

Wealth distribution in villages. Transition from socialism to capitalism in view of exhaustive wealth data and a master equation approach.

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2 ABSTRACT

3 Socio-economic inequalities derived from an exhaustive wealth distribution is studied in a closed
4 geographical region from Transylvania (Romania). Exhaustive wealth data is computed from
5 the agricultural records of the Sancraiu commune for three different economic situations. The
6 gathered data is spanning two different periods from the communist economy and the present
7 situation after 28 years of free market economy in Romania. The local growth and reset model
8 based on an analytically solvable master equation is used to describe the observed data. The
9 model with realistically chosen growth and reset rates is successful in describing both the
10 experimentally observed distributions and the inequality indexes (Lorenz curve, Gini coefficient
11 and Pareto point) derived from this data. The observed changes in these inequality measures are
12 discussed in the context of the relevant socio-economic conditions.

13 **Keywords:** socio-economic inequalities, wealth distribution, master equation, Gini index, Lorenz curve, Pareto point

1 INTRODUCTION

14 Fascinating statistics related to cities or smaller settlements have been intensely studied by physicists in the
15 last few decades. On the data mining and analyzing side, the studies coming from physics revealed many
16 universalities and scaling laws. Modeling was realized with simple physics inspired models that were able
17 to prove by their success the relevancy of some socio-economic processes in the investigated phenomenon.
18 Numerous universalities have been revealed and successfully modeled [1, 2, 3, 4, 5, 6, 7].

19 It has been shown that despite the large differences in their population, cities are all qualitatively similar
20 from the point of view of most of the sociometric indices. Many of the urban sociometric measures, such as
21 length of roads, total income, GDP, total wages, gross urban product etc... are scaling with the population
22 of the settlement [1, 3, 5]. Based on the value of the scaling exponent, for cities from the USA, Germany
23 and China many of these urban indicators were categorized by Bettencourt et al. in three regimes: sublinear,
24 linear and superlinear [3]. An elegant explanation for the reason why larger cities are growing on the
25 expense of smaller ones were offered by interpreting this different scaling regimes.

26 The social inequality in a settlement's population is also affected by the size of the population, however
27 the methodology of measuring and modeling social inequalities is more complex than the one used for

28 most of the other urban indices mentioned above. Social inequalities have been studied beginning from
29 the early days of Economics and presently is one of the main direction in Econophysics [8]. Everybody
30 is aware of Vilfredo Pareto's seminal works [9], revealing the universality of the fat-tailed distributions
31 in income and wealth and the related 80-20% law. Econophysics targets the problem of inequalities in
32 a society starting from the experimental distribution of income or wealth of individuals (or groups of
33 individuals) of a well-delimited population [10].

34 The most commonly accepted measure that characterizes the inequality in a society is the Gini index [11].
35 It has been shown that the value of the Gini index grows with the size of the city, meaning that inequality
36 is more pronounced in larger cities, than in case of smaller ones [6]. Recently, a more profound study
37 focusing on the effect of city size on the income distribution was published by E. Heinrich Mora et. al. [2],
38 showing that the income does not scale in the same manner for all regions of the society. The scaling is
39 sub-linear for the lower regions of the society and scales super-linear in case of the higher regions. (*This*
40 *result is in agreement with the wealth data from a small settlement (about 1000 households) processed in*
41 *this article.*) The results of Mora et. al. illustrates nicely the effect of increasing inequality with the city
42 size.

43 Not only the fat-tail of social inequalities, but also the understanding of the underlying mechanism leading
44 to the unusual distribution of such socioeconomic measures like income or wealth are fascinating questions.
45 It is known nowadays that the distribution of income and wealth is not a simple one, different type of
46 distributions apply to different regions of income or wealth. The richer end of both distributions can
47 be described with the power-law type distribution [9, 10]. The low and middle classes of income and
48 wealth can be described better with an exponential distribution. In case of wealth a third region should be
49 considered as well, the region of negative wealth (debts), which is also characterized by an exponential
50 trend, different from the one which applies for the low and middle classes [12].

51 Modeling the experimental data is by many different methods, ranging from simple mean-field type
52 models, to more complex models involving network-science approach or agent based computational
53 simulations [10, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27].

54 Recently, we proposed a simple master-equation approach based on a Local Growth and Global Reset
55 (LGGR) [28] process to describe in a similar manner the distribution of both income and wealth [26, 12].
56 The novelty of this approaches is also it's ability to describe all income and wealth regions in unified
57 manner, proposing a compact form of the distribution function for all income/wealth categories, capturing
58 the regions of the negative wealth as well.

59 Although income and wealth seems to be related and can be modeled with a similar approach, from
60 data mining side there are however big differences between them. While incomes are present in many
61 electronically available data (taxation for example), wealth is more difficult to quantify and measure directly
62 and raises many private issue problems. Wealth is usually estimated via some proxies and it is hard to
63 find exhaustive data for a well-delimited and statistically significant community. In our previous studies
64 targeting income distributions [29, 26] we have shown the advantages of having a complete statistics of
65 income (exhausting data) in a population for many consecutive years. Such data allows not only to test
66 the statistics offered by the model, but it also allows verification of some hypothesis used in modeling the
67 dynamics of the system.

68 Exhaustive real-world wealth data are rare to find in the literature and as a consequence, these could be
69 extremely precious from the point of view of any modeling studies on socio-economics problems targeting
70 social-inequalities. Here we construct such an exhaustive wealth database extracted from taxation and

71 ownership data that is available at the mayor's office in a Romanian village community, *comuna Sâncraiu*,
72 (*Kalotaszentkirály*), having about 1000 households. The database includes data from three different years:
73 1961, 1989 and 2021. The real beauty of this data is that the studied years are relevant snapshots for three
74 very different political periods, influencing in a different manner private wealth. The year 1961 is exactly
75 the year before collectivization, when the lands given to the peasants by the communists after 1947 were
76 again confiscated and collectivized. 1989 was the last year of the communism regime in Romania and
77 finally 2021 is the present situation after more than 30 years after the fall of communism offering the
78 picture of the effects of the free market economy in Romanian villages.

79 Beside presenting and discussing the relevant wealth distributions derived from the data, our aim is
80 also to validate once again the modeling power of the LGGR model [12] in describing social inequalities.
81 Possessing an exhaustive wealth data for three different economic periods in Romania we are also able to
82 show how social inequalities varied in these turbulent time and how the growth and reset rates should be
83 adjust in the LGGR model to account for the measured wealth-distributions. Beside the relevant distribution
84 functions we discuss and compare the Lorenz curves, Pareto points and the value of the Gini indices for all
85 the studied periods.

86 The rest of this manuscript is organized as follows: (1) we present and discuss the data; (2) the LGGR
87 modeling framework is briefly discussed; (3) the LGGR model is applied to the obtained wealth data by
88 using different growth and reset rates; (4) the obtained results are discussed in view of socio-economic
89 inequalities, and (5) finally we summarize our findings.

2 THE EXHAUSTIVE WEALTH DATA

90 Wealth is hardly quantifiable since it is composed by all valuables that a person possesses. Previous studies
91 regarding wealth distributions were based either on the inheritance tax data [30], estimated wealth data
92 provided by media companies (Forbes) or organizations such as the one managing the World Inequality
93 Database(WID) [26]. A first shortcoming of these data is it's incomplete nature and a biased sampling:
94 targeting the aging part of the population or the rich, for example. Analysis performed on exhaustive wealth
95 data is lacking from the literature to our knowledge. Importance of such exhaustive data was recognized in
96 our previous works on income distribution. The exhaustive data for income derived from a anonymized
97 social-security database in ten consecutive years in the Cluj county (Romania) [29, 12], allowed to model
98 realistically the dynamics of the income and to describe successfully its distribution.

99 Here we aim to understand wealth distribution by first constructing an exhaustive data for a delimited
100 geographical territory in Romania. The used data and the compiling method that is presented in the
101 following allowed to infer the wealth of each household in a commune of Cluj county. Wealth datasets
102 from three radically different economic life situations of the villages from Romania are considered:

- 103 • **1961** The year under the communist regime where most of the agriculture destined land was confiscated
104 and collectivized, following the distribution of these lands to peasants in 1947.
- 105 • **1989** The last year of the communist regime, when most of the private property is already abolished,
106 leaving households with limited valuables.
- 107 • **2021** The current year, after 32 years the abolishment of the communism and transition to a free market
108 economy.

109 Following an agreement between the Babes-Bolyai University of Cluj, and commune Sâncraiu (in
110 Hungarian: Kalotaszentkirály–Zentelke) records regarding the wealth of households in the commune were

111 obtained in anonymized format. The commune is a well-delimited region in Transylvania, consisting of five
 112 villages: Alunisu (Magyarokereke), Braisoru (Malomszeg), Domsu (Kalotadamos), Horlacea (Jakotelke)
 113 and the eponymous Sancraiu. The region and these villages can be located on the map of Figure 1. The
 114 current population of the commune is 1628 inhabitants according to the census from 2011. The 1956 census
 115 enumerates 3557 inhabitants [31] and the census from 1992 records a population of 2.053 individuals [31].

116 The wealth component data for 1961 and 1989 was obtained by digitalizing in an anonymous manner the
 117 data agricultural registers of the mayor office (Agricultural Register of Sancraiu commune for 1959-1960-
 118 1961, Agricultural Register of Sancraiu commune for 1959-1960-1961), while for the year 2021 we used
 119 the anonymized taxation database for land and buildings.

120 The "agricultural register" is a complete agricultural record kept by the local authorities. These records
 121 contain each household in the commune along with the owned land area, house area, auxiliary building
 122 area (such as barns etc.), along with the number of owned livestock per different types (horses, cows, sheep,
 123 etc.). As the commune is located historically in an agricultural area, we assumed that before 1990 the
 124 agricultural records contain the bulk of the valuables that a household owns. With a realistic weighted sum
 125 of all recorded valuables one can create a good proxy, that estimates the wealth of an individual household.
 126 In the following we describe each dataset in detail and the estimation method for the total wealth, as the
 127 used records changed during the years.

128 2.1 Wealth data for 1961

129 The Agricultural Registers 1959-1960-1961 contain information about each household in the commune.
 130 The total number of individual households that are recorded are 1133. For each household the the following
 131 data are used to construct a proxy for the wealth:

- 132 • A_L - total land owned in hectares (ha). All types of land are included. The weight parameter will be
 133 denoted by P_{A_L} .
- 134 • A_{Bh} - area of the house owned in m^2 . Weight parameter: $P_{A_{Bh}}$.
- 135 • A_{Ba} - total area of the auxiliary buildings (such as barns, etc.). Weight parameter: $P_{A_{Ba}}$.
- 136 • N_C - number of cows owned. Weight parameter: P_{N_C} .
- 137 • N_{WB} - number of domestic water buffaloes owned. Weight parameter: $P_{N_{WB}}$.
- 138 • N_H - number of horses. Weight parameter: P_{N_H} .
- 139 • N_P - number of pigs. Weight parameter: P_{N_P} .
- 140 • N_S - number of sheep. Weight parameter: P_{N_S} .
- 141 • N_G - number of goats. Weight parameter: P_{N_G} .

The dataset is diverse enough to allow a robust approximation of the wealth. The total wealth of household i is calculated as a simple weighted sum of these valuable categories:

$$W_i = A_{Li}P_{A_L} + A_{Bhi}P_{A_{Bh}} + A_{Bai}P_{A_{Ba}} + N_{Ci}P_{N_C} + N_{WBi}P_{N_{WB}} + \\ + N_{Hi}P_{N_H} + N_{Pi}P_{N_P} + N_{Si}P_{N_S} + N_{Gi}P_{N_G} \quad (1)$$

142 Since the values of the weighting parameters are largely disputable, we estimate the individual wealth
 143 values with 10 different (but realistic) parameter set, allowing also an estimation for the uncertainty of
 144 the wealth estimation method. The chosen parameter sets are presented in Table 1. To fully understand

145 the effect of different parameterizations, we calculate also the share of a single "category" from the total
 146 wealth in the commune. The total wealth is calculated as $W_{tot} = \sum_i W_i$. The share of the category C with
 147 weighting parameter P_C (this can be the land A_L , house A_{Bh} etc.) in percents will be:

$$S(C) = \frac{P_C \sum_i C_i}{W_{tot}} \times 100\% \quad (2)$$

148 We present the shares by categories for the parameter sets from Table 1, in the Table 2. The data from
 149 this table indicates that the used parameter sets covers a wide range of acceptable methods to compound a
 150 wealth proxy and the uncertainty estimated from here is realistic.

151 The experimental wealth distribution $\rho(w)$ is calculated for each parameter set. The probability density
 152 function is built up from the individual household wealth values with the histogram method. For all
 153 parameter sets we used the same number of bins for the histogram, however the middle point of each bin
 154 becomes slightly different, different leading to an average value and also a corresponding error bar. The
 155 error bars for the probability density function is estimated from the different bin intervals and histogram
 156 values similarly. The error bars on the points in the direction of both axes signify the greatest deviation from
 157 the mean of the bin. The use of these error bars allows us to represent in a compact manner the ensemble
 158 of distributions obtained with the used parameter sets. The obtained probability density functions are
 159 presented in such manner on Figure 2. This figures suggest that the different parameter sets introduce some
 160 uncertainties affecting the location of the data points, but the overall qualitative shape of the distribution is
 161 well delimited.

162 2.2 Wealth data for 1989:

163 The records from the Agricultural register 1989 were digitalized and anonymized. There were in total of
 164 921 individual households. Before proceeding, one has to note that the composition of the wealth will be
 165 very different from the year 1961. First, this is because the agricultural lands were all fully collectivization
 166 and for a household was allowed a home garden of maximum 40 acres. This area also included the surface
 167 of the buildings. Secondly new categories appears in the records, such as the owned cars. The methodology
 168 for estimating the total wealth is the same as for 1961. We assume again that the the wealth of a household
 169 is the weighted sum of the following relevant "categories":

- 170 • A_L - total land area in acres ($a, 1a = 100m^2$). Weight parameter: P_{A_L} .
- 171 • A_{Bh} - area of the house owned in m^2 . Weight parameter: $P_{A_{Bh}}$.
- 172 • A_{Ba} - total area of the auxiliary buildings (such as barns, etc.) owned. Weight parameter: $P_{A_{Ba}}$.
- 173 • N_{cc} - number of carriages. Weight parameter: $P_{N_{cc}}$.
- 174 • N_{ca} - number of cars owned. Weight parameter: $P_{N_{ca}}$.
- 175 • N_C - number of the cow. Weight parameter: P_{N_C} .
- 176 • N_{WB} - number of domestic water buffaloes. Weight parameter: $P_{N_{WB}}$.
- 177 • N_H - number of horses. Weight parameter: P_{N_H} .
- 178 • N_P - the number of pigs. Weight parameter: P_{N_P} .
- 179 • N_S - the number of sheep. Weight parameter: P_{N_S} .

180 The used different sets of weigh parameters are presented in Table 3. The shares in the total wealth of the
 181 different categories, as it was discussed for 1961, are presented in Table 4.

182 The probability densities of wealth distribution $\rho(w)$ was computed in the same manner as for 1961 and
 183 the error bars were estimated again by using the different weight parameter sets. The result is shown on
 184 Figure 3.

185 2.3 Wealth data for 2021:

186 The wealth distribution for the year 2021 was derived from the anonymized local taxation records. These
 187 records contain all the estimated value of the owned real estates, and the size of the owned land inside
 188 the villages (possible built area, with running water, electricity and waste management). The land sizes
 189 and types owned outside of the village are also present in the database. For 2021 there are 1595 taxpaying
 190 individuals in these records. The tax an individual pays after their owned valuables are calculated from
 191 these records, however we did not have the information regarding payed total tax. Since the values of
 192 different land types are not fixed, again realistic weights are needed to combine different assets. The
 193 selected "categories" and weights for computing the total wealth of an individual are:

- 194 • V_b - total estimated value of the owned buildings. It is calculated by taking into account the type of
 195 the owned house, the heating apparatus, building materials and etc. by the local authority. Weight
 196 parameter: P_{V_b} .
- 197 • A_{pb} - the area of built-up territories inside the villages in hectares ha . Weight parameter: $P_{A_{pb}}$.
- 198 • A_a - the arable field outside the villages in hectares ha . Weight parameter: P_{A_a} .
- 199 • A_p - the pasture land outside the villages in hectares ha . Weight parameter: P_{A_p} .
- 200 • A_g - the owned grassland outside the villages in hectares ha . Weight parameter: P_{A_g} .
- 201 • A_f - the owned forest outside the villages in hectares ha . Weight parameter: P_{A_f} .

202 In Table 5 we present the different parameter sets for the weight factors used for 2021. The percentile shares
 203 for the different wealth categories calculated according to (2) are presented in Table 6. The methodology of
 204 the individual wealth calculation remains the same as in the previous cases. The probability density for
 205 wealth distribution with the error bars calculated with the used parameter sets, $\rho(w)$, is given in Figure 4.

3 THE LGGR MODELING FRAMEWORK

206 A master equation approach describing uni-directional local growth and global reset processes (LGGR)
 207 was recently introduced for modeling various distributions that are frequently encountered in complex
 208 systems. The appropriateness of such a simple model to describe income and wealth data in modern
 209 societies was also discussed in a series of recent articles [26, 12]. For a better understanding of the LGGR
 210 model let us consider a system composed of identical entities, each of them characterized by the amount
 211 of quanta they possess. An immediate example of such a system would be the individuals of a society
 212 owning different amount of wealth. Let us denote by $P_n(t)$ the probability that a person has n quanta of
 213 wealth at time t . The $P_n(t)$ probability has to satisfy normalization: $\sum_{\{n\}} P_n(t) = 1$. For some fixed μ_n
 214 growth rates and γ_n reset rates some possible dynamical scenarios are sketched in Figure 5. In the scenario
 215 from Figure 5a, the reset rate γ_n is positive for all n values. The model allows however a scenario with
 216 γ_n state-dependent rates where $\gamma_n < 0$ if $n < n_c$, and $\gamma_n > 0$ for $n > n_c$. This would mean that in
 217 average actors with low wealth $n < n_c$ are coming in the system and system and those leaving the system
 218 would have $n > n_c$ amount of quanta, in general. The schematic representation of the process in case
 219 of this scenario is represented on Figure 5b. In [26, 12] it has been shown, that this second scenario is
 220 extremely appropriate to model socio-economic inequalities. Independently however whether we are in the

221 case (a) or (b), the analytical investigation of the LGGR model follows the same route. In case only local
 222 unidirectional transitions ($n \rightarrow n + 1$) are considered for growth, the dynamical evolution equation will
 223 have the following form:

$$\frac{dP_n(t)}{dt} = \mu_{n-1}P_{n-1}(t) - \mu_n P_n(t) - \gamma_n P_n(t) + \delta_{n,0} \langle \gamma \rangle (t). \quad (3)$$

224 The term containing the $\langle \gamma \rangle$ quantity, guarantees the normalization of $P_n(t)$ by feeding the system at the
 225 state $n = 0$ if needed:

$$\langle \gamma \rangle (t) = \sum_j \gamma_j P_j(t). \quad (4)$$

226 In our previous studies we have demonstrated the generalization of the dynamical Eq. 3 to continuous
 227 states by converting it into a partial differential equation in the limit when $dt \rightarrow 0$ [32]. Generalizing the
 228 growth and reset rates to continuous states ($\mu_n \rightarrow \mu(x)$, $\gamma_n \rightarrow \gamma(x)$), the evolution equation corresponding
 229 to Eq. 3 has the following form:

$$\frac{\partial \rho(x, t)}{\partial t} = -\frac{\partial}{\partial x} [\mu(x) \rho(x, t)] - \gamma(x) \rho(x, t) + \langle \gamma(x) \rangle (t) \delta(x). \quad (5)$$

230 Here $\rho(x, t)$ is the probability density ($\int_{\{x\}} \rho(x, t) dx = 1$) for an individual possessing x amount of wealth
 231 at time moment t . The feeding term at 0 is similar to the discrete limit, and it is described with the $\delta(x)$
 232 Dirac functional. The $\langle \gamma \rangle$ feeding at 0 should be:

$$\langle \gamma(x) \rangle (t) = \int_{\{x\}} \gamma(x) \rho(x, t) dx \quad (6)$$

233 In [32, 28] it was proven, that the above dynamical evolution equation converges to a steady-state with a
 234 $\rho_s(x)$ stationary probability density:

$$\rho_s(x) = \frac{\mu_0 \rho_s(0)}{\mu(x)} e^{-\int_0^x \frac{\gamma(u)}{\mu(u)} du}, \quad (7)$$

235 By correctly choosing the $\mu(x)$ growth- and $\gamma(x)$ reset rates, the LGGR model will lead to $\rho_s(x)$
 236 distributions that are frequently encountered in complex systems [32]. We will apply thus the LGGR
 237 modeling framework to describe the wealth distributions obtained in the mentioned three different economic
 238 period of the studied geographical region.

4 APPLICATION OF THE LGGR MODEL

239 Using particularized growth and reset rates we apply now the LGGR model for the three distinct economic
 240 situations in order to explain the obtained wealth distributions. First we will identify the proper kernels
 241 for the reset and growth rates and then calculate the resulting stationary probability density functions. We
 242 then adjust the model parameters to obtain a qualitatively acceptable overlap between the experimental and
 243 model data. In a later section we will discuss some aspects related to the chosen growth and reset kernels
 244 and derive also some accepted economic indicators of wealth inequalities. like the Gini index, Lorentz
 245 curve or the much-discussed Pareto point.

246 As a starting point in our endeavor, we note that unlike to our last work related to wealth inequalities,
 247 [12], in our present data there is no information on negative wealth , i.e. debts. As a consequence of this,
 248 the application of the LGGR model for describing our data should be possible using much simpler kernels
 249 for the growth and reset rates.

250 4.1 Wealth distribution in Communism - constant growth and linear reset rates

251 For modeling the data in years 1961 and 1989 we considered the following rates:

- 252 • a constant growth rate, resulting in a slow growth independently of the existing wealth amount, in
 253 agreement with the principles of communism, $\mu(x) = k$.
- 254 • a linear reset rate in the form $\gamma(x) = x - r$. Assuming that only positive wealth exists such a rate will
 255 have a negative value in the interval $[0, r)$, and becomes positive on $[r, \infty)$. As discussed in the previous
 256 section, we are now in the case illustrated in Figure 5b. A positive reset value means in average exiting
 257 from the system at wealth value x , while negative reset means in average an entering into the system
 258 with wealth x . In this manner, the value of the r value marks the $n = n_c$ boundary. Wealth above this
 259 favor a reset, while wealth under it is considered as starting assets for a new individuals incoming in
 260 the statistics.

261 Using the above growth and reset rates, equation (7) leads to the stationary probability density:

$$\rho_{s1}(x) = \sqrt{\frac{2}{k\pi}} e^{-\frac{x(x-2r)}{2k}} \left[\operatorname{erf}\left(\frac{r}{\sqrt{2k}}\right) + 1 \right]^{-1} \quad (8)$$

262 This is a normalized normal distribution restricted on the $x \geq 0$ interval with its peak shifted into r . We
 263 denoted here by $\operatorname{erf}()$ the well-known error-function. By properly selecting the r and k parameters, this
 264 approach leads to a good fit for the wealth distributions both for the 1961 and 1989 data.

265 For the data and wealth distributions in year **1961** the best fit can be achieved with $k = 1.5$ and
 266 $r = 1.08$. The fit along with the experimental results for the wealth distribution are presented on Figure
 267 2. Using the median points for the data, the fit with the above parameters results in a coefficient of
 268 determination $R^2 = 0.96$. The average wealth in the calculated analytically for this normal-like distribution
 269 is $\langle x \rangle_{theo} = 1.488 \text{ a.u.}$, which can be compared with the average calculated from the experimental data,
 270 for each different parametrization $\langle x \rangle_{exp} \in [1.36 \text{ a.u.}; 1.49 \text{ a.u.}]$. (Here *a.u.* stands for the arbitrary units
 271 in wealth resulting from our estimation method)

272 The same normal-like distribution offers a good fit also for the wealth distribution derived from the
 273 **1989** data. The best fit parameters are however: $k = 0.5$ and $r = 1.3$. This fit is illustrated on Figure 3.
 274 Using again the median points of the experimentally estimated data the above fit leads to a coefficient of
 275 determination $R^2 = 0.9$. The average wealth from the fitted distribution is $\langle x \rangle_{theo} = 1.353 \text{ a.u.}$, which
 276 is in good agreement with the values calculated from our parameterizations of the weight coefficients:
 277 $\langle x \rangle_{exp} \in [1.199 \text{ a.u.}; 1.391 \text{ a.u.}]$

278 From Figures 2 and Figure 3 and from the fit statistics we learn that the chosen LGGR method with
 279 the proper k and r parameters describes well the wealth distribution in the communism periods, more
 280 specifically the ones derived for 1961 and 1989. We note that the average wealth in this case can be given

281 analytically:

$$\langle x \rangle = r \left(1 + \frac{1}{r} \frac{k \sqrt{2}}{\sqrt{k\pi} e^{\frac{r^2}{2k}} [1 + \operatorname{erf}(\frac{r}{2k})]} \right) \quad (9)$$

282 For small k values the mean shifts towards the value of r , which is consistent with our data and fit for
283 1961 and 1989.

284 4.2 Wealth distribution for the free market - preferential growth with constant reset rate

285 As it was previously discussed by [32], for the capitalistic free market economy the growth in wealth
286 should be preferential. This leads to the kernel used in our recent study on wealth distribution in modern
287 societies [12]. A constant reset rate is the simplest approach, assuming that growth starts from zero and
288 there is a constant probability of getting out from the considered statistics (either by relocating or by
289 death). For modeling the wealth distribution observed in year 2021 we used thus the LGGR model with the
290 $\mu(x) = x + \beta$ growth rate and $\gamma(x) = \gamma$ reset rate. The preferential growth rate is in agreement with the
291 much discussed Matthew principle [33], while the constant reset rate does not differentiate between wealth
292 values, each individual in the system can be reseted at any given time with the same probability.

293 The above growth and reset rates results in equation (7) in the Lomax II type (or Tsallis-Pareto) stationary
294 probability density function:

$$\rho_{s2}(x) = \frac{\gamma}{\beta} \left(1 + \frac{x}{\beta} \right)^{-1-\gamma} \quad (10)$$

295 For the data from 2021 we found that the best fit can be achieved with $\gamma = 8.32$ and $\beta = 3.46$. On Figure 4
296 we present the experimental probability density function for wealth along with the Tsallis-Pareto distribution
297 obtained with the previously mentioned parameters. The used regression has a coefficient of determination
298 $R^2 = 0.89$. The average wealth computed from the Tsallis-Pareto distribution is $\langle x \rangle_{theo} = 0.472 a.u.$ in
299 comparison with the average wealth obtained from the data: $\langle x \rangle_{exp} \in [0.279 a.u.; 0.682 a.u.]$.

5 SOCIO-ECONOMIC INEQUALITY MEASURES

300 We turn now our attention on estimating also the well-known inequality measures used by social sciences.

301 We will first construct both the experimental and theoretical Lorenz curves [34] calculated from the
302 experimental and fitted probability density functions, respectively. The Lorenz curve indicates the relation
303 between the cumulative share of wealth owned by the households with wealth above x , $F(x)$, and the
304 cumulative share of households with wealth greater than x , $C(x)$.

$$C(x) = \int_x^\infty \rho(w) dw \quad (11)$$

$$F(x) = \frac{1}{\langle w \rangle} \int_x^\infty w \rho(w) dw \quad (12)$$

306 with:

$$\langle x \rangle = \int_0^\infty w \rho(w) dw \quad (13)$$

307 One obtains therefore the Lorenz curve by plotting $F(x)$ as a function of $C(x)$. For a totally uniform
308 wealth distribution, i.e. no socio-economic inequality, the Lorenz curve would be the first diagonal ("equity

309 line”) in the $F - C$ square. Deviation from this line characterizes the social inequalities. The area between
 310 the Lorenz curve and the equity line (Γ) is related to the well-known Gini index [35], G , by $G = 2\Gamma$. We
 311 recall here that if one has a discrete set of wealth values, x_i in a society (the case of our experimental data)
 312 composed by N individuals, the Gini index is a number between 0 and 1, defined as

$$G = \frac{1}{2\langle x \rangle} \sum_i^N \sum_j^N |x_i - x_j| \quad (14)$$

313 with $\langle x \rangle$ the average wealth:

$$\langle x \rangle = \frac{1}{N} \sum_i^N x_i \quad (15)$$

314 A 0 Gini index means no social inequality (all wealths are equal) why a Gini index 1 means that all wealth
 315 is owned by one individual, i.e. the most extreme inequality. For a more pronounced social inequality the
 316 Gini index is higher.

317 Alternatively, if one has a continuous probability density function for the wealth distribution, the Gini
 318 index is computable as:

$$G = \frac{1}{\langle x \rangle} \int_0^\infty dx \int_x^\infty dy (y - x) \rho(x) \rho(y) \quad (16)$$

$$\langle x \rangle = \int_0^\infty x \rho(x) dx$$

319 Following the above definitions one can construct both the Lorenz curve and Gini index from the
 320 experimental and model results. The Lorenz curves for the studied years are plotted on Figure 6. The
 321 regions spanned by the experimentally observed Lorenz curves for different weight parameters are indicated
 322 with a lighter shaded region. The theoretical Lorenz curve computed with the fitted probability density is
 323 indicated with a bold continuous line. As expected our theoretical model describes in an acceptable manner
 324 also the Lorenz curves. Some deviations are however observed for year 2021 in the limit of high wealths.

325 The Gini index can be estimated from the experimental data for all weight parameter sets using the
 326 definition (14). One can compute also a theoretical Gini index using equation (16) with the probability
 327 density function given by the LGGR model and best fit parameters. Results in such sense are summarized
 328 in the columns corresponding to G in Table 7. There is a reasonable agreement between the experimentally
 329 calculated and theoretically computed Gini index, confirming once again the applicability of the
 330 theoretically derived probability density functions. One can note that the theoretically calculated Gini index
 331 is usually slightly higher than the experimental one. The reason for this is that the theoretical probability
 332 density functions are defined on the whole $[0, \infty]$ interval, capturing also the wealth values over the largest
 333 value observed experimentally. This will inevitably lead to a higher G value.

334 Another possibility to quantify social inequalities is by defining the P Pareto point. The original Pareto
 335 law states that in any society in general 20% of individuals own 80% of the total wealth. Starting from this
 336 hypothesis for any specific wealth distribution data in a society one can define a P Pareto point from the
 337 Lorenz curve, assuming that the P point is that $P = C$ value for which $F = 1 - P$. Naturally, for a society
 338 that confirms the 80-20 Pareto law $P = 0.2$. The Pareto point should be a number between 0 and 0.5,
 339 smaller values meaning higher social inequalities. Our experimental and theoretically constructed Lorenz

340 curves allow the identification of the P Pareto point. From our data we get the Pareto points specified
341 in the columns corresponding to P in Table 7. One will note again that the theoretical and experimental
342 Pareto points are in reasonable agreement. Similarly with the results on the Gini index however, the Pareto
343 points estimated from the theoretically obtained probability density functions are higher. The same obvious
344 reasons apply which we have mentioned for the discrepancies in the G values.

6 DISCUSSION AND CONCLUSIONS

345 Before discussing in detail the obtained results and derive the usual socio-economic inequality measures,
346 let us recall here that the chosen weight parameters were crucial in giving a realistic estimate over the
347 total wealth of an individual or household. Looking back to the chosen values of the weight parameters
348 summarized in Tables 2, 4 and 6 one will observe that the chosen sets indeed affects the share of wealth
349 categories. This uncertainty will have a direct effect in the wealth averages too, however the error bars from
350 Figures 2 3 and 4 suggests that the overall shape of the probability density functions are not altered in a
351 qualitative manner. The reason for this is relatively simple. As previously said the commune is primarily
352 agricultural in its economy, meaning that for the year 1961 all the different wealth categories may be
353 considered as proportional to the size of the owned land. Indeed, the number of livestock, the size of the
354 barn and house should all be proportional to it, as the land is needed to support the number of livestock,
355 and dictates the size of a barn owned by a household. In the 1961 social situation the distribution of wealth
356 is already quite egalitarian because the wealthy peasants were eliminated by the communistic system, and
357 the land of nobles were already redistributed after the first World War. As a consequence of these, in 1961
358 the largest owned estate is only 11.76 hectares of land.

359 After 1961 all lands were forcefully collectivized, leaving households with a garden, the owned smaller
360 buildings and the house. The maximal size of the garden was limited to 40 acres, although some larger
361 ones exist in the records (these gardens were located at places where they could not be meaningfully used.)
362 Anecdotal evidence from the commune says that after the collectivization most of the earned yearly income
363 was invested in rebuilding, extending and to building new houses. This is well supported by the data also.
364 While in 1961 the total area of houses owned by households in the commune was $44273m^2$, in 1989 this
365 number became $65396m^2$ which means a 47.7% growth.

366 As it is observable in Figure 4, in 2021 one will observe a larger scattering of the probability densities,
367 caused by the modified and uncorrelated wealth components used in the estimation of the total wealth. This
368 is a results of less categories in the taxation database and also reflects that the agriculture based society
369 diversified to other sectors such as tourism. As a result of this second effect the proportionality between
370 the size of the land owned and the other categories may not be true anymore. Clearly, the shape of the
371 distribution is shifted towards the characteristic power-law like tail by the current year.

372 We found once again that the LGGR model provides a usefull modeling base for many complex systems.
373 For the considered problem in particularly, it allowed a realistic modeling of wealth distribution at each
374 historically significant economic period. For the communism years (1961 and 1989) the growth rate was
375 chosen as a fixed k constant. A state-dependent growth rate would have raised ideological problems for the
376 communist regime. The constant growth rate leads to a scenario where people may only produce enough
377 for themselves and only trade for the essentials, instead of investing for a greater profit. The reset rate
378 was considered to be linear, with an r offset. This can be interpreted in the context of a wealth control
379 mechanism, imposing a desired wealth amount, above which a resetting is favored. Households enter in
380 their wealth evolution dynamics bellow this r value and leave the system over r in average, in agreement

381 with the ideology supported by a communistic regime. As the communist economy evolves our regression
382 results suggests that the growth slows from $k = 1.5$ in 1961 to $k = 0.5$ in 1989, while the reset threshold
383 grows from $r = 1.08$ to $r = 1.3$. The results also suggests that for the smaller k growth rate and the larger
384 r reset threshold the resulting wealth distributions tend to peak at around r , with an average wealth also
385 around r , as seen in the results for 1989 on Figure 3.

386 With the fall of communism in 1989 the dynamics governing wealth inequalities has changed. The rules
387 of the open market economy allowed the "rich gets richer" effect which is modeled here by the linear
388 growth rate. Such a linear growth rate was used in our previous approaches to describe the distribution
389 of income and wealth [26, 12]. The constant reset rate implemented by us means that everybody can
390 leave the system with the same likelihood. The linear growth rate and the constant reset rate in the LGGR
391 model leads to the Tsallis-Pareto stationary distribution. The power-law tail of this distribution is consistent
392 with the accepted experimental results in the current literature. It is interesting to note that the tail of the
393 distribution observed for the studied commune in 2021 is $b = -9.32$ which is much steeper than the tails
394 observed on larger population scales. One can compare this exponent for the one observed in the wealth
395 distributions on country level, where for USA and Russia one gets $b = -2.4$ and France with $b = -2.68$
396 [12]. This steeper decay indicates that the smaller community studied here is much more homogeneous in
397 wealth, and therefore also the socio-economic inequality indicators should be smaller.

398 Concerning the inequality measures used in social sciences our results are consistent with the ones
399 expected for the investigated economic periods. The experimentally and theoretically constructed Lorenz
400 curves seems to be in good agreement, confirming from another perspective the validity of the theoretically
401 proposed probability density functions. The experimentally and theoretically calculated G Gini index are
402 also in reasonable agreement, and the differences are resulting from the infinite tail of the theoretically
403 used probability density functions. The same observations hold for the value of the P Pareto point. The G
404 and P values in Table 7 shows that social inequalities were low in the communist regime. The G value
405 is around ~ 0.38 in 1961, decreasing to as low as ~ 0.3 in 1989. After 28 years of a market economy
406 the value of G increased in this region to a value around ~ 0.55 . The same tendency in the dynamics of
407 social inequalities is observable in the variation of the P Pareto point. The value of P is ~ 0.37 in 1961
408 increasing to a value ~ 0.40 in 1989. The value of P nowadays in this region is ~ 0.3 , indicating the
409 deepening social inequalities.

410 In summary we can state that the experimental and theoretical investigation of wealth distribution in a well-
411 delimited social environment (traditional commune in Transylvania) for economically different situations
412 proved expected variations in social inequalities measures. Along with obtained very precious inequality
413 data, the study proves once again the modeling power of the LGGR model in various interdisciplinary
414 problems related to complex systems.

CONFLICT OF INTEREST STATEMENT

415 The authors declare that the research was conducted in the absence of any commercial or financial
416 relationships that could be considered as a potential conflict of interest.

AUTHOR CONTRIBUTIONS

417 Conceptualization and research design by ZN; theoretical model by TB and ZN; data mining by IG; data
418 analysis by IG and SzK; Figures by IG and SzK; interpretation by ZN and TB; first draft of the manuscript
419 by IG, SzK and ZN; all author contributed to the final form of the manuscript.

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423 Agricultural records from the archives, and the help they gave for the extraction of the anonymized taxation
424 data.

DATA AVAILABILITY STATEMENT

425 The datasets [GENERATED/ANALYZED] for this study can be found in the [NAME OF REPOSITORY]
426 [LINK].

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FIGURE CAPTIONS

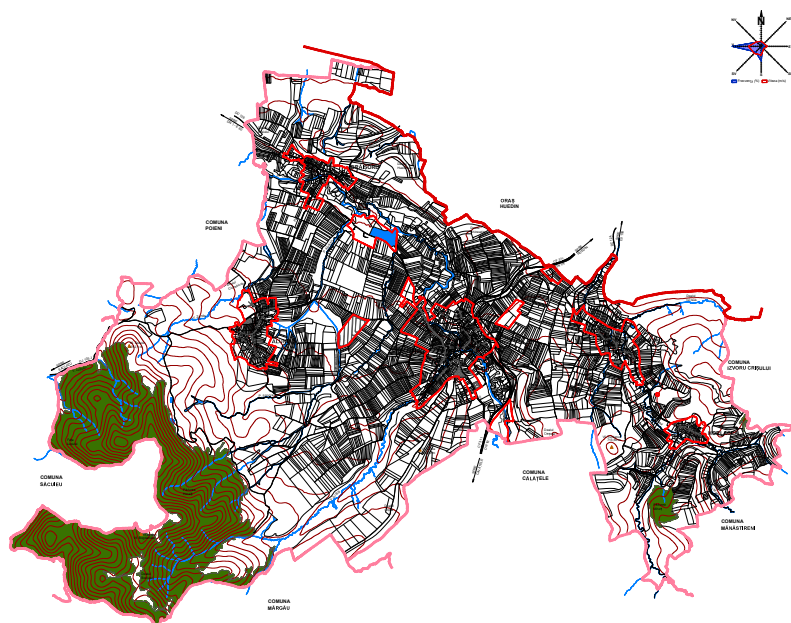


Figure 1. The recent publicly available map of commune Sancaiu. The map presents the boundaries of the commune, the neighboring communes and city, along with the constituent villages, intra-village territory, and agricultural land parcels. Courtesy of Sancaiu Mayor's office.

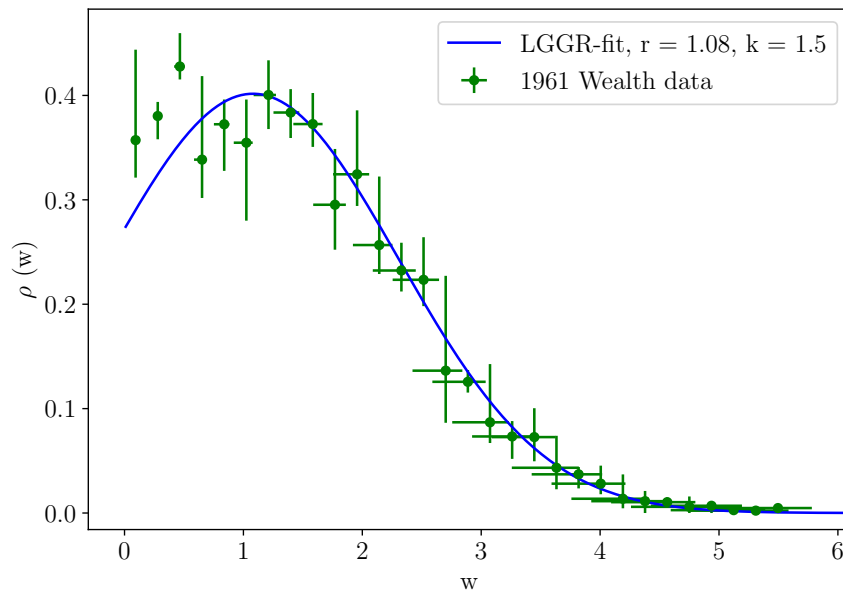


Figure 2. Wealth distribution for 1961. Error bars are obtained by combining the results of the different weight parameter sets shown in Table 1. The theoretical distribution (8) fitted to the averaged experimental distribution ($k = 1.5$ and $r = 1.08$) is shown by the continuous line.

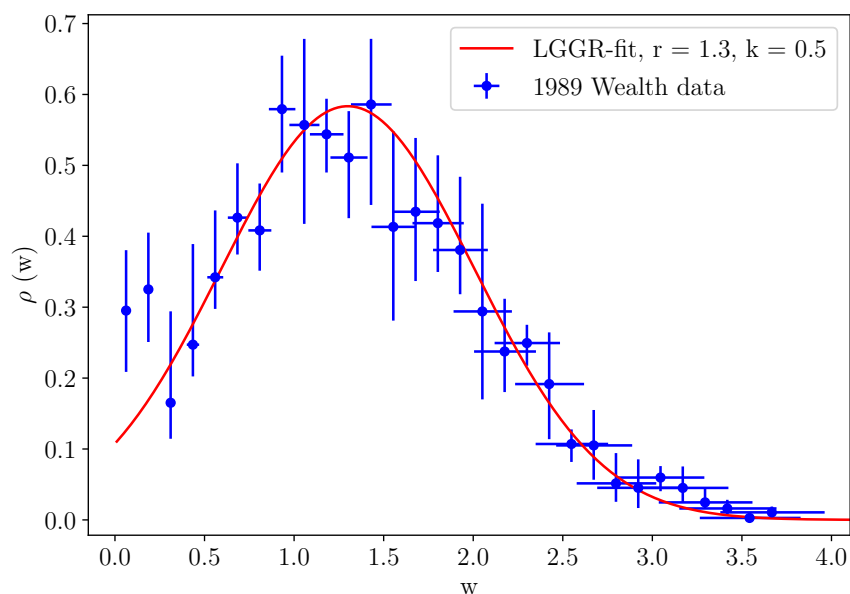


Figure 3. Wealth distribution for 1989. Error bars are obtained by combining the results of the different weight parameter sets shown in Table 3. The theoretical distribution (8) fitted to the averaged experimental distribution ($k = 0.5$ and $r = 1.3$) is shown by the continuous line.

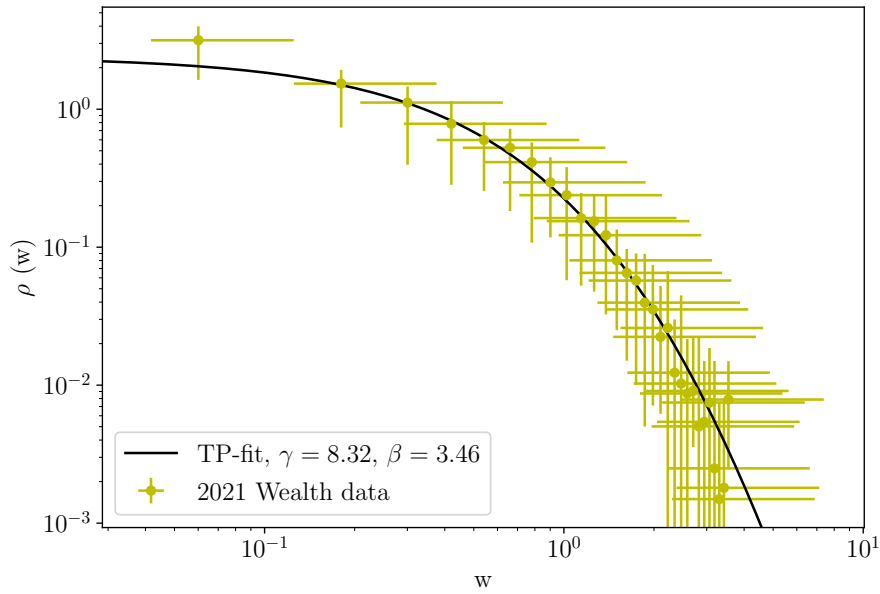


Figure 4. Wealth distribution for 2021. Error bars are obtained by combining the results of the different weight parameter sets shown in Table 5 . The theoretical distribution (10) fitted to the averaged experimental distribution ($\gamma = 8.32$ and $\beta = 3.46$) is shown by the continuous line. Please note the logarithmic scales.

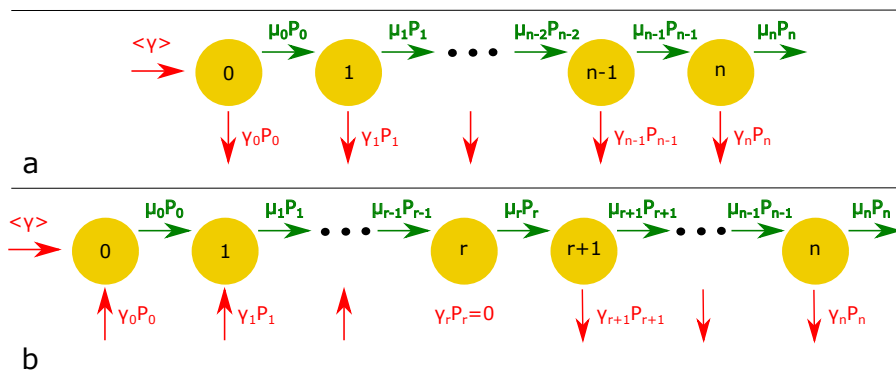


Figure 5. Illustration of the growth and reset process: (a) the general mechanism of the process with a positive reset rate, (b) the process considering a reset rate which can be both positive and negative.

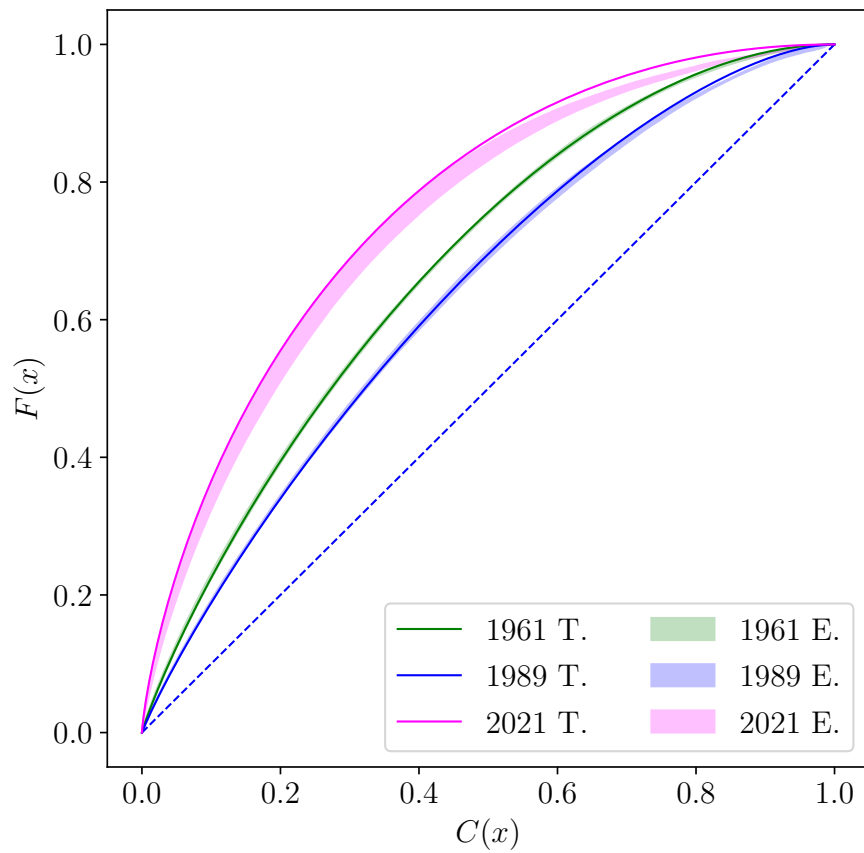


Figure 6. Experimental and theoretical Lorenz curves for the years 1961,1989 and 2021. The shaded region indicates the region spanned by the experimental results for different weight parameter sets. The theoretical curves were calculated from the fitted distributions, and are plotted with the continuous bold line.

Params.	P_{A_L}	$P_{A_{Bh}}$	$P_{A_{Ba}}$	P_{N_C}	$P_{N_{WB}}$	P_{N_H}	P_{N_P}	P_{N_S}	P_{N_G}
Nr. 1	0.189322	0.0068156	0.00302916	0.189322	0.215827	0.378644	0.0151458	0.00151458	0.000378644
Nr. 2	0.243487	0.00620891	0.00255661	0.182615	0.17531	0.36523	0.0219138	0.00219138	0.000486973
Nr. 3	0.279884	0.00580123	0.00223907	0.178108	0.148084	0.356216	0.0264618	0.00264618	0.000559768
Nr. 4	0.306024	0.00550844	0.00201102	0.174871	0.12853	0.349742	0.0297281	0.00297281	0.000612049
Nr. 5	0.325708	0.00528796	0.00183929	0.172434	0.113806	0.344867	0.0321876	0.00321876	0.000651416
Nr. 6	0.353379	0.00497803	0.00159789	0.169007	0.0931076	0.338014	0.0356451	0.00356451	0.000706757
Nr. 7	0.363474	0.00486496	0.00150981	0.167757	0.0855561	0.335514	0.0369066	0.00369066	0.000726947
Nr. 8	0.3719	0.00477058	0.0014363	0.166714	0.0792531	0.333427	0.0379594	0.00379594	0.0007438
Nr. 9	0.379039	0.00469061	0.00137402	0.16583	0.0739126	0.331659	0.0388515	0.00388515	0.000758078
Nr. 10	0.385166	0.00462199	0.00137402	0.165071	0.0693298	0.330142	0.039617	0.0039617	0.000770331

Table 1. Weight parameter sets considered for the data from year1961.

Params.	$S(A_L)$	$S(A_{Bh})$	$S(A_{Ba})$	$S(N_C)$	$S(N_{WB})$	$S(N_H)$	$S(N_P)$	$S(N_S)$	$S(N_G)$
Nr. 1	35.3678%	19.5784%	10.752%	5.46632%	22.9659%	4.32392%	1.33648%	0.203519%	0.00569971%
Nr. 2	44.2776%	17.3616%	8.83354%	5.13253%	18.1588%	4.05989%	1.88231%	0.286638%	0.00713557%
Nr. 3	50.0034%	15.937%	7.60065%	4.91803%	15.0695%	3.89022%	2.23309%	0.340053%	0.00805831%
Nr. 4	53.9932%	14.9443%	6.74156%	4.76856%	12.9169%	3.77199%	2.47751%	0.377274%	0.00870128%
Nr. 5	56.9326%	14.213%	6.10864%	4.65844%	11.331%	3.68488%	2.65758%	0.404695%	0.00917498%
Nr. 6	60.9736%	13.2076%	5.23852%	4.50706%	9.15075%	3.56513%	2.90514%	0.442393%	0.00982621%
Nr. 7	62.422%	12.8472%	4.92663%	4.45279%	8.36925%	3.52221%	2.99388%	0.455906%	0.0100596%
Nr. 8	63.6207%	12.549%	4.66853%	4.40789%	7.72253%	3.48669%	3.06731%	0.467088%	0.0102528%
Nr. 9	64.6291%	12.2981%	4.45141%	4.37011%	7.17849%	3.45681%	3.12908%	0.476495%	0.0104153%
Nr. 10	65.4891%	12.0841%	4.26623%	4.33789%	6.71447%	3.43132%	3.18177%	0.484518%	0.0105539%

Table 2. Share in the total wealth for different valuable categories. The rows are the results for the considered parameter sets in year 1961

Params.	P_{A_L}	$P_{A_{Bh}}$	$P_{A_{Ba}}$	$P_{N_{cc}}$	$P_{N_{ca}}$	P_{N_C}	$P_{N_{WB}}$	P_{N_H}	P_{N_P}	P_{N_S}
Nr. 1	0.0116134	0.00414766	0.00705102	0.0746578	0.564081	0.0746578	0.0746578	0.149316	0.0331813	0.00663625
Nr. 2	0.0103034	0.0057241	0.00629651	0.0801374	0.532341	0.0801374	0.0801374	0.160275	0.0372066	0.00744133
Nr. 3	0.00930993	0.00691954	0.00572435	0.0842926	0.508272	0.0842926	0.0842926	0.168585	0.0402592	0.00805183
Nr. 4	0.0085307	0.00785722	0.00527556	0.0875519	0.489393	0.0875519	0.0875519	0.175104	0.0426535	0.0085307
Nr. 5	0.00790314	0.00861239	0.00491413	0.0901768	0.474188	0.0901768	0.0901768	0.180354	0.0445818	0.00891636
Nr. 6	0.00695475	0.00975362	0.00436792	0.0941436	0.451211	0.0941436	0.0941436	0.188287	0.0474959	0.00949917
Nr. 7	0.00658772	0.0101953	0.00415654	0.0956788	0.442318	0.0956788	0.0956788	0.191358	0.0486236	0.00972473
Nr. 8	0.00627211	0.0105751	0.00397477	0.0969989	0.434672	0.0969989	0.0969989	0.193998	0.0495934	0.00991868
Nr. 9	0.00599782	0.0109051	0.00381679	0.0981461	0.428026	0.0981461	0.0981461	0.196292	0.0504362	0.0100872
Nr. 10	0.00575724	0.0111946	0.00367823	0.0991524	0.422197	0.0991524	0.0991524	0.198305	0.0511754	0.0102351

Table 3. Weight parameter sets considered for the data from year 1989.

Params.	$S(A_L)$	$S(A_{Bh})$	$S(A_{Ba})$	$S(N_{cc})$	$S(N_{ca})$	$S(N_C)$	$S(N_{WB})$	$S(N_H)$	$S(N_P)$	$S(N_S)$
Nr. 1	20.3913%	24.5722%	41.446%	0.527541%	1.94183%	1.40001%	4.24062%	0.933342%	4.16923%	0.378146%
Nr. 2	17.4679%	32.7431%	35.736%	0.546754%	1.76944%	1.451%	4.39506%	0.967333%	4.51397%	0.409414%
Nr. 3	15.3818%	38.5737%	31.6616%	0.560463%	1.64643%	1.48738%	4.50526%	0.991589%	4.75997%	0.431726%
Nr. 4	13.8185%	42.9434%	28.6081%	0.570738%	1.55424%	1.51465%	4.58785%	1.00977%	4.94433%	0.448447%
Nr. 5	12.6032%	46.3401%	26.2345%	0.578724%	1.48257%	1.53585%	4.65205%	1.0239%	5.08764%	0.461445%
Nr. 6	10.8366%	51.2778%	22.7841%	0.590334%	1.3784%	1.56666%	4.74538%	1.04444%	5.29596%	0.48034%
Nr. 7	10.1745%	53.1285%	21.4908%	0.594686%	1.33936%	1.5782%	4.78036%	1.05214%	5.37404%	0.487422%
Nr. 8	9.61432%	54.6941%	20.3968%	0.598367%	1.30632%	1.58797%	4.80995%	1.05865%	5.4401%	0.493413%
Nr. 9	9.1343%	56.0358%	19.4593%	0.601522%	1.27802%	1.59635%	4.83531%	1.06423%	5.4967%	0.498547%
Nr. 10	8.71837%	57.1983%	18.6469%	0.604255%	1.25349%	1.6036%	4.85728%	1.06907%	5.54575%	0.502996%

Table 4. Share in the total wealth for different valuable categories. The rows are the results for the considered parameter sets in year 1989

Params.	P_{V_b}	$P_{A_{pb}}$	P_{A_a}	P_{A_p}	P_{A_q}	P_{A_f}
Nr. 1	9.55622e-06	0.682587	0.150169	0.0136517	0.150169	0.00341294
Nr. 2	6.6176e-06	0.735289	0.117646	0.0257351	0.117646	0.00367645
Nr. 3	5.1264e-06	0.762033	0.101143	0.0318668	0.101143	0.00381016
Nr. 4	4.22455e-06	0.778207	0.0911614	0.0355752	0.0911614	0.00389103
Nr. 5	3.62032e-06	0.789043	0.0844741	0.0380597	0.0844741	0.00394522
Nr. 6	2.86162e-06	0.80265	0.0760773	0.0411794	0.0760773	0.00401325
Nr. 7	2.60788e-06	0.807201	0.073269	0.0422228	0.073269	0.004036
Nr. 8	2.40458e-06	0.810847	0.071019	0.0430588	0.071019	0.00405423
Nr. 9	2.23804e-06	0.813833	0.0691758	0.0437435	0.0691758	0.00406917
Nr. 10	2.09912e-06	0.816325	0.0676383	0.0443148	0.0676383	0.00408162

Table 5. Weight parameter sets considered for the data from year 2021.

Params.	$S(V_b)$	$S(A_{pb})$	$S(A_a)$	$S(A_p)$	$S(A_q)$	$S(A_f)$
Nr. 1	54.3539%	10.8964%	24.5545%	0.102012%	10.0492%	0.0440462%
Nr. 2	49.0569%	15.2982%	25.0717%	0.250637%	10.2608%	0.0618391%
Nr. 3	44.9162%	18.739%	25.4759%	0.366816%	10.4263%	0.0757478%
Nr. 4	41.5905%	21.5026%	25.8006%	0.460129%	10.5592%	0.086919%
Nr. 5	38.8608%	23.771%	26.0672%	0.536722%	10.6683%	0.0960885%
Nr. 6	34.6456%	27.2737%	26.4787%	0.654992%	10.8367%	0.110247%
Nr. 7	32.9846%	28.6541%	26.6409%	0.701599%	10.9031%	0.115827%
Nr. 8	31.5426%	29.8523%	26.7817%	0.742059%	10.9607%	0.120671%
Nr. 9	30.279%	30.9023%	26.9051%	0.777511%	11.0112%	0.124915%
Nr. 10	29.1628%	31.8299%	27.014%	0.808832%	11.0558%	0.128665%

Table 6. Share in the total wealth for different valuable categories. The rows are the results for the considered parameter sets in year 1989

Year	G		P	
	Exp.	Theo.	Exp.	Theo.
1961	[0.377;0.379]	0.356	[0.366;0.368]	0.374
1989	[0.304;0.315]	0.273	[0.390;0.395]	0.407
2021	[0.543;0.579]	0.531	[0.282;0.299]	0.305

Table 7. Inequality measures for the studied years: the Gini (G) and Pareto-point (P). Value limits obtained from the data with different weight parameters and the value obtained from the theoretically fitted probability density function.