Inheritances and Wealth Inequality: a Machine Learning Approach

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Outline

Inheritances and Wealth Inequality

Many factors have been blamed for the increase in wealth inequality experienced in the last decades: financial knowledge disparities (Lusardi et al, 2017), the decline in progressive taxation (Zucman, 2019)... But, what about inheritances?

- Some argue that inheritances are the main vehicle through which inequalities are transmitted and increased across generations (Piketty and Zucman, 2015; Palomino et al, 2020; Nolan et al, 2020).
- Others say that, since inheritances are more equally distributed than wealth, their intergenerational transmission actually decreases overall inequality (Boserup et al, 2016; Elinder et al, 2018).

What is this paper about?

- We assess the relation between inheritances and wealth from the perspective of the Inequality of Opportunity (IOp) literature.
- We propose some Machine Learning methods that deal with some traditional limitations of this literature.
- We measure the share of overall inequality that can be attributed to inheritances.
- Finally, we employ Single-Parameter Gini indexes to study the impact of inheritances through the wealth distribution.

Outline

Inequality of Opportunity framework

- Economic outcomes are a function of circumstances (factors beyond individual's control, such as gender, race, inheritances or parental education) and efforts (chosen by individuals).
- Thus, overall inequality can be decomposed as the sum of two terms: Inequality of Opportunity (IOp), attributed to circumstances, and Inequality of Efforts (IE).

$$Ov.Inequality = IOp + IE$$

- The first component is undesirable not only for social justice matters (Rawls, 1971, Sen 1980), but also for economic growth (Marrero and Rodríguez, 2013; Carranza, 2020).

The measurement of IOp

According to individual circumstances, any population can be divided into exhaustive and mutually exclusive groups (types). Then, a society has equality of opportunity if, for an outcome variable w and types T_s and T_m:

$$\int w|T_m d_{T_m} = \int w|T_s d_{T_s}$$

However, distributions can cross (Atkinson, 1970). Thus, following Van de Gaer (1993) a society has unequal opportunities if:

$$\overline{w} T_m d_{T_m} = \overline{w} T_s d_{T_s}$$

The measurement of IOp

Following the IOp literature, if we take inheritances as our circumstance and use it to build types, we can measure the part of overall inequality attributed to bequests:

$$Ov.Inequality = IOp(inheritances) + IE$$

But there is a problem:

- The construction of types is straightforward with categorical circumstances (sex, race, parental education).
- However, for continuous circumstances, a problem arises. To generate types we need to divide the population into groups. If this is done under researchers criteria, results are inconsistent and arbitrary (see Appendix)
- We need a way to systematize the generation of types with continuous circumstances.

Machine Learning Algorithms

A possible solution: employing Machine Learning (ML) algorithms, in particular conditional inference trees and forests (Hothorn et al, 2006, Brunori et al, 2019).

- These algorithms divide all observations into exhaustive and mutually exclusive groups (types), based on the statistical properties of a dependent variable (wealth) conditioned on a set of factors (circumstances).
- Once this partition is done, they assign each observation with its expected outcome.
- In particular, forests are found to deliver quite consistent results (Schlosser et al, 2019)

We can deep into this at the end of the presentation.

Outline

Data

- The data comes from the Luxembourg Wealth Study (LWS) database.
- We analyze four countries: Canada (2016), Italy (2014), Spain (2014) and the U.S. (2016).
- We use three wealth definitions: real estate, financial and total wealth.
- We control for age and gender, avoiding the effects of life cycle related to wealth accumulation.

Summary Statistics

Canada (N=3627)	Total	Financial	Real Estate	Inheritances
Mean	379.05	72.07	306.96	46.94
Gini	70.66	83.70	74.90	92.26
Italy (N=4142)	Total	Financial	Real Estate	Inheritances
Mean	272.60	31.35	241.25	19.35
Gini	59.00	73.96	60.61	93.89
Spain (N=4792)	Total	Financial	Real Estate	Inheritances
Mean	303.55	46.72	256.83	34.79
Gini	59.24	84.13	60.20	88.55
U.S. (N=3325)	Total	Financial	Real Estate	Inheritances
Mean	1697.20	426.51	1270.70	9.35
Gini	80.28	91.6	82.17	95.24

Table: Values in Thousand $US of 2011

Outline

Main Results

Once we used the ML algorithms (random forests) to create types and attribute each individual with its expected wealth, we compute the between-type inequality and obtain the share of overall inequality (measured with Gini) attributed to inheritances:

Canada	Total	Financial	Real Estate
	41.88%	56.98%	36.57%
Italy	Total	Financial	Real Estate
	37.31%	43.94%	38.28%
Spain	Total	Financial	Real Estate
	68.82%	65.15%	76.43%
U.S.	Total	Financial	Real Estate
	68.58%	74.96%	66.57%

Table: Share of overall inequality attributed to inheritances

Some Comments

- Ratios are particularly high for the U.S. and Spain: inheritances always represent, at least, 65% of total inequality.
- Financial wealth is particularly affected by inheritances. These assets are more risky and volatile, and bequests may work as "safety nets" (Jordá et al, 2019)
- However, inheritances are not orthogonal to other circumstances.

Disentangling Effects

For Italy and the U.S. we have information on parentals' education, so we repeat the complete analysis including this circumstance. Then, we apply a Shapley value decomposition to check the effect of each sepparate covariate.

Italy	Total	Financial	Real Estate
IOp	52.44%	61.63%	51.51%
Contribution of parental education	26.27%	35.27%	23.92%
Contribution of inheritances	26.17%	26.36%	27.59%
U.S.	**Total**	**Financial**	**Real Estate**
IOp	69.32%	75.14%	65.17%
Contribution of parental education	22.01%	23.25%	21.72%
Contribution of inheritances	47.31%	51.89%	43.45%

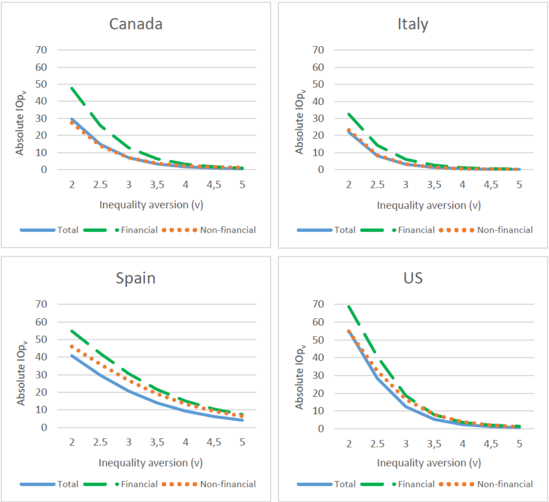
Table: Share of overall inequality attributed to inheritances (from random forests)

Inheritances and Wealth Distribution

Is the effect of inheritances homogeneous along the wealth distribution?
We check it by using Single Parameter Ginis, who weight IOp along the wealth distribution.
Interpretation: The higher the parameter aversion, the higher the effect of inheritances on the bottom tail of the wealth distribution.

Inheritances and Wealth Distribution

The effect of inheritances is disappears as we focus on the bottom-tail of the wealth distribution (the poorer).



Inheritances and Wealth Distribution

What determines the opportunities at the left tail of the wealth distribution?
We repeat the analysis using parental education as a circumstance.

Outline

Take-home ideas

- Inheritances explain a remarkable share of overall wealth inequality.
- The effect of bequests particularly conditions the opportunities at the right tail of the wealth distribution.
- At the left tail, other factors such as the parental education play a major role.

Farewell

Thank you!

Comments, questions or miscelanea: pedsalas@ucm.es

Outline

Trees

From Hothorn et al (2006):
Consider a dependent variable w conditioned on the circumstances set C. Trees perform a t-test on the global null hypothesis of independence for each circumstance considered:

$$H_C = D(w|C) = D(w)$$

Then, obtain a p-value for each C and adjust with Bonferroni correction:

$$p_{adj} = 1 - (1 - p)^p$$

The algorithm selects the circumstance with the lowest p_{adj}.
If $p_{adj} > \alpha$, the algorithm stops.

Trees

Otherwise, the algorithm continues and selects the splitting point:

$$w_z = \{w_i : C_i < x\}$$
$$w_{-z} = \{w_i : C_i \geq x\}$$

Where x is each possible partition value of the continuous variable, and z each subsample.
For every x, test de discrepancy between both subsamples and obtain an associated p-value. The algorithm selects the splitting point delivered by the smallest p-value, and generates two nodes.
Repeat the whole algorithm in each node until the null hypothesis of independence cannot be rejected.
Finally, the algorithm assigns the mean w to each node.

Forests

From Strobl et al (2007):
Conditional inference forests are the bootstrapped version of trees.

- Get a subsample from the original data, with no replacement.
- Run the tree on this subsample, and save the results.
- Repeat n times.
- Average all saved results.

Advantages: trees are highly data-dependent. This bootstrapped version performs well out of sample, smoothing discrepancies across trees.

Ferreira and Guignoux (2011) method

Run an OLS regression:

$$ln(w_i) = \alpha + \psi C_i + \epsilon_i$$

Where w_i is wealth of individual i, and C_i represent all circumstances. Then, obtain the smoothed vector $(\overline{w})$ by fitting the parameters obtained in the previous regression:

$$(\hat{w}_i) = exp[\hat{\alpha} + \psi \hat{C}_i]$$

The vector $\hat{w}$ assigns to each individual its expected wealth, given her own type.

Ferreira and Guignoux (2011) results

Results are for Spain. Examples for the remaining three countries can be found in the paper.

Partitions	Total	Financial	Real Estate
$0	44.07%	32.79%	55.20%
Median	42.20%	25.83%	53.55%
Terciles	59.81%	39.58%	72.39%
p75	25.71%	15.80%	32.21%

Table: Share of overall inequality attributed to inheritances (different partitions)

Palomino et al (2020) adjustment

We regress the natural logarithm of wealth of individual -i, w_i, against its gender F_i and age A_i to the fourth power:

$$ln(w_i) = \alpha + \beta F_i + \sum_{n=1}^{4} \gamma_n (A_i - 65)^n + \sum_{n=1}^{4} \delta_n F_i (A_i - 65)^n + \epsilon_i$$

Then, obtain adjusted wealth $w_{ajd,i}$:

$$ln(w_{ajd,i}) = ln(w_i) - \hat{\beta} F_i - \sum_{n=1}^{4} \hat{\gamma}_n (A_i - 65)^n - \sum_{n=1}^{4} \hat{\delta}_n F_i (A_i - 65)^n$$

Palomino et al (2020) adjustment (example)

For men in the U.S.

Single-Parameter Gini Results

The Single-Paramater Gini (S-Gini) can be formally assessed as:

$$I_{S-Gini}(F;v) = 1 - v[v-1]\int_0^1 [1-q]^{v-2} L(F;q)dq$$

Where L is the Lorenz curve, q is the percentile position and v is an inequality aversion parameter.
Note that for v=2, S-Gini deploys the traditional Gini index.