circumstances from the household head. After taking this into account, we apply the squared root equivalence scale (Bover 2010; Salas-Rojo and Rodríguez 2020) to make households of different size comparable. Because the use of equivalences of scale has provoked a strong debate in the literature on wealth inequality (Cowell and Van Kerm 2015), we also apply for robustness the OECD equivalence scale, which weights 0.7 every extra adult in the household and 0.5 every child below 14 years, and replicate the analysis without scale. The main conclusions of the paper remain the same (the results are available from the authors upon request). Finally, we follow Palomino et al. (2020) and limit the life cycle effects by restricting our analysis to household heads aged between 35 and 80 years old, so we are left with a final sample composed by 4809 individuals in the USA and 4747 individuals in Spain.[8]

3.1 Dependent variables

To make our analysis as comprehensive as possible, we dissect three different gross wealth concepts. First, *financial wealth* is composed by deposits, listed and unlisted shares, stocks, bonds, fixed income securities, mutual funds and insurances. Second, *non-financial wealth* is defined by the aggregated value of real estate properties such as houses, offices, garages and so on. Finally, *Gross total wealth* is just the sum of both, financial and real estate wealth.

We use wealth measures in gross terms (instead of net terms) because including debts into the analysis may distort the measurement of IOp. Higher debts are usually associated with high collaterals, which are possibly assured through parental wealth. This fact reflects an alternative channel of intergenerational transmission of opportunities that, unfortunately, we cannot control for due to data limitations since we do

[8] Changing these age benchmarks does not significantly alter our main results.

Table 1 Summary statistics of age and sex

	Mean/population share	Standard deviation
Spain ($N = 4747$)		
Age	54.09	12.48
Gender (Female = 1)	38.13%	0.49
USA ($N = 4809$)		
Age	55.73	12.13
Gender (Female = 1)	25.91%	0.44

The data come from the EFF (2014) for Spain and the SCF (2016) for the USA

not have information on parental wealth. Consequently, individual opportunities to accumulate wealth are better understood with gross wealth measures. Nonetheless, for robustness, we have replicated the whole analysis with net wealth. Because the MLD index is not defined for negative nor zero wealth values, we have to restrict the sample to those households with strictly positive net wealth values, reducing the sample size by 6% in Spain and 11% in the USA. The main results that we obtain are similar to the ones we show below.

In principle, age and sex are exogenous factors that should be included in our set of circumstances. Thus, being a stock variable, wealth is strongly affected by life-cycle dynamics, and gender discrimination in the labor market hinders their opportunities to acquire wealth. However, in this paper we are focused in the comparison of wealth IOp based on factors related to the intergenerational transmission of opportunities. For this reason, we employ the adjustment proposed in Palomino et al. (2020) and control for both, the life cycle and sex. This adjustment centers the accumulated wealth at 65 years, the moment in life in which most people retire and start de-accumulating wealth. To do so, the following regression is estimated:

$$\ln(W_i) = \alpha + \sum_{n=1}^{4} \gamma_n (A_i - 65)^n + \beta F_i + \sum_{n=1}^{4} \delta_n F_i (A_i - 65)^n + \varepsilon_i, \tag{13}$$

where A_i expresses the age of the household head and F_i is a dummy variable that takes 1 for female household heads. As shown in Solon (1992), a fourth-degree specification is enough to control for wealth accumulation non-linearities through the life cycle, while the interaction term controls for the joint effect of both variables. Table 1 deploys the summary statistics of these variables for both countries, highlighting the similarity of both samples: mean age is around 55 years old in both cases, and women household heads are under-represented, particularly in the USA.[9]

Once Eq. (13) is estimated, each wealth variable is finally adjusted as follows:

$$W_i^{adj} = exp\left(\ln(W_i) - \sum_{n=1}^{4} \hat{\gamma}_n (A_i - 65)^n - \hat{\beta} F_i - \sum_{n=1}^{4} \hat{\delta}_n F_i (A_i - 65)^n\right) \tag{14}$$

[9] The large difference in the share of female household heads between Spain and the USA probably lies on the fact that the Bank of Spain puts extra efforts on considering female household heads in their sample (see Bover et al. 2018).

Table 2 Summary statistics of (adjusted) wealth

	Mean	Sd	Gini	MLD
Spain ($N = 4747$)				
Total assets	125.14	542.78	59. 67	1.10
Financial	25.14	221.71	79.56	2.22
Real estate	100.00	414.64	60.06	1.67
USA ($N = 4809$)				
Total assets	332.02	2,368.96	84.70	2.60
Financial	113.31	1,170.49	90.54	1.59
Real estate	218.71	1,863.54	86.16	3.91

Values expressed in thousand US Dollars of 2011. The term Sd stands for standard deviation. The data come from the EFF (2014) for Spain and the SCF (2016) for the USA

In Table 2, we present the summary statistics of the three adjusted wealth variables: financial, real estate and total wealth, which is obtained as the sum of the other two wealth definitions. US citizens are, on average, wealthier than their Spanish counterparts. In both countries, real estate assets constitute the lion's share of total household wealth, but financial assets still represent a high share in the US portfolios. All wealth measures seem to be more unequally distributed in the USA (the Gini index is 84.7 for total wealth, 90.5 for in financial wealth and 86.2 for real estate wealth) than in Spain (59.7 Gini points in total wealth, 79.6 in financial wealth and 60.1 in real estate wealth).[10] Figures 6, 7, 8, 9 in "Appendix" show the adjusted wealth distributions, confirming that the effects of both, age and gender, have been controlled for in our final wealth measures.

3.2 Covariates

We check whether the distribution of three socioeconomic factors—education, income and labor status—explains the differences for overall wealth inequality and wealth IOp between the USA and Spain. The selection of covariates is not arbitrary, as the related literature has found them to be important determinants of the wealth distribution (Sierminska et al 2008; Leitner 2016; Cowell et al. 2018a, b).[11] The first covariate, *education attainment*, reflects the highest level of education achieved by the household head. Here, we consider three groups of household heads: illiterate or with primary education, with secondary education (high school and/or professional formation) and, finally, those with tertiary education (graduate or postgraduate). The second variable, *income*, expresses the decile of the equalized household income distribution that the

[10] Despite the Gini index is defined between 0 and 1, we multiply it by 100 to make the exposition clearer.

[11] Another socioeconomic factor that has been considered in the literature is the household structure, defined as those households living or not with children below 14. We consider this definition to be weak since older sons or other relatives living in the family are not explicitly considered. Nonetheless, we have used this covariate in an earlier version of the paper and its effect was found to be non-significant, so we finally decided not to include it in the last version. In any case, as we use equivalences of scale, this effect should be already controlled for.

household occupies.[12] Finally, our third covariate, *labor status*, is also defined upon three categories: workers (employed or self-employed), unemployed, and those workers retired or disabled.[13]

Table 3 shows the main statistics of the three covariates under consideration. It is observed that people are, on average, more educated in the USA (35.4% of people have high education and just 6.0% of people are illiterate or have basic studies) than in Spain (26.1% with high education and 32.4% with low education), that the levels of equalized household income are higher and more unequally distributed in the USA (Gini = 59.8) than in Spain (Gini = 40.9), and that there are more people working in the USA (60.4%) than in Spain (51.7%).

3.3 Circumstances

The first circumstance we use to estimate wealth IOp is parental education, which collects information on the family background of the household head. Recent contributions to the literature highlight that parental education or occupation is one of the main drivers of intergenerational inequality transmission, strongly conditioning the educational, occupational and income prospects of the descendants (see Adermon et al. 2018; Palomino et al. 2019; Cabrera et al. 2020). While the 2016 wave is the first occasion in which the SCF publishes parental education of the respondent, the EFF has traditionally provided information about parental occupation. To make this information comparable, we use the National Classification of Occupations in Spain and create three educational categories based on the education necessary to perform the reported occupational activities: basic (jobs that require only primary education), secondary (jobs that require high school or professional formation) and tertiary (those jobs that require a university degree). As for the SCF, four categories are provided—illiterate, primary, secondary and tertiary education—so we merge the two first definitions into one, generating a basic studies category. The final variable is defined as the highest level of education achieved by any of the two parents.

In Table 4, we compare the summary statistics of this circumstance in the USA and Spain. Spanish parents are, on average, less educated. While up to 44% of household heads have both parents with low education in Spain, the share descends to 21% in the USA. Intermediate parental education is 54.5% in the USA, while it is 34.5%

[12] Note that if we use absolute income when running the logits for the estimation of (6), the associated parameters will say little about the income distribution of the countries. Therefore, to get a meaningful counterfactual that reflects the income distribution of the objective country, we follow Cowell et al (2018a) and split the income distribution of the USA by deciles. Then, by using the income threshold levels associated with those deciles we generate ten income brackets for Spain. Both income partitions (by deciles for the USA and by brackets for Spain) are included as dummy variables in our analysis. For robustness, we have also split the income distribution by quintiles and ventiles, obtaining similar results.

[13] For robustness, we have repeated the whole analysis in the paper after implementing a method that isolates our study from the potential interaction between covariates: Consider a linear regression in which the dependent variable is one covariate, being the rest of covariates the independent variables. As a result, the residual in such regression will collect the part of the covariate that is unrelated to the rest of covariates. Then, after applying this procedure for each covariate, the whole DiNardo–Fortin–Lemieux and IOp analysis is replicated. However, in our case, the main results remain the same. For simplicity, we have decided not to include this proposal into the paper, but the results can be obtained from the authors upon request.

Table 3 Summary statistics of socioeconomic factors

	Population Share	Standard deviation
Spain ($N = 4747$)		
High education respondent	26.07%	0.44
Intermediate education respondent	41.54%	0.49
Low education respondent	32.39%	0.47
Working	51.74%	0.50
Unemployed	15.42%	0.37
Retired	32.84%	0.50
	Mean	Standard deviation
Income	13.71	33.34
	Population share	Standard deviation
USA ($N = 4809$)		
High education respondent	35.36%	0.48
Intermediate education respondent	58.61%	0.49
Low education respondent	6.03%	0.24
Working	60.35%	0.49
Unemployed	3.65%	0.19
Retired	36.00%	0.48
	Mean	Standard deviation
Income	49.02	251.71

Monetary values expressed in thousand US Dollars of 2011. The data come from the EFF (2014) for Spain and the SCF (2016) for the USA

Table 4 Summary statistics of parental education

	Population share (%)	Standard deviation
Spain ($N = 4747$)		
High parental education	21.49	0.41
Intermediate parental education	34.53	0.47
Low parental education	43.98	0.50
USA ($N = 4809$)		
High parental education	24.60	0.42
Intermediate parental education	54.52	0.48
Low parental education	20.88	0.40

The data come from the EFF (2014) for Spain and the SCF (2016) for the USA

in Spain. Finally, the highest parental education share is similar for both countries, reaching 24.6% in the USA and 21.5% in Spain.

The second circumstance considered in the paper is the value of the gifts and bequests received.[14] In Spain, around 41.11% of our sample reports to have received a positive amount of inheritance, while this share descends to 21.60% in the USA. Reporting zero inheritances may be due to the life-cycle phase of the individual—for example, when she is young and her parents are still alive—and misreporting (see Wolff and Gittleman 2014). In both cases, we assume that individual opportunities to accumulate gross wealth have not yet been affected by the potential reception of future inheritances.[15]

As explained in the methodology section, to estimate wealth IOp we need to define mutually exclusive and exhaustive types. Despite this is straightforward for categorical variables, such as parental education, it might be problematic for continuous variables such as the inheritances received, as they need to be discretized under the researcher's criteria.[16] Following Salas-Rojo and Rodríguez (2020), we could try to apply Machine Learning algorithms to generate types in each country based on the statistical properties of their respective data. Unfortunately, this procedure will hinder the correct application of the DFL method since disparities between countries could be explained not only by their different distributions of covariates, but also by the different statistical treatment given to circumstances in each country. For this reason, in this paper we prefer to split the recipients of inheritances in terciles. Hence, we have four groups: household heads who have not inherited and the three terciles just created. As a result, we have 12 types, steaming from the interaction between the three parental education categories and the four inheritance groups. For robustness, we checked other type definitions, for instance, once we separate those who inherit from those who do not, by dividing the former group by quartiles, quintiles or the mean of the inheritance distribution. Interacting with the three parental education categories, these different partitions generate 15, 18 and 9 types, respectively. The main conclusions remained the same.[17]

We present the summary statistics of the inheritances received in Table 5. US citizens receive, on average, more inheritances than their Spanish counterparts in all terciles. Moreover, when we look at the standard deviations, we find that bequests are more unequally distributed in the USA than in Spain, particularly in the third tercile.

[14] Despite that the inheritances received are a flow variable, they can be significantly affected by the life cycle. For this reason, we have developed the whole analysis in the paper for bequests adjusted by age and gender, adjusting only for positive inheritances and also for all—positive or zero—inheritances. However, our main results remained the same. Results are not shown but can be obtained from the authors upon request.

[15] Unfortunately, we have no valid data for future bequeath expectations, so we cannot deal with this issue in our analysis.

[16] The inclusion of a continuous variable in Eq. (2) creates at least one type for each possible value of the inheritances received. However, as explained in Brunori et al. (2019b), this provokes an over-fitted type-creation that upward-biases the IOp estimates. Consequently, continuous circumstances are discretized to obtain meaningful types.

[17] The results with different type definitions can be obtained from the authors upon request.

Table 5 Summary statistics of inheritances

	Mean	Standard Deviation	Share of the Population
Spain ($N = 4747$)			
No Inheritances	0	0	58.89%
Total inheritances	144.20	802.01	41.11%
First tercile of inheritances	6.54	5.30	13.65%
Second tercile of inheritances	48.42	21.65	14.90%
Third tercile of inheritances	377.83	1,359.40	12.56%
USA ($N = 4809$)			
No Inheritances	0	0	78.40%
Total inheritances	467.61	2,593.84	21.60%
First tercile of inheritances	21.91	14.35	7.69%
Second tercile of inheritances	116.50	45.25	7.45%
Third tercile of inheritances	1,267.49	4,390.56	4.46%

Monetary values expressed in thousand US Dollars of 2011. Shares expressed as percentage of total population. The data come from the EFF (2014) for Spain and the SCF (2016) for the USA

4 Results

In this section, we estimate first overall wealth inequality and wealth IOp and, then, apply the DFL method to decompose the differences of these two dimensions between Spain and the USA. Bear in mind that the DFL approach is an accounting methodology, so causal explanations from our results will not be possible. Results are presented in two twin tables that share the same structure: first, we show overall wealth inequality and wealth IOp for Spain, the USA and the counterfactual. Later, we analyze the relative contributions of the compositional effect and the residual. Finally, we apply the Shapley decomposition value over the compositional effect to disentangle the effects of the covariates. To determine whether the changes of the counterfactual and the relative contribution of socioeconomic factors are statistically significant, we apply bootstrapping, using the replication weights provided by the surveys.[18]

4.1 Wealth inequality analysis

Table 6 decomposes the differences in overall wealth inequality between Spain and the USA by using three covariates: education, labor status and income. First, we focus on the compositional effect, which expresses the inequality differences between Spain and the counterfactual. Total gross wealth inequality descends from 59.7 Gini points in Spain to 58.9 in the counterfactual, financial inequality slightly rises from 79.6 (Spain) to 79.7 (counterfactual), and finally, real estate inequality descends from 60.1 in Spain to 58.9 in the counterfactual. All these differences are very small and, as the bootstrapped standard errors overlap for the three definitions of wealth, overall wealth

[18] By following Hedges (1992), we assume that 500 bootstrap replications provide a significance level equal to 5%.

Table 6 Wealth inequality decomposition (Gini index)

	Total wealth	Financial wealth	Real estate wealth
Spain Gini (a)	59.67	79.56	60.06
	(1.10)	(0.88)	(1.14)
US Gini (b)	84.70	90.54	86.16
	(0.63)	(0.39)	(0.65)
Counterfactual Gini (c)	58.89	79.69	58.91
	(1.28)	(1.50)	(1.34)
Actual difference ($d = a - b$)	−25.03	−10.98	−26.10
Compositional effect (e $= a - c$)	0.78	−0.13	1.16
Relative comp. effect ($e\cdot 100/d$)	−3.12%	1.15%	−4.43%
Residual ($f = c -$ b)	−25.80	−10.85	−27.25
Relative residual ($f\cdot 100/d$)	103.12%	98.85%	104.43%
Shapley decomposition			
Education	2.45*	2.14*	1.85*
	(0.16)	(0.24)	(0.22)
Income	−2.42*	−3.26*	−2.06*
	(0.01)	(0.24)	(0.12)
Labor	0.75	1.00	1.36*
	(0.07)	(0.14)	(0.09)

The asterisk (*) indicates that the change is statistically significant for an alpha of 5%. Standard errors, based on the overlapping of the confidence intervals calculated after 500 replications, are in parenthesis. Appropriate replication weights are used. The data come from the EFF (2014) for Spain and the SCF (2016) for the USA

inequality in Spain and the counterfactual are considered to be equivalent. Indeed, when the compositional effect is put in relative terms, it barely explains the −3.1% of total, 1.2% of financial and −4.4% of real estate wealth inequality disparities between countries.[19]

In line with the literature (Christelis et al. 2013; Doorley and Sierminska 2017; Cowell et al. 2018a, b), we find that imposing the US covariate aggregate distribution into Spain does not meaningfully alter its wealth distribution, so the remarkable wealth distribution disparities between both countries have to be attributed to their own particular institutions and other non-controlled factors. The results in Table 8 (see "Appendix") confirm for the MLD inequality index the robustness of this result. Despite that the relative compositional effects are higher, reaching −1.7% for total, 17.8% for financial and −2.4% for real estate wealth inequality, all standard errors overlap, so they maintain their statistical insignificance.

To get an insight on how the selected covariates explain the small compositional effect, we focus on the Shapley decomposition values in Table 6. We observe that

[19] Note that since total and real estate wealth inequalities in the counterfactual are slightly smaller than that in Spain, the sign of the compositional effect is negative. If the compositional effect had been defined as (Counterfactual Inequality—Spain Inequality), the signs would have been the opposite, maintaining the implications of our results.

the educational attainment of the USA when imposed into Spain reduces total wealth inequality by 2.45 Gini points, while the opposite happens with the income distribution, which increases total wealth inequality by 2.42 Gini points. Similar effects are found for financial and real estate wealth. This is not surprising if we look at the original distribution of covariates. As shown in Table 3, US citizens are more educated and less unemployed than their Spanish counterparts. Being both factors more related to low wealth levels (Azpitarte 2012), the new structure in the counterfactual reduces inequality in absolute terms. However, imposing the income deciles of the USA into Spain increases wealth inequality in the counterfactual, particularly in financial wealth. Because both effects are conflicting and compensate each other in aggregate terms, we finally obtain the observed small compositional effects.

The size of the residuals is remarkable, meaning that the largest share of the disparities between wealth distributions remains unexplained. Trying to unmask those latent variables collected in the residual, some studies apply the DFL analysis over a pool of countries and, then, run OLS regressions using the residual as dependent variable and several macroeconomic and institutional factors as regressors (Christelis et al. 2013; Doorley and Sierminska 2017). These analyses show that the stock ownership, the entrepreneurial activity, the mortgage maturity, the degree of economic freedom or the financial development, among others, are important variables collected in such residual. In our case, given the limited data available, we leave the study of the residual in these countries of wealth inequality for further research.

4.2 Wealth inequality of opportunity analysis

We disentangle wealth IOp differences between Spain and the USA in Table 7. To obtain these differences, we assign first the conditioned average of total, financial and real estate wealth to every individual in the distribution to construct the corresponding vector $\overline{w}$ (recall Sect. 2). Then, an inequality index is applied over vector $\overline{w}$ to obtain the IOp measures, and finally, the DFL decomposition method is developed to estimate the effect of covariates.

We find wealth IOp to be always smaller in Spain (41.8 Gini points for total, 43.3 for financial and 53.5 for real estate wealth) than in the USA (54.7 Gini points for total, 56.1 for financial and 70.0 for real estate). Second, the aggregate effect of the covariates of the USA, when imposed into Spain, rises wealth IOp in the counterfactual. Now, the part of overall inequality explained by circumstances (IOp) becomes 44.4 for total, 53.1 for financial and 54.6 for real estate wealth in the counterfactual. Thus, the relative compositional effects ascend to 20.4% of the actual differences in total, 76.3% in financial and 6.2% in real estate wealth. Opposed to the overall inequality analysis derived from Table 6, all these effects are statistically significant, since the bootstrapped confidence intervals do not overlap. Table 9 in "Appendix" replicates the analysis for the MLD index, confirming the robustness of these results.

Table 10 in "Appendix" presents the relative contribution of each circumstance to the IOp estimates deployed in Table 7. In Spain, the inheritances represent up to 60.4% of total, 43.3% of financial and 66.7% of real estate wealth IOp, being the remainder attributed to parental education. In the USA, the part explained by the inheritances

Table 7 Wealth IOp decomposition (Gini index)

	Total wealth IOp	Financial wealth IOp	Real estate wealth IOp
Spain IOp (*a*)	41.83	43.31	53.53
	(0.46)	(0.49)	(0.41)
US IOp (*b*)	54.66	56.11	70.03
	(0.44)	(0.46)	(0.40)
Counterfactual IOp (*c*)	44.44*	53.07*	54.55*
	(0.65)	(0.54)	(0.52)
Actual difference ($d = a - b$)	−12.84	−12.80	−16.50
Compositional effect ($e = a - c$)	−2.62	−9.76	−1.02
Relative comp. effect ($e/d \cdot 100$)	20.38%	76.26%	6.18%
Residual ($f = c - b$)	−10.22	−3.04	−15.48
Relative residual ($f/d \cdot 100$)	79.62%	23.74%	93.82%
Shapley decomposition			
Education	−2.03*	−4.87*	−1.09*
	(0.13)	(0.08)	(0.01)
Income	1.18*	−0.97*	0.71*
	(0.01)	(0.05)	(0.07)
Labor	−1.76*	−3.92*	−0.64*
	(0.08)	(0.02)	(0.11)

The asterisk (*) indicates that the change is statistically significant for an alpha of 5%. Standard errors, based on the overlapping of the confidence intervals calculated after 500 replications, are in parenthesis. Appropriate replication weights are used. The data come from the EFF (2014) for Spain and the SCF (2016) for the USA

received ascends to 72.0%, 65.9% and 75.4% of total, financial and real estate wealth IOp, respectively. Finally, in the counterfactual, 58.3% of total, 60.0% of financial and 52.4% of real estate wealth IOp is attributed to bequests. In line with the literature (Palomino et al. 2020; Salas-Rojo and Rodríguez 2020), inheritances are found to be the main vehicles through which opportunities to accumulate wealth are transmitted across generations, particularly in the USA. Data limitations impede us the analysis of other factors such as the educational loans, which might reflect the impact of different public education policies. However, Cowell et al. (2018a) find these loans to slightly decrease net worth inequality in the USA (Gini falling from 83 to 82 points) while, in Spain, given the wide public tertiary education, the effect is probably negligible.

To understand better the role of socioeconomic factors, the Shapley value decomposition in Table 7 shows that the education attainment and labor status distributions of the USA are the main contributors to the increase in wealth IOp in the counterfactual, particularly for financial wealth (rising 4.9 and 3.9 Gini points, respectively). Accumulating high financial wealth stocks requires investment skills usually found among highly educated and low risk-averse individuals (Demirgüc-Kunt and Levine 2009; Azpitarte 2012; Lusardi et al 2017), both characteristics being related to more advantageous circumstances. In particular, two simultaneous effects are found: while highly qualified parents tend to have well educated descendants with more profitable investment skills, bequests foster entrepreneurship attitudes and reduce risk aversion

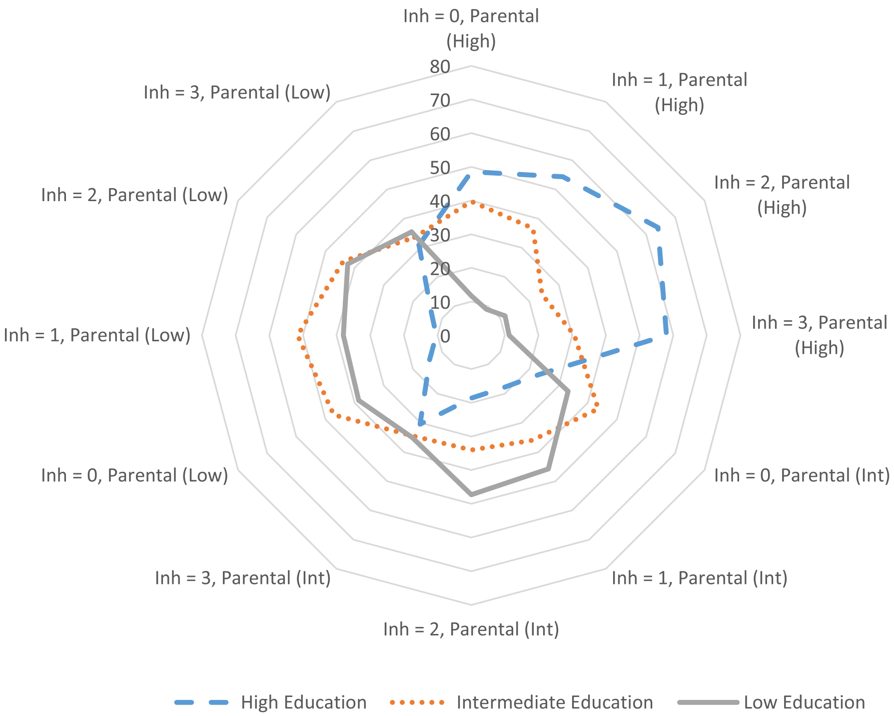

Fig. 1 Education by types (Spain). Note: Types are defined by three categories of parental education (high/intermediate/low) and four categories of inheritances received (Inh = 0 for those who have not inherited anything, and Inh = 1, 2. 3 for those who inherit, depending on the inheritance terciles they belong). The data come from the EFF (2014)

(Faria and Wu 2012; Adermon et al. 2018). In Table 10, we show that the former effect is particularly salient in Spain, with a 56.7% of financial wealth IOp attributed to parental education. On the contrary, the latter effect seems to be more prevalent in the USA, with a 65.9% of financial wealth IOp explained by the inheritances received.

Consistent with previous literature, our results highlight the role of the labor market and educational system as two important transmission channels of individual opportunities (Palomino et al. 2019; Bussolo et al. 2019; Cabrera et al. 2020). On the contrary, the income distribution effect is small enough to not compensate the increase provoked by the other two covariates. Providing more evidence on this, Figs. 1, 2, 3, 4, 5 plot the covariates distribution by types for Spain and the counterfactual, while Tables 11, 12, 13 in "Appendix" deploy the corresponding shares.

Figure 1 for Spain, Fig. 2 for the counterfactual, and Table 11 show the share of the three categories of education (low, intermediate and high) by types. We find that the imposition of the education distribution of the USA into Spain increases the intergenerational persistence in education. Thus, in the counterfactual, individuals with high educated parents are, regardless their inheritances, more likely to achieve high education levels, while the opposite happens with low educated individuals. The higher

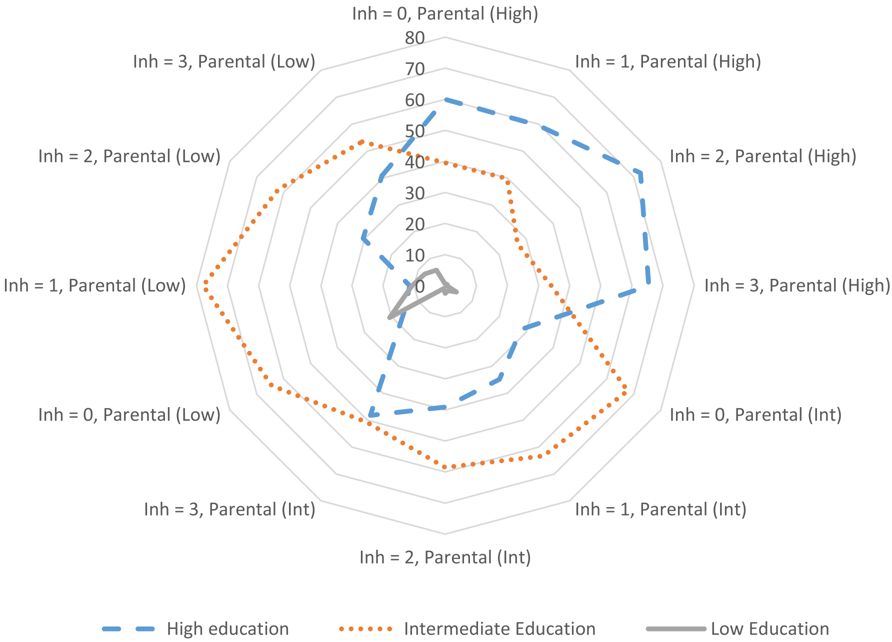

Fig. 2 Education by types (counterfactual). Note: Types are defined by three categories of parental education (high/intermediate/low) and four categories of inheritances received (Inh = 0 for those who have not inherited anything, and Inh = 1, 2. 3 for those who inherit, depending on the inheritance terciles they belong). The data come from the EFF (2014) for Spain and the SCF (2016) for the USA

relative importance of parental background and inheritances in the counterfactual explains the negative sign of education in Tables 7 and 9.[20]

Deploying the decile-based partition of income for each type would hamper a straightforward graphical interpretation and, for this reason, Fig. 3 and Table 12 in "Appendix" present the Gini index applied over the income groups (from 1 to 10) by types in Spain and the counterfactual. A higher (lower) Gini index would indicate that income groups in a certain type are more heterogeneous (homogeneous), i.e., there is a higher (lower) disparity in the opportunities to accumulate wealth. Following this reasoning, we find Gini indices to be lower in the counterfactual than in Spain for all types constructed with high and intermediate educated parents, which would explain the positive effect of income for total and real estate wealth in Tables 7 and 9. On the contrary, for those with low parental education, income inequality in the counterfactual is higher (or the same) than in Spain, which might explain the negative effect of income on financial wealth observed in Tables 7 and 9.

Finally, Figs. 4 and 5 present the labor status distribution in Spain and the counterfactual, respectively, and Table 13 in "Appendix" deploys the corresponding shares. In the counterfactual, having parents with high and intermediate education increases the chances of being employed. Moreover, the unemployed with high educated parents

[20] For example, for those individuals who attain low education and receive zero inheritances, the proportion of high- to low-educated parents descends from 0.30 (11.7/38.6) in Spain to 0.02 (0.5/20.7) in the counterfactual.

Fig. 3 Income by types (Spain and counterfactual). Note: Types are defined by three categories of parental education (High/Intermediate/Low) and four categories of inheritances received (Inh = 0 for those who have not inherited anything, and Inh = 1, 2. 3 for those who inherit, depending on the inheritance terciles they belong). The data come from the EFF (2014) for Spain and the SCF (2016) for the USA

descend their share as the inheritances received rise in the counterfactual (from 4.9% in those who have not inherited anything to 1.9% in those who inherit in the third tercile). However, in Spain, these ratios are maintained. Overall, the effect of circumstances on the individuals' performance in the labor market is stronger in the counterfactual than in Spain, which explains the negative sign of labor status in Tables 7 and 9.

With respect to the residuals obtained in Tables 6 and 7, notice that they are not directly comparable because they are obtained for two different concepts of wealth inequality, total wealth inequality and wealth IOp. Despite this fact, they could be collecting some common variables like, for example, different existing tax schemes. While both countries have inheritances taxes (*Estate Tax* in the USA and *Impuesto de Sucesiones y Donaciones* in Spain), only Spain has a national wealth tax (*Impuesto sobre el Patrimonio*). In this respect, it is important to note that the effects of taxing a stock variable such as wealth are still unclear. While some argue that it might disincentive capital accumulation and hinder economic growth (Mankiw 2015), others propose that it would provide resources to defray public policies aimed to benefit the most disadvantaged, which would promote human capital acquisition (Zucman 2019). Unfortunately, given our data limitations, we cannot check the effects nor the implications of these institutional settings, leaving this analysis for further research.

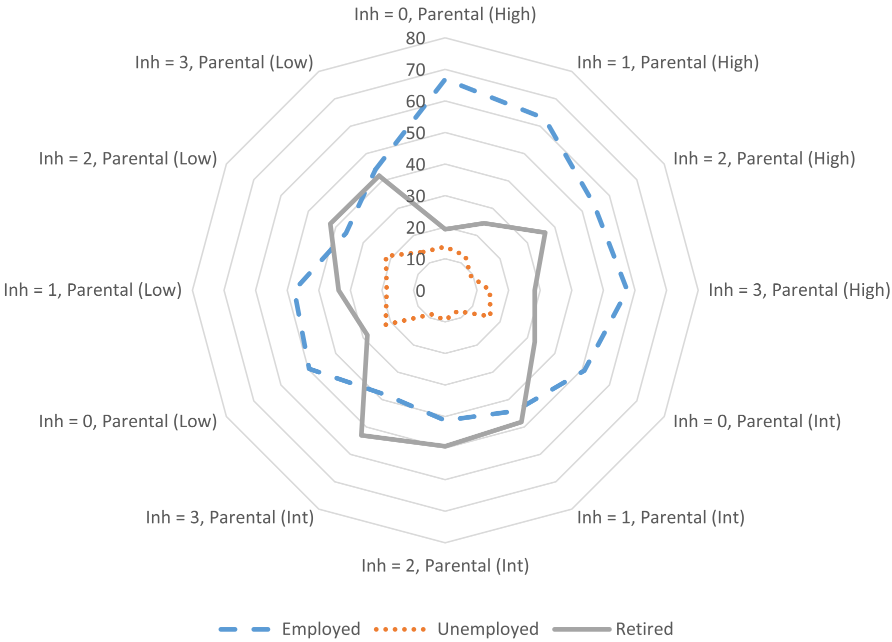

Fig. 4 Labor status by types (Spain). Note: Types are defined by three categories of parental education (high/intermediate/low) and four categories of inheritances received (Inh = 0 for those who have not inherited anything, and Inh = 1, 2. 3 for those who inherit, depending on the inheritance terciles they belong). The data come from the EFF (2014)

5 Concluding remarks

This article remarks the relevance of socioeconomic factors or covariates to explain wealth disparities between countries. In particular, we analyze the wealth distribution in Spain and the USA. After applying the DiNardo–Fortin–Lemieux counterfactual method, we decompose the differences between both countries in overall wealth inequality and wealth IOp. These disparities are attributed to a set of covariates (education, labor status and income), while the remaining residual condenses the role of institutions and other non-observed factors. Moreover, by means of a Shapley value decomposition, we analyze the effect of each covariate separately.

Consistent with previous literature, we find that imposing the covariates distribution of the USA into Spain does not affect total, financial nor real estate wealth inequality. Consequently, the remarkable disparities of wealth inequality between both countries found are attributed to the residual. However, when wealth IOp is analyzed, we find that imposing the covariates distribution of the USA into Spain significantly increases wealth IOp measures. The Shapley value decomposition shows that this result is mainly provoked by the education and labor status variables, highlighting two important transmission channels for individual opportunities (Palomino et al. 2019). For both types of wealth inequality, our findings are robust to different data settings, measurement approaches and inequality indexes.

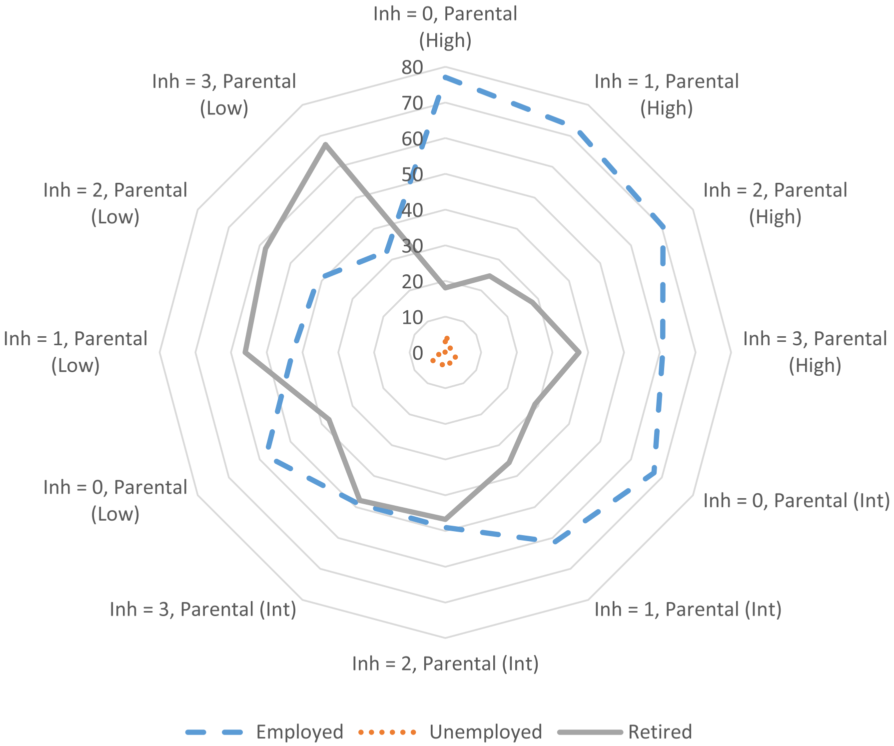

Fig. 5 Labor status by types (Counterfactual). Note: Types are defined by three categories of parental education (high/intermediate/low) and four categories of inheritances received (Inh = 0 for those who have not inherited anything, and Inh = 1, 2. 3 for those who inherit, depending on the inheritance terciles they belong). The data come from the EFF (2014) for Spain and the SCF (2016) for the USA

In addition, we find that a remarkable share of overall wealth inequality is explained by circumstances beyond individuals' control. In particular, the inheritances received seem to be the main vehicle through which real estate wealth inequalities are transmitted across generations, explaining up to 67% and 75% of IOp in Spain and the USA, respectively. The effect of parental education is also remarkable, explaining up to 57% and 34% of financial wealth IOp in Spain and the USA, respectively. These results suggest that equalizing individual opportunities to accumulate wealth requires complementary policies with a bearing on both, inheritances and educational persistence across generations.

All in all, our results do not contradict but, rather, complement those exposed by the literature that finds the distribution of covariates to be independent from wealth inequality disparities between countries. Wealth is a stock variable susceptible of being affected by a variety of factors, such as macroeconomic shocks, the life cycle, the individual's occupation and education, and also by individual circumstances. Being endowed with a certain bequest or having more educated parents may significantly widen individual opportunities to accumulate wealth. By focusing on the opportunities that people have to acquire wealth, we show that institutions are not as important as for overall wealth inequality, so covariates play a clear and well-defined role. Our results call for a deeper analysis of the effects that socioeconomic factors have on the accumulation of wealth, and how they are channeled through the opportunities of individuals.

Appendix

See Tables 8 , 9, 10, 11, 12, 13 and Figs. 6, 7, 8, 9.

Table 8 Wealth inequality descomposition (MLD index)

	Total wealth	Financial wealth	Real estate wealth
Spain MLD (a)	1.12	2.22	1.67
	(0.05)	(0.06)	(0.07)
US MLD (b)	2.60	1.59	3.91
	(0.03)	(0.05)	(0.06)
Counterfactual MLD (c)	1.09	2.11	1.62
	(0.07)	(0.10)	(0.10)
Actual difference ($d = a - b$)	−1.48	0.63	−2.24
Compositional effect ($e = a - c$)	0.03	0.11	0.05
Relative comp. effect ($e{\cdot}100/d$)	−1.69%	17.78%	−2.38%
Residual ($f = c - b$)	−1.51	0.52	−2.29
Relative residual ($f{\cdot}100/d$)	101.69%	82.22%	102.38%
Shapley decomposition			
Education	0.13*	0.26*	0.20*
	(0.00)	(0.01)	(0.01)
Income	−0.27*	−0.38*	−0.42*
	(0.02)	(0.03)	(0.03)
Labor	0.16*	0.23*	0.27*
	(0.01)	(0.00)	(0.01)

The asterisk (*) indicates that the changes are statistically significant for an alpha of 5%. Standard errors, based on the overlapping of the confidence intervals calculated after 500 replications, are in parenthesis. Appropriate replication weights are used. The data come from and the EFF (2014) for Spain and the SCF (2016) for the USA

Table 9 Wealth IOp decomposition (MLD index)

	Total wealth IOp	Financial wealth IOp	Real estate wealth IOp
Spain IOp (a)	0.29	0.31	0.52
	(0.01)	(0.01)	(0.01)
US IOp (b)	0.54	0.58	0.97
	(0.01)	(0.01)	(0.02)
Counterfactual IOp (c)	0.33*	0.50*	0.56*
	(0.01)	(0.01)	(0.01)
Actual difference ($d = a - b$)	−0.25	−0.27	−0.45
Compositional effect ($e = a - c$)	−0.04	−0.18	−0.04
Relative comp. effect ($e/d \cdot 100$)	17.52%	67.79%	7.97%
Residual ($f = c - b$)	−0.21	−0.09	−0.41
Relative residual ($f/d \cdot 100$)	82.48%	32.21%	92.03%
Shapley decomposition			
Education	−0.03*	−0.09*	−0.03*
	(0.00)	(0.00)	(0.00)
Income	0.02*	−0.01	0.02*
	(0.00)	(0.00)	(0.00)
Labor	−0.03*	−0.08*	−0.03*
	(0.00)	(0.00)	(0.00)

The asterisk (*) indicates that the changes are statistically significant for an alpha of 5%. Standard errors, based on the overlapping of the confidence intervals calculated after 500 replications, are in parenthesis. Appropriate replication weights are used. The data come from and the EFF (2014) for Spain and the SCF (2016) for the USA

Table 10 Contribution of circumstances to wealth IOp

	Total wealth (%)	Financial wealth (%)	Real estate wealth (%)
Spain			
Inheritances	60.38	43.31	66.67
Parental education	39.62	56.69	33.33
USA			
Inheritances	72.03	65.89	75.35
Parental education	27.97	34.11	26.65
Counterfactual			
Inheritances	58.26	60.00	52.37
Parental education	41.74	40.00	47.63

Shares estimated with a Shapley decomposition over IOp measures. The data come from and the EFF (2014) for Spain and the SCF (2016) for the USA

Table 11 Education distribution by types (%)

Types	Spain			Counterfactual		
	High	Intermediate	Low	High	Intermediate	Low
Parental (High), Inh = 0	48.55	39.75	11.70	59.98	39.54	0.48
Parental (High), Inh = 1	54.38	36.69	8.93	59.63	39.79	0.58
Parental (High), Inh = 2	64.07	24.29	11.64	72.45	26.82	0.73
Parental (High), Inh = 3	58.03	30.68	11.29	65.47	34.06	0.47
Parental (Int), Inh = 0	23.22	43.59	33.19	28.14	67.73	4.13
Parental (Int), Inh = 1	18.18	36.00	45.82	34.83	63.25	1.92
Parental (Int), Inh = 2	18.63	34.06	47.31	39.06	58.48	2.46
Parental (Int), Inh = 3	30.47	34.50	35.03	48.20	50.73	1.07
Parental (Low), Inh = 0	14.25	47.16	38.59	14.92	64.38	20.7
Parental (Low), Inh = 1	10.42	51.61	37.97	11.45	77.88	10.67
Parental (Low), Inh = 2	13.72	43.92	42.36	30.45	61.96	7.59
Parental (Low), Inh = 3	30.97	33.59	35.44	40.80	53.42	5.78

Types are defined by three categories of parental education (High/Intermediate/Low) and four categories of inheritances received (Inh = 0 for those who have not inherited anything, and Inh = 1, 2. 3 for those who inherit, depending on the inheritance terciles they belong). Education in Spain and the counterfactual is defined as high/intermediate/low. The data come from the EFF (2014) for Spain and the SCF (2016) for the USA

Table 12 Income inequality by types (Gini index)

Types	Spain	Counterfactual
Parental (High), Inh = 0	25.73	21.27
Parental (High), Inh = 1	21.91	19.50
Parental (High), Inh = 2	23.87	18.87
Parental (High), Inh = 3	20.37	15.82
Parental (Int), Inh = 0	30.14	30.20
Parental (Int), Inh = 1	27.82	25.04
Parental (Int), Inh = 2	27.33	21.01
Parental (Int), Inh = 3	22.89	21.39
Parental (Low), Inh = 0	32.66	36.21
Parental (Low), Inh = 1	26.57	26.39
Parental (Low), Inh = 2	25.55	26.01
Parental (Low), Inh = 3	27.82	28.51

Types are defined by three categories of parental education (High/Intermediate/Low) and four categories of inheritances received (Inh = 0 for those who have not inherited anything, and Inh = 1, 2. 3 for those who inherit, depending on the inheritance terciles they belong). Education in Spain and the counterfactual is defined as high/intermediate/low. The data come from the EFF (2014) for Spain and the SCF (2016) for the USA

Table 13 Labor status distribution by types (%)

Types	Spain			Counterfactual		
	Employed	Unemployed	Retired	Employed	Unemployed	Retired
Parental (High), Inh = 0	66.85	13.78	19.37	77.05	4.89	18.06
Parental (High), Inh = 1	62.88	12.59	24.53	72.72	2.56	24.72
Parental (High), Inh = 2	54.31	9.22	36.47	70.34	1.59	28.07
Parental (High), Inh = 3	57.57	14.1	28.33	60.81	1.85	37.34
Parental (Int), Inh = 0	50.84	16.45	32.71	67.39	3.69	28.92
Parental (Int), Inh = 1	44.14	7.65	48.21	61.28	3.06	35.66
Parental (Int), Inh = 2	41.22	9.40	49.38	49.03	4.19	46.78
Parental (Int), Inh = 3	38.15	8.82	53.03	48.93	3.18	47.89
Parental (Low), Inh = 0	49.73	21.77	28.5	57.96	4.43	37.61
Parental (Low), Inh = 1	47.75	18.54	33.71	42.77	1.17	56.06
Parental (Low), Inh = 2	36.26	21.68	42.06	41.16	0.75	58.09
Parental (Low), Inh = 3	44.17	13.99	41.84	32.71	0.14	67.15

Types are defined by three categories of parental education (high/intermediate/low) and four categories of inheritances received (Inh = 0 for those who have not inherited anything, and Inh = 1, 2. 3 for those who inherit, depending on the inheritance terciles they belong). Education in Spain and the counterfactual is defined as high/intermediate/low. The data come from the EFF (2014) for Spain and the SCF (2016) for the USA

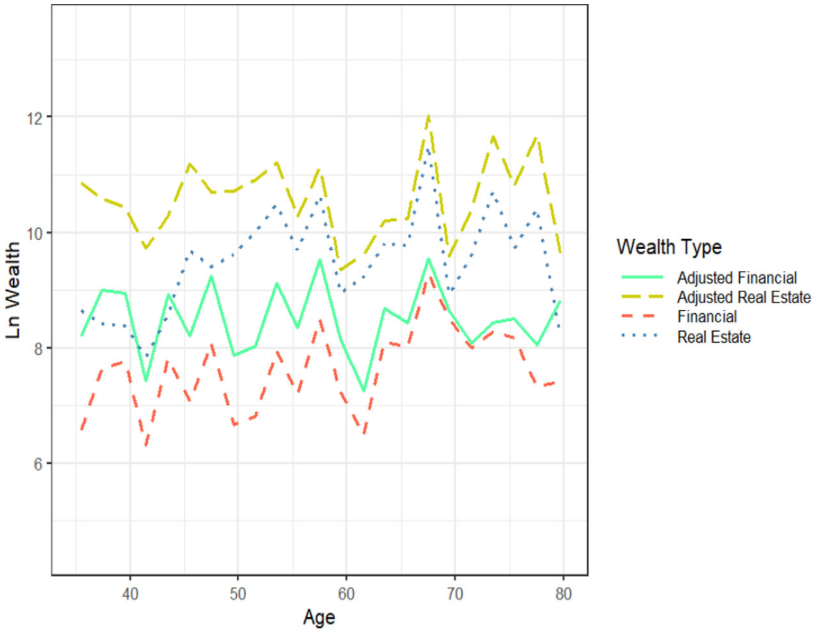

Fig. 6 Adjusted wealth in Spain (women). Note: The data come from and the EFF (2014)

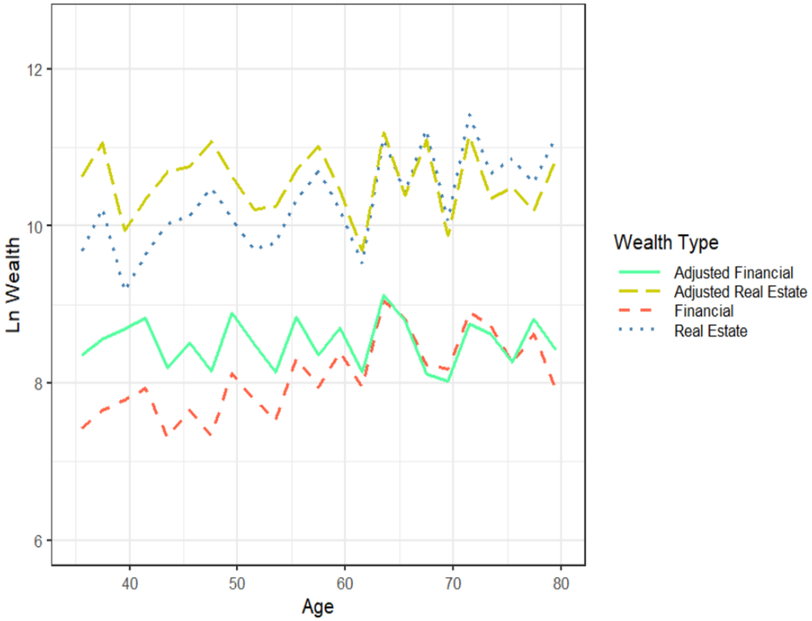

Fig. 7 Adjusted wealth in Spain (men). Note: The data come from and the EFF (2014)

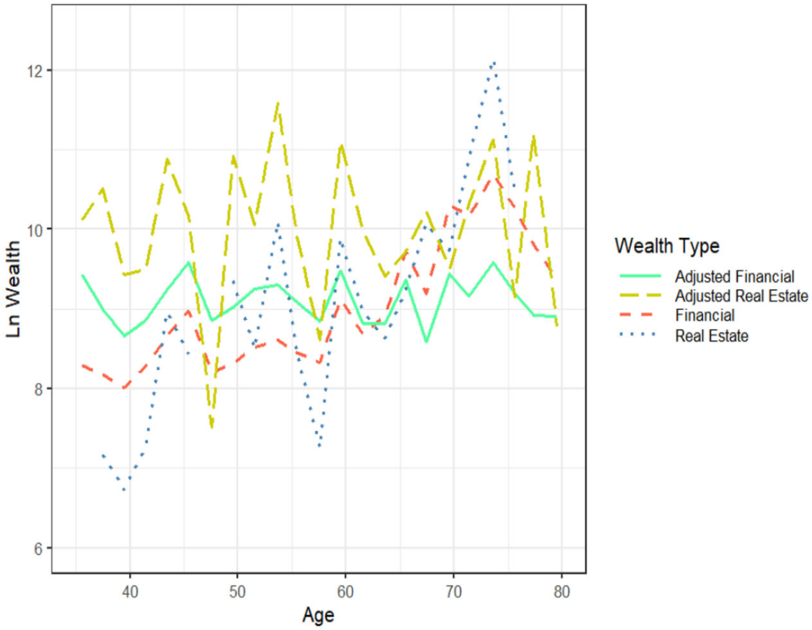

Fig. 8 Adjusted wealth in the USA (women). Note: The data come from and the SCF (2016)

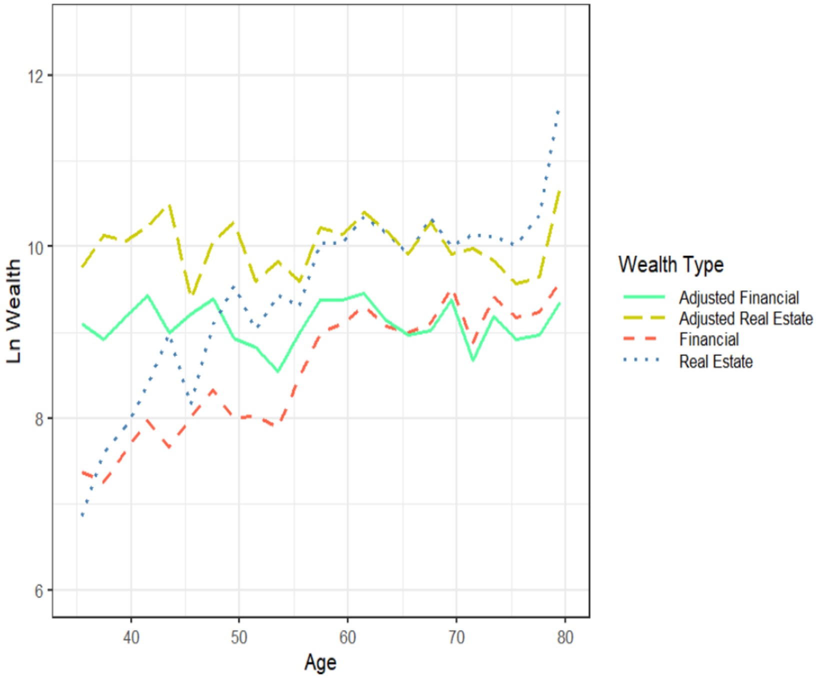

Fig. 9 Adjusted wealth in the USA (men). Note: The data come from and the SCF (2016)

References

Adermon A, Lindahl M, Waldenström D (2018) Intergenerational wealth mobility and the role of inheritance: evidence from multiple generations. Econ J 128:482–513

Ampudia M (2013) Stockholding in Spain. SERIEs 4:415–135

Anastasiade MC, Tillé Y (2017) Gender wage inequalities in Switzerland: the Public versus the private sector. Stat Methods Appl 26:293–316

Anghel B, Basso H, Bover O, Casado JM, Hospido L, Izquierdo M, Kataryniuk IA, Lacuesta A, Montero JM, Vozmediano E (2018) Income, consumption and wealth inequality in Spain. SERIEs 9:351–387

Azpitarte F (2012) Measuring poverty using both, income and wealth: a cross country comparison between the U.S. Spain Rev Income Wealth 58:24–50

Atkinson AB (1970) On the measurement of inequality. J Econ Theory 2:244–263

Autor D (2019) Work of the past, work of the future. Am Econ Rev Papers Proc 109:1–32

Badarinza C, Campbell JY, Ramadorai T (2016) International comparative household finance. Annu Rev Econ 8:111–144

Björklund A, Jäntti M, Roemer JE (2012) Equality of opportunity and the distribution of long-run income in Sweden. Soc Choice Welfare 39:675–696

Bourguignon F, Ferreira FHG, Menéndez M (2007) Inequality of opportunity in Brazil. Review of Income and Wealth 53:585–618

Bover O (2010) Wealth inequality and household structure: U.S. vs Spain. Review of Income and Wealth 56:259–290

Bover O, Crespo L, Gento C, Moreno I (2018) The Spanish survey of household finances (EFF): description and methods of the 2014 wave. Documentos Ocasionales no. 1804 (Banco de España)

Brunori P, Palmisano F, Peragine V (2019a) Inequality of opportunity in Sub-Saharan Africa. Appl Econ 60:6438–6458

Brunori P, Peragine V, Serlenga L (2019b) Upward and downward bias when measuring inequality of opportunity. Soc Choice Welfare 52:635–661

Bussolo M, Checchi D, Peragine V (2019) Long term evolution of inequality of opportunity. World Bank Working Paper Series, 8700.

Cabrera L, Marrero GA, Rodríguez JG, Salas-Rojo P (2020) Inequality of opportunity in Spain: new insights from new data. Hacienda Pública Española/Review of Public Economics 237:153–185

Checchi D, Peragine V (2010) Inequality of opportunity in Italy. J Econ Inequal 8:429–450

Christelis D, Georgarakos D, Haliassos M (2013) Differences in portfolios across countries: economic environment versus household characteristics. Rev Econ Stat 95:220–236

Cobb-Clark DA, Hildebrand VA (2006) The wealth of Mexican Americans. J Human Resour 41:841–868

Cowell F, Karagiannaki E, Mcknight A (2018a) Accounting for crosscountry differences in wealth inequality. Rev Income Wealth 64:332–356

Cowell F, Karagiannaki E, Mcknight A (2018b) The changing distribution of wealth in the pre-crisis U.S., UK: the role of socio-economic factors. Oxf Econ Pap 71:1–24

Cowell F, Van Kerm P (2015) Wealth inequality: a survey. J Econ Surv 29:671–710

Demirgüç-Kunt A, Levine R (2009) Finance and inequality: theory and evidence. Ann Rev Fin Econ 1:287–318

De Nardi, M. (2015) Quantitative models of wealth inequality: a survey. NBER Working Paper, 21106.

DiNardo J, Fortin NM, Lemieux T (1996) Labor market institutions and the distribution of wages, 1973–1992: a semiparametric approach. Econometrica 64:1001–1044

Doorley K, Sierminska E (2017) To own or not to own? household portfolios, demographics and institutions in a cross-national perspective. J Income Distrib 26:1–43

Faria JR, Wu Z (2012) From unemployed to entrepreneur: the role of the absolute bequest motive. Econ Lett 114:120–123

Ferreira FHG, Gignoux J (2011) The measurement of inequality of opportunity: theory and an application to Latin America. Rev Income Wealth 57:622–657

Foster JE, Shneyerov A (2000) Path independent inequality measures. J Econ Theory 91:199–222

Gamboa LF, Waltenberg FD (2012) Inequality of opportunity for educational achievement in Latin America: evidence from PISA, 2006–2009. Econ Educ Rev 31:694–708

Gennaioli N, Shleifer A, Vishny R (2014) Finance and the preservation of wealth. Q J Econ 129:1221–1254

Gradín C (2013) Conditional occupational segregation of minorities in the U.S. J Econ Inequal 11:473–493

Hedges SB (1992) The number of replications needed for accurate estimation of the boostrap P value in phylogenetic studies. Mol Biol Evol 1:366–369
Jusot F, Tubeuf S, Trannoy A (2013) Circumstances and efforts: how important is their correlation for the measurement of inequality of opportunity in health? Health Econ 22:1470–1495
Lasso de la Vega C, Lekuona A, Orbe S (2020) Reexamining the inequality of opportunity in education in some European countries. Appl Econ Lett 27:544–548
Leitner S (2016) Drivers of wealth inequality in euro area countries: the effect of inheritance and gifts on household gross and net wealth distribution analysed by applying the shapley value approach to decomposition. Eur J Econ Econ Pol 13:114–136
Li Donni P, Rodríguez JG, Días PR (2015) Empirical definition of social types in the analysis of inequality of opportunity: a latent classes approach. Soc Choice Welfare 44:673–701
Lusardi A, Michaud PC, Mitchell OS (2017) Optimal financial knowledge and wealth inequality. J Polit Econ 125:431–477
Mankiw NG (2015) Yes, r>g. So what? Am Econ Rev 105:43–47
Marrero GA, Rodríguez JG (2011) Inequality of opportunity in the U.S.: trends and decomposition. Res Econ Inequal 19:217–246
Marrero GA, Rodríguez JG (2012) Inequality of opportunity in Europe. Rev Income Wealth 58:597–621
Marrero GA, Rodríguez JG (2013) Inequality of opportunity and growth. J Dev Econ 104:107–122
Marrero GA, Rodríguez JG, Van Der Weide R (2016) Unequal opportunity, unequal growth. Working Paper 7853, World Bank.
Nolan B, Palomino JC, Van Kerm PV, Morelli S (2020) The intergenerational transmission of wealth in rich countries. Centre for Studies in Economics and Finances at Oxford Martin School Working Papers, 578.
Niehues J, Peichl A (2014) Upper bounds of inequality of opportunity: theory and evidence for Germany and the U.S. Soc Choice Welfare 43:73–99
Palencia-Esteban A (2019) Occupational segregation of female and male immigrants in the European Union: accounting for cross-country differences. Int Labour Rev. https://doi.org/10.1111/ilr.12207
Palomino JC, Marrero GA, Rodríguez JG (2019) Channels of inequality of opportunity: the role of education and occupation in Europe. Soc Indic Res 143:1–30
Palomino JC, Marrero GA, Nolan B, Rodríguez JG (2020) Inheritances, family background and wealth inequality. ECINEQ Working Paper, 537
Ramos X, Van de Gaer D (2016) Approaches to inequality of opportunity: principles, measures and evidence. J Econ Surv 30:855–883
Rawls J (1971) A theory of justice. Harvard University Press, Cambridge
Rodríguez JG (2004) Descomposición Factorial de la Desigualdad de la Renta. Rev Econ Appl 12:25–46
Rodríguez JG (2008) Partial equality-of-opportunity orderings. Soc Choice Welfare 31:435–456
Roemer JE (1998) Equality of opportunity. Harvard University Press, Cambridge, MA
Salas-Rojo P, Rodríguez JG (2020) Inheritances and wealth inequality: a machine learning approach. LWS Working Paper Series No. 32
Sastre M, Trannoy A (2002) Shapley inequality decomposition by factor components: some methodological issues. J Econ 77:51–89
Sen A (1980) Equality of what? The Tanner lectures on human values. University of Utah Press, Salt Lake City, Salt Lake City
Shorrocks AF (2013) Decomposition procedures for distributional analysis: a unified framework based on the shapley value. J Econ Inequal 11:99–126
Sierminska E, Frick JR, Grabka M (2008) Examining the gender wealth gap in Germany. Oxf Econ Pap 62:669–690
Solon G (1992) Intergenerational income mobility in the United States. American Economic Review 82:393–408
Trannoy A, Tubeuf S, Jusot F, Devaux M (2010) Inequality of opportunities in health in France: a first pass. Health Econ 19:921–938
Tsawe M, Susuman AS (2020) Examining inequality of opportunity in the use of maternal and reproductive health interventions in Sierra Leone. J Public Health 42:254–261
Van de Gaer D (1993) Equality of opportunity and investment in human capital. Ph-D Dissertation, Catholic University of Leuven
Wolff EN, Gittleman M (2014) Inheritances and the distribution of wealth or whatever happened to the great inheritance boom? J Econ Inequal 12:439–468

Zucman G (2019) The triumph of injustice: how the rich dodge taxes and how to make them pay. Norton and Company, New York