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Wealth Inequality and Mobility

Evidence from the Forbes World Billionaires List

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Abstract

The paper analyses data from the "Forbes World Billionaires List" from 1996 to 2015. Decomposing the sample finds, that inherited wealth exhibits higher levels of inequality than self-made wealth. Overall inequality decreases and the inequality level of the self-made subgroup converges to the one of inherited wealth. In addition, self-made billionaires also experience higher social mobility. However, social mobility decreases on average within the observed sample. Both results are in line with the theories on wealth inequality which claim, that inherited wealth is a key driver of heavy Pareto tails in the wealth distribution.
The results are based on the assumption that the wealth distribution obeys a power law. A goodness-of-fit test returns low and insignificant results for Pareto distributed data. Hereby, the self-made subsample displays a better Paretian behaviour. The overall results of the estimation point to measurement errors in the data, rather than a misspecified model. Therefore, the assumption that wealth obeys a power law distribution cannot be ultimately ruled out.

Keywords: wealth inequality, wealth mobility, Pareto distribution, power law estimation

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1 Introduction

Inequality is a prime concern in research and for some it should be "at the heart of economic analysis" (Atkinson & Bourguignon 2015, p.xviii). Since the release of Piketty (2014), increasing wealth inequality re-emerged in the public debate, although the topic has been of interest to economists for over a century. Pareto (1897) first described a power law by observing that income follows a distribution where very few individuals hold the majority of income while the majority of the people remain poor. Later, it was also discovered that wealth follows a Pareto distribution in its upper right tail (Wold & Whittle 1957, Atkinson & Harrison 1978, Levy & Solomon 1997). A broad literature has explored the causes of wealth inequality and a prominent argument is that inherited wealth is a prime source (Atkinson 1971, Benhabib & Zhu 2008) driven by idiosyncratic returns on capital (Benhabib et al. 2011, 2015, Jones 2015, Saez & Zucman 2016, Benhabib & Bisin 2016). In addition, Aghion et al. (2015) find evidence that self-made wealth which is generated by life-time income only, exhibits higher social mobility compared to inherited wealth. Hereby, mobility is understood as the relative change of individual wealth through time (Shorrocks 1978*b*).
Despite these theoretical attempts empirical research faces the problem of data availability. Although there is a concrete concept of wealth indicators (see section 2), data is not consistently collected through public authorities which would allow to proof some of the propositions (Jones 2015).
A common way to study the top wealth shares is to use the *Forbes 400* (Levy & Solomon 1997, Klass et al. 2006, Vermeulen 2016). However, it only covers the US and the data has only 400 observations. I attempt to provide some new empirical evidence to the discussion by collecting data from the *Forbes World Billionaires List* that covers the years 1996 to 2015. The data has been used before as it allows a glance at the global perspective (Ogwang 2013, Brzezinski 2014, Capehart 2014). More importantly, I decompose the wealth data into an inherited as well as a self-made subsample as an attempt to study the drivers of inequality.

Having said this, the purpose of the study is to find empirical evidence that inherited wealth exhibits higher inequality than self-made wealth, but also experiences lower social mobility. I measure wealth inequality by estimating and comparing the tail exponent. To do so different estimation methods are applied. Social mobility is analysed with non-parametric measures for short-run as well as long-run mobility. I find that inherited wealth indeed exhibits higher inequality levels than self-made wealth. However, the inequality levels of self-made wealth converge to those of inherited wealth in most recent years. In order to evaluate the results for significance a goodness-of-fit test is performed, which returns low significance for a power law distribution of wealth in all (sub)samples. In addition, I find that social mobility in the self-made subsample is on average higher in the short run.

The rest of the paper organises as follows: Section 2 highlights some recent research on wealth inequality from which the research hypotheses are developed. Section 3 describes the conduction of the database and highlights the main features in the context of self-made and inherited wealth. Furthermore, shortcomings are outlined. The underlying methodology of the analysis is described in section 4. In section 5, I evaluate the results as well as its implications. In addition, I also discuss the limitations. Section 6 concludes and provides an outline for further research.

2 Literature Overview and Hypothesis Development

A broad literature has explored cause and scope of wealth inequality. While a lot of attention is drawn to the drivers of wealth inequality in the theoretical literature, empirical research mostly stops at estimating its scope.

At first, a working definition of the term wealth is given in section 2.1, followed by highlighting some properties of the Pareto distribution in section 2.2. In section 2.3, I provide an overview on recent empirical findings on wealth inequality. In sections 2.4 and 2.5, stylised facts on wealth inequality as well as wealth mobility are presented, from which I derive two research hypotheses.

2.1 Definition of Wealth

Wealth is a stock which means it is measured at a certain point in time, implying that it gradually accumulates over time (Piketty & Zucman 2015, Jones 2015).

Following the "UN System of National Accounts" (UN 2009), private wealth W_t is defined as net wealth of all households which implies the sum of all non-financial assets and financial assets "over which ownership rights can be enforced and that provide economic benefit to their owner" (Piketty & Zucman 2014, p.1268) minus liabilities. Non-financial assets include land, real estate, patents, machines, commercial inventory and other directly owned professional assets. Financial assets are for example bank accounts, stocks and financial investments of all kind including life insurance and pension funds, but not future governmental transfers (Piketty 2014, Quadrini & Ríos-Rull 2015, Piketty & Zucman 2014). Human capital is excluded unless it is possible to express it in monetary terms such as patents (Piketty 2014).

For simplicity, public wealth is assumed to be zero. This assumption is not too unrealistic as a gradual transfer from public to private wealth is observed world wide. In China for example, public wealth reduced from around 70% in 1978 to 35% in 2015, and in the US, the UK and Japan public wealth is negative, while in other industrialised countries such as France or Germany public wealth is just little more than zero (Alvaredo et al. 2017). Thus, private wealth is equal to national wealth $W_{nt} = W_t$ which in turn can be written as the sum of national capital K_t and net foreign assets NFA_t such that $W_{nt} = K_t + NFA_t$ (Piketty & Zucman 2014). Net foreign assets essentially become irrelevant when considering wealth globally as in this case and thus it is assumed that $W_w = K_w$.

2.2 The Pareto Distribution

The distribution of wealth is described by an exponential distribution at the bottom for the majority of the population and obeys a power-law at the top (Yakovenko & Rosser 2009). This implies that the upper right tail decays slower than lower percentiles, causing a higher wealth concentration at the top (Benhabib & Bisin 2016). The distribution of a power law or in this case a Pareto distribution is given by its density such that

$$p(x) = Cx^{-(\alpha+1)}, \quad \alpha > 0 \tag{1}$$

where α is called the Pareto exponent, x is a continuous real variable, here the wealth of an individual from the Forbes list, and C is a normalisation constant (Newman 2005).
If $\alpha > 0$ the distribution diverges as $x \to 0$ and thus cannot hold for all $x \geq 0$ (Clauset et al. 2009). This implies the necessity of a lower bound x_{min} to define the range of the Pareto tail and the probability density function (PDF) from equation 1 can be written as

$$p(x) = \frac{\alpha}{x_{min}} \left(\frac{x}{x_{min}} \right)^{-\alpha-1}, \tag{2}$$

where $\alpha \cdot x_{min}^{\alpha-1}$ denotes the normalisation constant C (Newman 2005).

For $\alpha > 1$ the mean of a power law is given such that

$$E[X] = \frac{\alpha}{\alpha - 1} \cdot x_{min}$$

and ∞ otherwise (Newman 2005). This property implies that in finite samples the mean would diverge to the largest value x_{max}. The second moment is only defined for $\alpha > 2$ (Newman 2005). In this case it is denoted as

$$Var(X) = \frac{\alpha}{(\alpha - 2)(\alpha - 1)^2} \cdot x_{min}^2.$$

However, most α's in the analysis of wealth inequality stay below this threshold and consequently, the variance is undefined. In general, moments m for a Pareto distribution are only defined if $m < \alpha$ (Newman 2005).
An important part of analysing wealth inequality is the heaviness of the tail, which increases as α decreases. To clarify, consider the complementary cumulative distribution function

(CCDF)

$$P(X \geq x) = \int_x^{\infty} f(x')dx' = \Big(\frac{x}{x_{min}}\Big)^{-\alpha}, \quad for \quad x \geq x_{min} \tag{3}$$

which states the probability that some value will be larger than x (Newman 2005).

Equation 3 may be rewritten into the fraction of total wealth $W(x)$ (Newman 2005), such that

$$W(x) = \frac{\int_x^{\infty} f(x')dx'}{\int_{x_{min}}^{\infty} f(x')dx'} = \Big(\frac{x}{x_{min}}\Big)^{-\alpha+1}. \tag{4}$$

Combining equation 3 with equation 4, it is straight forward to derive the wealth share held by the richest p of the population sh_x^p, which yields

$$sh_x^p = p^{\frac{\alpha-1}{\alpha}} \tag{5}$$

and from which can be seen, that sh_x^p increases as $\alpha \rightarrow 1$ (Newman 2005).
Visualising the sorted rank of an individual $r(x_i)$ from largest to smallest, and wealth x_i $(i = 1, ..., n)$ on a log-log-plot or a histogram yields approximately a descending straight line with $-\alpha$ as its slope (Ogwang 2013). Alternatively, the logarithm of wealth normalised to a complementary cumulative distribution function or CCDF (see equation 3) looks very similar as it also becomes a straight line. However, the slope here is $-(\alpha + 1)$ (Newman 2005).

2.3 Empirical Findings on Wealth Inequality

The investigation of wealth inequality is subject to multiple empirical studies (Piketty 2014, Piketty & Zucman 2014, Piketty 2015, Jones 2015, Saez & Zucman 2016). It is, however, challenging to collect comparable data as there are no official statistics which can sufficiently summarise wealth such as official tax records in the case of income inequality (Jones 2015). In addition, official statistics do not collect data on wealth on an individual level (Yakovenko & Rosser 2009). Finding comparable data that reaches beyond national borders is an even more difficult task.
One popular solution is to use data from so called *rich lists*, most prominently the *Forbes 400* richest Americans. Although it is not an official statistical record and thus not free of critique (Piketty 2014), it is frequently used by researchers in the context of analysing wealth inequality. The *rich lists* seem to give stable results concerning the heavy tails of the Pareto distribution, which range between 1.3 and 2.1 throughout the literature (Gabaix 2009). For the US, Levy & Solomon (1997) find a Pareto coefficient of 1.36 in 1996, Klass et al. (2006)

calculate an average α of 1.49 for the years 1988 to 2003 and Clauset et al. (2009) estimate 1.3 for the year 2003. Nirei & Souma (2007) find an average α of 1.8 for the US and 2.1 for Japan in the years between 1960 and 2000. The findings mentioned above, are more or less close to the value of 1.5 suggested by Gabaix (2009) and Gabaix (2016).
The *Forbes World Billionaires List* which is also used here, provides similar results on a cross country level. Brzezinski (2014) finds an average Pareto exponent of 1.5 analysing the years between 1998 and 2003[1] and Ogwang (2013) finds a tail exponent between 1.2 and 1.4 for the years 2000 to 2009.

Vermeulen (2014, 2016) and Eckerstorfer et al. (2016) use survey data on household wealth, which are compiled by public authorities and more recently exist for some developed economies such as the US, the UK as well as the Eurozone. However, the data only provides short time series and suffers from the under-representation of top wealth shares. Saez & Zucman (2016) combine the Survey of Consumer Finance, data on US income taxes as well as foundation and estate taxes to the *income capitalisation method*. It allows the authors to decompose individual wealth into different assets (Saez & Zucman 2016). The method has attracted a lot of attention as it is considered to generate good quality data on wealth from official statistical records (Piketty 2015).
Finally, some studies try to combine different data sources to overcome the obvious limitations of the aforementioned methods. Vermeulen (2014) for example combines survey data with rich lists whereas the *World Wealth and Income Database*[2] tries to collect data obtained from the sources mentioned above as well as data on inheritance and estate tax returns and national accounts (Alvaredo et al. 2017). However, longer time series are only available for very few countries.
This being said, the current research is inconclusive about the actual distribution. Earlier research simply estimated the slope of the log-linearised density with ordinary least squares (OLS) as suggested by Pareto himself (Levy & Solomon 1997, Klass et al. 2006, Nirei & Souma 2007). Since this method is found to be biased and underestimates the tail exponent in small samples, Gabaix & Ibragimov (2011) recommend to modify the rank before running OLS. Clauset et al. (2009) bring forward their concerns about the suitability of a linear approach in general and propose to use Maximum Likelihood (ML) instead. In addition, the authors question the long believed assumption of the existence of a Pareto distribution and argue

[1] Note that his formula implies $1 + \alpha$ in the exponent.
[2] www.wid.world

that wealth might actually not obey a power law after all (Clauset et al. 2007, 2009). Based on their work, this argument has found support in the literature (Ogwang 2013, Brzezinski 2014, Chan et al. 2017).

2.4 Causes of Wealth Inequality

A large literature is dedicated to derive a Pareto distribution for wealth from which Benhabib & Bisin (2016) identify three major drivers most commonly used in the literature: skewed income distribution through labour earnings, stochastic returns on wealth and exponentially increasing wealth accumulation. Very often, however, a combination of these are used to generate heavy tails in the theory.

Saez & Zucman (2016) argue that rising incomes of the very rich are a prime source of increasing wealth inequality as individuals with high incomes can save a larger proportion of their income than lower percentiles. Thus, they find that the top 0.1% of the population in the USA hold 22% of the country's wealth (Saez & Zucman 2016). Piketty (2014) supports the argument of stochastic returns as a key driver of wealth inequality. The author's argument $r > g$ implies that wealth inequality is created by the long-run return on capital r being larger than the long-run growth rate g. Indeed, the world GDP only grew with 3.3%, whereas the wealth of the super rich grew with 6.8% between 1987 and 2013 (Piketty 2015). Jones (2015) adapts this argument and derives a Pareto distribution which emerges through an exponential age distribution in combination with exponential growth due to returns on capital. Benhabib et al. (2011), Benhabib et al. (2015) as well as Fischer (2017) also identify stochastic idiosyncratic returns on capital as the key driver for creating fat tails in the wealth distribution.

Modelling the above properties of stochastic returns on capital together with the importance of lifetime incomes as well as a positive bequest motive yields inherited wealth as a prime source of inequality (Atkinson 1971, Benhabib & Zhu 2008, Benhabib et al. 2011, Piketty 2011, Benhabib et al. 2015). This line of argumentation may be explained formally in an overlapping generations economy with life-cycle consumption of finitely lived agents as has been derived in detail by (Benhabib et al. 2011). To highlight their main points, consider that wealth of generation n is given by x_n such that

$$x_n = \lambda_n x_{n-1} + \mu_n, \tag{6}$$

where λ and μ are stochastic processes that represent the effective life-time rate of return on capital and the permanent income of the individual respectively (Benhabib et al. 2011). λ is determined by idiosyncratic and stationary shocks – i.e. capital income risk – r_n, while μ is governed by a trend stationary process of life-time earnings y_n as well as r_n. Thus, equation 6 may be rewritten as

$$x_n = \lambda(r_n)_n x_{n-1} + \mu(y_n, r_n)_n, \tag{7}$$

where both parameters, $\lambda(r_n)$ as well as $\mu(y_n, r_n)$ are persistent across generations, encounter positive autocorrelation and are correlated with each other (Benhabib et al. 2011). Equation 7 shows, that labour income – under the assumption of stationarity – additively accumulates into wealth, while the overall evolutionary process of wealth is determined by the multiplicative part of capital income (Benhabib et al. 2011). Thus, idiosyncratic returns on capital rather than labour income determine the wealth accumulating process. Benhabib et al. (2011) show in detail that from equation 7 the distribution of wealth converges to a stationary Pareto distribution with an exponent that only depends on λ_n. Its probability density function is given by

$$p(x) = Cx^{-\lambda}, \quad x > 0, \tag{8}$$

where $\lambda = 1 + \alpha$. Thus, equation 8 is equal to equation 1 (Benhabib et al. 2011, Gabaix et al. 2016). Since the lifetime wealth accumulation process in equation 7 is multiplicatively linked to the inheritance from the previous generation and a positive bequest motive is assumed, particularly well performing dynasties of individuals – i.e. dynasties that score a high r over many generations – move to the upper end of the wealth distribution (Benhabib et al. 2011). Indeed, empirical evidence reports that rates of return on capital increase in wealth, which implies that people who inherited a large amount from the previous generation do not only have a higher capital income in general, but they also tend to invest in riskier assets which on average yield higher return rates (Benhabib & Bisin 2016). Consequently, high labour earnings alone cannot produce heavy Pareto tails through the savings rate of one generation of life time earnings only (Benhabib & Bisin 2016).[3]

Having said this, the first research hypothesis is stated as follows:

Hypothesis 1 *Given the assumption that wealth actually obeys a power law, inherited wealth should exhibit higher levels of inequality than self-made wealth.*

[3]However, people with extreme life time returns, for example due to personal ability such as Bill Gates in the list, can outperform those who rely on inherited wealth but are the exception (Benhabib & Bisin 2016).

This hypothesis is tested by estimating the heaviness of the Pareto tail as will be further explained in section 4.

2.5 Social Mobility

Social mobility may be defined as changes in relative individual wealth through time (Shorrocks 1978*a*). Benhabib et al. (2011) measure social mobility as the correlation of rates of return on capital across generations. Mobility in the wealth distribution is linked to the level of autocorrelation of returns on capital λ and income μ which are correlated with each other due to their relation to the return rate r and lifetime earnings y. Since the wealth distribution only depends on μ, mobility can be measured as one minus the persistence in the process for the rate of return.

Saez & Zucman (2016) note that the top 0.1% in the US are becoming younger, while wealth in general is very often tied to the pensions, implying that the majority of individuals with a positive capital income gets older. These findings point to upwards social mobility of individuals with extreme life time returns due to personal ability.

Aghion et al. (2015) extend the standard economic model to a Schumpeterian growth model and argue that innovation driven growth causes creative destruction, which increases income inequality especially in the top income shares, but also social mobility which is primarily due to new people entering the very top income shares. By combining data from the *Forbes 400* and patent data from the US States, the authors indeed find a positive relationship between innovation and income inequality as well as social mobility (Aghion et al. 2015). Jones & Kim (2017) further develop this approach and argue, that innovation which comes from newcomers does actually decrease inequality through creative destruction in the long run. Hereby, the authors assume that wealth is essentially equal to capital income.

The dynamics in income may be related to the distribution of wealth through the capitalisation method developed by Saez & Zucman (2016). It can be summarised as

$$sh_x^p = sh_y^p \cdot \frac{s^p}{s}. \tag{9}$$

The wealth share of some part p of the population, sh_x^p is equal to their income share, sh_y^p multiplied by their relative savings rate s^p/s (Saez & Zucman 2016). Given that especially high incomes have a higher savings rate, they can quickly climb up the wealth distribution. Applying their capitalisation method to data from the US, Saez & Zucman (2016) find that high wealth shares indeed have higher savings rates, while at the same time top income shares have doubled their contribution to national income since the 1970s, implying a multiplicative effect combined through the savings rate as noted in equation 7.

Combining these findings with the assumptions of Aghion et al. (2015) as well as Jones & Kim (2017), high salaries may cause increasing income inequality but have a disturbing effect within the wealth distribution. Thus, social mobility increases with the presence of individuals with extreme life time returns in the distribution of top wealth shares.

In line with this argumentation, I define the second research hypothesis:

Hypothesis 2 *Self-made billionaires should exhibit higher social mobility than billionaires with inherited wealth.*

3 Data

An excessive data collection is an essential component of this study in order to enable a decomposition for the subsequent analysis. This chapter describes in detail the gathered data on which this study is founded in order to get an understanding of the sample at hand. Section 3.1 provides an overview of the data collection process. In section 3.2, flaws and limitations of the data are highlighted. Section 3.3 presents insights by featuring different variables as well as descriptive statistics.

3.1 Conduction of the Database

The data is extracted from the *Forbes Worlds Billionaires List* from 1996-2015 and includes 2958 individuals from 79 countries around the world. According to the magazine's methodology the individuals' net wealth is estimated from individual assets which include shares in private and public firms, real estate, other non financial assets (if possible to account for) and cash minus debt (Dolan 2012). Forbes generally excludes country leaders and monarchs if their wealth is originated due to their political position. As this is not the case for the years of 1997 and 1998, these entries are excluded. In addition, people who generate wealth due to illegal activities such as the heads of drug cartels and corrupt statesmen are excluded (Freund & Oliver 2016).

The database mainly combines two data sets found in the "Billionaires Characteristics Database" provided by Freund (2016)[4]. The first data set includes a long time series with few variables[5] besides wealth and the name of the billionaire. In a second data set, Freund (2016) provides further variables[6] including a self-made dummy but only for three years (1996, 2001 and 2014). In order to create a continuous time series such that every year can be divided into a self-made and an inherited subsample, I add the indicators from the three years to the long time series and extend them to all years. As individuals appear and drop out of the list again on a yearly basis, some 500 individuals that are reported in the long time series did not appear in one of the three years. These had to be added through online research. Table 6 in Appendix B provides an overview as well as a description of all variables included in the database on which the subsequent analysis is based.

[4]The complete database may be downloaded from: https://piie.com/publications/wp/data/wp16-1.zip.

[5]The long time series contains name, rank, wealth and citizenship individuals as well as two variables categorising the source of wealth into industry sectors.

[6]The detailed list includes also the variables age, gender, whether the wealth is self-made or inherited and if yes, the generation of inheritance as well variables that separate the individuals in different industry groups. In addition, the variable realnetworth deflates the time series to 1996 USD.

Besides wealth and rank the actual variable of interest in this study is the self-made dummy. Self-made wealth categorises all individuals who have not obtained their fortunes due to some kind of family connected transfers. Therefore, it does not only collect the individuals that owe their fortunes due to innovation, but also due to rent seeking and political connection. The data quality, especially for emerging economies does, however, not allow a further decomposition as done by Freund (2016) for the three years mentioned.

Unfortunately, the Forbes data only reports the wealth of an individual down to hundred millions USD. Therefore, many individuals share the same rank causing a discontinuous ranking. In order to prevent jumps in the analysis of the distribution as will be described in section 4.1, the rank variable is adjusted such that every individual is assigned a unique integer rank in each year.

Looking at the source of wealth, individuals are categorised according to the industry as their main source of wealth, on an aggregate level and on a more detailed level. Industry aggregates include six subcategories: resource related, new industries, traded sectors, non-traded sectors, financial as well as other which is the case for less than five percent of all observations (Freund & Oliver 2016). The categorisation of the industry variable originates from Kaplan & Rauh (2013) and includes 16 subcategories overall. Table 7 in Appendix B highlights the decomposition of industry aggregates into the relative subgroups.

3.2 Data Quality Concerns

A word of caution is appropriate when using Forbes data since it is not an official statistical record, but data assembled by journalists. According to the Forbes methodology, the data is collected through personal interviews, financial reports by companies, information for shareholders as well as current exchange rates (Freund & Oliver 2016, Dolan 2012). This does not mean that the data was not compiled with care, however, measurement errors are likely to emerge from the quality of data and especially the willingness of the individuals to be honest. Freund & Oliver (2016) point out that the reported numbers of billionaires are probably under-exaggerated as wealth might not just be centred in one company, private companies have not gone public yet or might only be detected when the former owner dies such that the wealth appears in the tax registers. This might be particularly the case for inherited wealth as these people have a great incentive to keep their wealth diversified and undetected from public authorities (Piketty 2014).

The descriptive statistics presented in table 2 report that the number of observations significantly drops in the years between 1997 and 2000 while mean wealth increases. This is due to a change in reporting family fortunes in family aggregates for these years only, while in all other periods the wealth is assigned to each family member accordingly as long as it is possible. If this is not the case, siblings are jointly mentioned and must have at least two billion USD together (Kroll 2013). Given this break in the time series, the years before 2001 are excluded from the analysis.

Some researchers point out a positive link between upwards social mobility and education, particularly in top wealth shares (Kaplan & Rauh 2013, Piketty 2015, Saez & Zucman 2016). Unfortunately, the data quality on *educational level* in the *Forbes World Billionaires List* outside the US is very poor, in particular for emerging economies. This is the reason why the indicator was not included in the database.

3.3 Data Description and Evaluation

Overall, the total number of observations increased from 423, in 1996, to 1825, in 2015, implying that the number of world billionaires more than quadrupled in 20 years according to Forbes (see figure 1). In the same time total wealth held by individuals increased from around one trillion USD to over seven trillion USD as shown in figure 2. When excluding the years before 2001, the total number of billionaires still increased more than three times and total wealth more than four times.

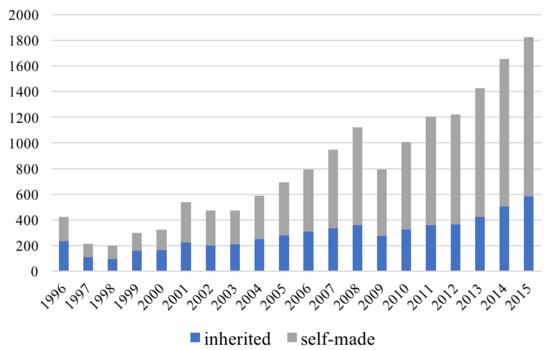

Figure 1: Number of billionaires from 1996 to 2015

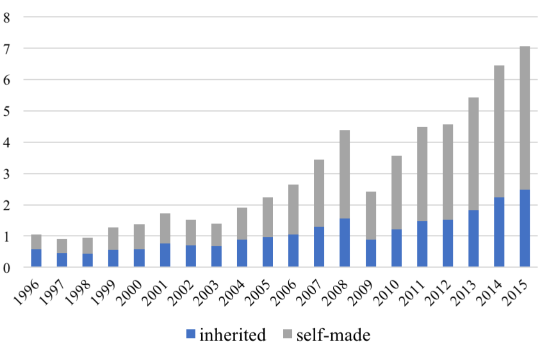

Figure 2: Total wealth in trillion USD from 1996 to 2015

Using the deflated data, average annual growth rate of total wealth was 19.23%, whereas per capita wealth only increased very slightly by 0.6%. Since this pattern is very similar across all other sub-groups of the sample (i.e. self-made, inherited, female, etc.), one can conclude that the wealth growth is driven by the number of billionaires rather than an increase in the average individual wealth. This result is also reported by Freund & Oliver (2016).

Separating the total number of billionaires into self-made and inherited wealth, allows insights into the dynamics of these two subgroups. Between 2001 and 2015 the share of self-made billionaires increases from 55% in 2001 to nearly 68% in 2015 while the share of inherited fortunes decreases accordingly. In 1996, the share of self-made billionaires is even lower at 45% implying that self-made billionaires used to be in the minority.

The development of numbers of billionaires and their fortunes seem to follow the business cycle as total fortune and number of billionaires drops in the aftermath of the financial crisis in 2009. Indeed, this intuition is reassured when looking at the individual level. On average, individual wealth drops from 3.9 billion USD to 3.05 USD and only recovers slowly until it reaches the value from 2008 again in the year 2014. Interestingly, self-made billionaires seemingly suffered less as they only lost around 20% of their wealth, whereas inherited billionaires lost 25% on average.

Figure 3: Average age in years of inherited and self-made billionaires from 2001 to 2015

When looking at gender, one finds that the majority of women in the list has inherited their fortune (81.6%) while more than 70% of all male billionaires are self-made which is a similar result found by Edlund & Kopczuk (2009). In addition, the average wealth for both genders is larger if it is inherited (for women 5.53 billion USD and men 11.83 billion USD) compared to self-made wealth (for women 1.93US billion USD and men 4.99 billion USD). This shows that men hold more wealth on average but also that wealth is centred around few rentiers. The age distribution in the sample does not show any sign that the population of billionaires gets younger or older on average as it stays quite stable around its mean of around 63 years between 2001 and 2015 as shown in figure 3. The average age of self-made billionaires is 62.96 years and 63.19 years for inherited billionaires. At first, self-made billionaires are older on average, but from 2008 onwards inherited billionaires are older except in 2015 (see figure 3). The average age of male individuals in the sample is slightly higher (62.4 years) compared to females (61.9 years). When looking at how wealth is spread across the different age groups, billionaires who are 70 years and older are on average wealthier. For younger age groups such a pattern cannot be identified, however there are very few billionaires younger than 30 years (numbers never reach double digits).

However, the average age of billionaires from the IT-sector are on average 7.5 years younger then the average billionaire. Unlike described by Saez & Zucman (2016) for income, the average age of the super wealthy has increased by around 3.5 years over the 20 year period from 59.8 to 62.4 years on average, a development which is consistent across genders, self-made as well as inherited billionaires. Finally, when looking at the distribution of wealth across generations the average wealth per individual gradually decreases with the generation of inheritance.

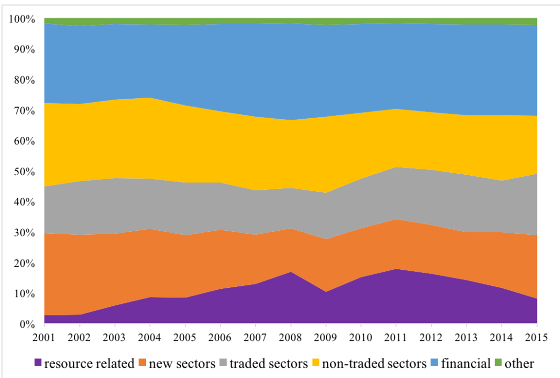

Figure 4: Industry decomposition of self-made billionaires from 2001 to 2015

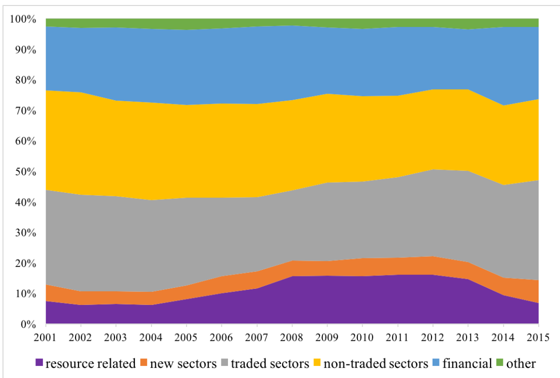

Figure 5: Industry decomposition of inherited billionaires from 2001 to 2015

Further insights into the dataset are possible when including the industrial decomposition. While in absolute numbers the financial sectors, the traded as well as the non-traded sectors dominate the group of inherited billionaires throughout the considered periods, self-made wealth it is overall spread more evenly. Figures 4 and 5 highlight the development of industry aggregates over the observed series. However, when looking at the average individual wealth in each sector, one can observe a different dynamic. Here, the new sectors outperform the others in particular the computer sector in which a billionaire on average holds 5.37 billion USD which is over two billion USD more than an average billionaire (3.1 billion USD).

Apart from looking at gender or the industry it may also be of interest to see how the billionaires are spread across the globe. Overall, the billionaires in the list come from 79 countries. Sorting by continent or nationality, the majority of the wealth is held by individuals from North America as well as Europe. Billionaires from the US constantly hold around 30% or more (in 2002 and 2003 even more than 50%) of total wealth. Most billionaires (on average around 38%) have the US citizenship, however, particularly wealthy billionaires live in Europe and Latin America. The country with the fastest growing billionaire population is China, from one in 2001 to 213 in 2015.

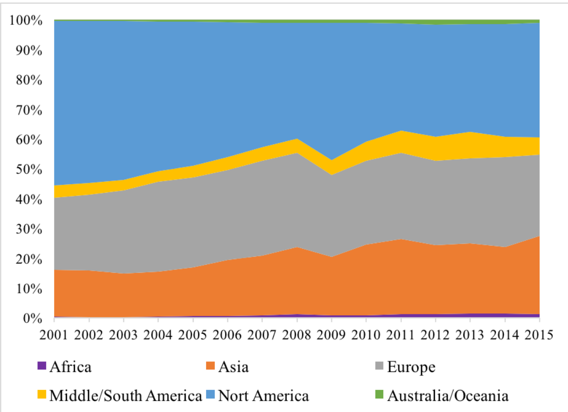

Figure 6: Yearly total wealth shares by continents in percent from 2001 to 2015

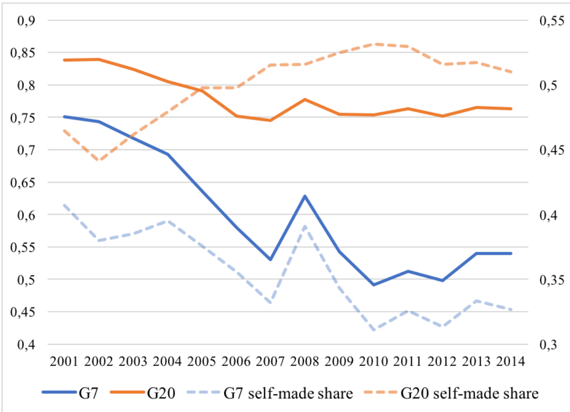

Figure 7: Percentage of total as well as self-made wealth held by billionaires with a citizenship of a G7 and a G20 country from 2001 to 2015. The scale on the right hand side depicts the self-made shares drawn as dashed lines.

The perspective changes when dividing into self-made and inherited billionaires. While in 2001 the US is leads in numbers as well as total wealth in both subgroups, most self-made billionaires live in Asia in 2015. This trend is mostly driven from China, as 16.6% of all self-made billionaires have the Chinese citizenship in 2015 compared to just 0.3% in 2001. Many self-made billionaires (7.8%) also come from Russia in 2015, compared to 2001 (2.6%), whereas other European countries only play a minor role. This changes when looking at the citizenships of inherited billionaires, where Europe is leading with 31.8% closely followed by North-America (29.1%) and Asia (26.5%) in 2015.

Figure 6 shows that most wealth is concentrated in North America and in particular in the USA, although the ratio declines from over 50% in 2001 to 37.5% in 2015. While the wealth concentrated in Europe remained quite stable, between 25% and 30%, wealth concentration increased the most in Asia from around 15.7% in 2001 to 26.2% in 2015, again mainly driven by China. The increasing importance of emerging economies in this context can also be seen in figure 7. While over 75% of the wealth is held by billionaires living in the G7 countries in 2001, the number drops to under 55% in 2015. At the same time, those billionaires with a G20 citizenship constantly hold more than 75% of the global wealth. The peak in 2009 of the G7 series indicates, that billionaires outside the G7 seem to be more affected by the last financial crises. This being said, most inherited wealth is still held in the traditional industrialised countries. The dashed lines in figure 7 illustrate the relative development of the self-made wealth in the G20 and the G7 countries. While the self-made share in the G7 decreases from over 40% to 32.5% the self-made wealth share increases from around 45% to over 50%. Apart from the US a lot of inherited wealth is also concentrated in Germany with constantly around 10% of total wealth. On the other hand, three out of five self-made billionaires did not live in one of the G7 member states any more in 2015.

	top 10		**top 100**	
year	self-made	inherited	self-made	inherited
2001	5	5	48	52
2002	6	4	44	56
2003	5	5	46	54
2004	8	2	49	51
2005	8	2	52	48
2006	8	2	54	46
2007	6	4	59	41
2008	8	2	62	38
2009	8	2	61	39
2010	7	3	62	38
2011	9	1	60	40
2012	7	3	61	39
2013	6	4	63	37
2014	5	5	61	39
2015	0	0	0	0

Table 1: Top performer, divided into self-made and inherited billionaires

Simple ranking already enables a first glance at the mobility within the data. Table 1 reports the richest ten and 100 billionaires divided into self-made and inherited wealth. In the top ten, self-made are more often in the lead. In 2011, nine out of the ten richest billionaires are self-made. Extending the range to 100, one can observe a gradual increase from 45/55 in favour of inherited wealth to around 60/40 in favour of self-made wealth.

Table 2 provides the summary statistics of the wealth variable in total and for each year separately. Throughout every cross-section the mean in column (2) stays relatively stable between 2.481 in 1996 and 3.905 in 2014 when ignoring the data between 1997 and 2000. The percentiles in columns (5) to (8) indicate a skewed distribution to the right, which shows that the data exhibits an unequal and a skewed heavy tail. A redistributing and equalising effect of the crisis is again visible for the year 2009. The number of observations reduces and the mean also gets smaller. Note, that higher moments are not defined for $\alpha \leq 2$.

	(1)	(2)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	N	mean	min	max	p25	p50	p75	sum
total wealth	16,216	3.627	1	90	1.400	2.100	3.700	58,823
1996	423	2.481	1	18.50	1.300	1.900	2.900	1,049
1997	215	4.177	1.100	36.40	2	2.800	4.900	898.1
1998	200	4.737	1.500	51	2.200	3.150	5.300	947.5
1999	297	4.273	1	90	1.700	2.900	4.700	1,269
2000	322	4.305	1	60	1.600	2.900	4.700	1,386
2001	538	3.213	1	58.70	1.300	1.900	3.300	1,729
2002	472	3.211	1	52.80	1.300	1.800	3.100	1,515
2003	476	2.948	1	40.70	1.200	1.700	2.900	1,403
2004	587	3.266	1	46.60	1.300	1.900	3.200	1,917
2005	691	3.236	1	46.50	1.300	2	3.200	2,236
2006	792	3.339	1	50	1.400	2	3.500	2,644
2007	946	3.649	1	56	1.500	2.100	3.700	3,452
2008	1,124	3.898	1	62	1.400	2.200	3.900	4,381
2009	792	3.048	1	40	1.300	1.850	3.100	2,414
2010	1,009	3.535	1	53.50	1.400	2	3.600	3,567
2011	1,207	3.724	1	74	1.400	2	3.700	4,495
2012	1,223	3.740	1	69	1.400	2.100	3.600	4,573
2013	1,425	3.812	1	73	1.400	2.100	3.800	5,432
2014	1,653	3.905	1	76	1.400	2.100	3.700	6,454
2015	1,824	3.870	1	79.20	1.400	2.100	3.800	7,059

Table 2: Descriptive statistics. Variable: wealth

4 Methodology

In this section, I explain the methodology which is used to analyse the data in terms of the research hypotheses. In section 4.1, I present the different methods for estimating the Pareto coefficient provided in the literature and explain how to determine the lower bound of a power law distribution. In section 4.2, I introduce the methods used to measure social mobility within the sample.

4.1 Measuring Wealth Inequality

From the properties of a Pareto distribution in section 2.2 it was shown, that wealth can be visualised as a straight line on a log log scale. Therefore, a common approach is to run a linear regression in order to estimate the Pareto exponent. Since this method suffers from a downward bias in small samples, a rank adjusted OLS regression is preposed instead (Gabaix & Ibragimov 2011, Ogwang 2013). Moreover, Clauset et al. (2009) argue that a linear least-squares approach is not capable of correctly estimating the power law and propose to apply maximum likelihood (ML) instead.

Estimating the Pareto Coefficient with OLS

Traditionally, the Pareto coefficient α is estimated with a linear regression of the log-linearised rank-wealth relation such that

$$ln(r(x_i)) = C - \alpha ln(x_i), \tag{10}$$

where x_i is the wealth of individual $i = 1, ..., n$. The method has already been proposed by Pareto (1897), but is still regularly applied (Levy & Solomon 1997, Klass et al. 2006, Ogwang 2013).

Using OLS in the context of estimating *rich lists* implies, that it is assumed that all observations of the list lie within the upper tail of the wealth distribution of a nation or a geographic region. Gabaix & Ibragimov (2011) note that the coefficient α as well as the standard error are underestimated in small samples. Therefore, they suggest to subtract 0.5 from the rank in equation 10 and run instead

$$ln(r(x_i) - 0.5) = C - \alpha ln(x_i). \tag{11}$$

The standard error is denoted as

$$SE(\hat{\alpha}) = \sqrt{\frac{2}{n}}|\hat{\alpha}|,$$

where n is the sample size (Gabaix & Ibragimov 2011).

Clauset et al. (2009) claim that OLS returns biased results for α. Due to taking the log, the errors loose normality and thus the R^2 as a goodness-of-fit measure cannot be trusted. In addition, least squares do not require to normalise the distribution. Unless this has been done beforehand, it fails to appropriately measure the slope of the log-linearised data. Since, (Gabaix & Ibragimov 2011) argue otherwise, the regression from equation 11 is applied a second time to all values $x \geq x_{min}$, in order to ensure a normalisation.

Estimating the Powerlaw with ML

The coefficient α may also be estimated with ML in combination with a goodness-of-fit test, which Clauset et al. (2009) propose as a more appropriate method.

Under the assumption that x_{min} is known, the ML estimator α_{ML}[7] from the density of equation 2 is given by

$$\hat{\alpha}_{ML} = n\left(\sum_{i=1}^{n} ln\frac{x_i}{x_{min}}\right)^{-1}. \tag{12}$$

The estimator is asymptotically normal and consistent for large n which implies that $\hat{\alpha} \to \alpha$ as $n \to \infty$, given the assumption that the model is correctly specified (Clauset et al. 2009). From the formula of the standard error

$$SE(\alpha\hat{_{ML}}) = \frac{\hat{\alpha}}{\sqrt{n}} + O\left(\frac{1}{n}\right)$$

one can see that it decreases in sample size n, where O denotes the order of the error (Clauset et al. 2009). This being said, unbiasedness of the ML estimator does not hold in small and finite samples such that a sample size of at least $n \geq 50$ is proposed for the estimator to be reasonably well behaved in the case of a power law estimation (Clauset et al. 2009).

Identifying the Lower Bound

Gabaix & Ibragimov (2011) argue that their adjusted OLS estimator is more robust than the ML estimator and performs well in finite samples. According to Clauset et al. (2009) results obtained from applying OLS, however, entail the problem since it is entirely based on the assumptions that first the data actually obeys a power law and second that the whole sample

[7]For the derivation of an ML estimator for the PDF see e.g. Clauset et al. (2009), Verbeek (2012).

lies within the tail of the distribution. However, it is not enough to simply assume that the upper tail encompasses the complete sample. Moreover, visually identifying a lower bound x_{min} from the log-log plot of a CCDF by excluding all observations below a certain threshold at which the results become noisy, is sensitive to the noise in the tail of the distribution (Clauset et al. 2009). Therefore, the real problem is to find the lower bound x_{min} in order to obtain consistent results. x_{min} may be identified by minimising the distance D between the CCDF of the real data and the CCDF of some synthetic power law fit, thus making the probability distributions as equal as possible (Clauset et al. 2009).

For this procedure the authors propose a Kolmogorow-Smirnow-Statistic (KS) for non-normally distributed data such that

$$D = \max_{x \geq x_{min}} |S(x) - P(x)|, \tag{13}$$

where $S(x)$ represents the CCDF of the real data set and $P(x)$ is the synthetic power law fit that best models the real data. The optimally estimated lower limit x^*_{min} is the value which minimises equation 13 (Clauset et al. 2009).

Hereby, equation 13 yields conservative results, since underestimating x_{min} bears more severe consequences than overestimating it (Clauset et al. 2009). On the one hand, overestimating the lower limit "only" causes a loss in valuable observations leading to less model accuracy due to a higher statistical error as well as an increasing finite sample bias. On the other hand, underestimating the lower bound such that $\hat{x}_{min} < x_{min}$ produces a biased estimator $\hat{\alpha}$ as well as a misspecified model since the power law model is fitted to data that does not obey a power law in the first place (Clauset et al. 2009). Therefore, it is important to estimate the lower bound such that $\hat{x}_{min} \geq x_{min}$ but as close to the real value as possible.

4.2 Measuring Social Mobility

Mobility is a normative concept, therefore, it is recommended to apply different approaches in order to give a more complete picture (Chetty et al. 2014). This has been done here as well by presenting three different ways for measuring mobility. I calculate the rank correlation as well as transition matrices for the short-run mobility and the Shorrocks Index of mobility as an attempt to also shed some light on the long-run mobility. All three methods have in common that they are non-parametric.

Short-run mobility is measured by creating matching subsamples of pairwise years using logged wealth. Again, I create subsamples for logged self-made and logged inherited wealth. The rank correlation is estimated to present an easy accessible overview. In addition, transition matrices are created for each year pair. An index, based on their traces, is calculated which presents a more elaborated measurement of mobility.[8] Moreover, it is also possible to study the magnitude as well as the direction of mobility from the transition matrices directly. Long-run mobility is measured by using the so called Shorrocks Index as proposed by Shorrocks (1978*b*) and Maasoumi & Zandvakili (1986).

Calculating the Rank Correlation

Spearman's rho is given by

$$\rho = 1 - \frac{\sum_{i=1}^{n}(x_{it} - x_{it(it+k)})^2}{n^3 - n}, \tag{14}$$

where n is the number of observations in year t that also appear in year $t-k$. Standard errors and test statistics are calculated as usual (Best & Roberts 1975). Its advantage over other measures of correlation is, that it is non-parametric and does not require a linear relationship. In addition, it is insensitive to outliers.

Transition Matrices

Transition matrices are convenient to measure mobility between two periods (Hochguertel & Ohlsson 2011). Shorrocks (1978*b*) suggests a mobility measure based on the trace of the transition matrix that allows to compare mobility between different periods. Mobility between two periods, $\hat{M}$, is defined as

$$\hat{M} = \frac{q - tr(P)}{q - 1}, \tag{15}$$

where q is the number of bins and $tr(P)$ is the trace of the q x q transition matrix P (Shorrocks 1978*b*). Here, q is equal to five in order to study the movement between wealth quintiles. The measure can take values between 0 and 1, where 0 means no mobility and 1 perfect mobility (Shorrocks 1978*b*).

[8] In the literature the name Shorrocks Index is used for two different methods. To clarify, the method developed in Shorrocks (1978*b*) is called here the trace index as it is based on calculating the trace from transition matrices, the method introduced by Shorrocks (1978*a*) is called the Shorrocks Index.

The Shorrocks Index

The mobility index proposed by Shorrocks (1978*a*) and Maasoumi & Zandvakili (1986) compares the long-run wealth inequality across several years with the weight adjusted sum of inequality from each year. Mobility rises (falls) as inequality has decreased (increased) by comparing long-term wealth with the development of wealth in each period (Schluter & Trede 2003). It is based on the assumption that the distribution of several periods combined is more equal than in each period. Mobility then describes the speed of convergence to an equilibrium at perfect mobility through time (Shorrocks 1978*a*), a concept that has not been without criticism (Fields 2010, Schluter & Trede 2003, Vittori 2008).

Mobility, M is given by the negative of the measured persistence, R,

$$M = 1 - R, \tag{16}$$

where R is denoted as

$$R = \frac{I(G_T)}{\frac{1}{T}\sum_{t=1}^{T} w_t I(G_t)}. \tag{17}$$

In the numerator, $I(G_T)$, denotes the long-run measure of inequality, here the Gini-coefficient, estimated from the average distribution of the sample period $t = 1, ..., T$. The denominator denotes the weighted sum of the single-period Gini-coefficient in period t, where the weights w_t are the ratio of the mean log wealth in each year μ_t over the mean log wealth $\bar{\mu}$ from all periods $t = 1, ..., T$, ie. $w_t = \frac{\mu_t}{\bar{\mu}}$ (Fields 2010).

Given the assumption that the observed data follows a Pareto distribution, the Gini-coefficient for period t is given by

$$G_t = \frac{1}{2\alpha_t - 1}, \tag{18}$$

where $\alpha > 1$ (Benhabib et al. 2011). α is the Pareto coefficient estimated with the methods presented earlier.

5 Results and Discussion

Section 5.1 discusses the results of the data fitted to a Pareto distribution as well as the estimation of its exponent α by applying the different estimation methods mentioned in chapter 4. Thereafter in section 5.2, I use a goodness-of-fit test to check the robustness of the results. In section 5.3, I discuss insights to social mobility within the data by presenting the mobility indices as well as analysing rank correlations across the whole panel. Finally in section 5.4, I outline and discuss implications gained from the results, but also its limitations and the problems I encountered.

5.1 Power Law Estimation

Table 3 presents the estimation results of the power law exponent α for each year respectively. In column (2) the exponent is estimated using the standard OLS method (equation 10), while in column (3) the rank adjusted OLS regression (equation 11) is applied. Column (6) presents the estimation results for equation 11 again but this time all data $x < x_{min}$ is discarded which is on average 56% of all observations. Column (7) presents the estimates for α using method of ML from equation 12. Standard errors are calculated from the respective formulas mentioned in section 4 and are reported in brackets below. Columns (1) and (5) show the included observations, where (5) reports all observations above the threshold reported in column (4).

Without acknowledging the lower bound, the tail exponent is clearly underestimated which leads to an over-reporting of the heaviness of the tail. Subtracting 0.5 from the rank, yields only slightly higher values for the tail exponent as reported by α_{adj} in column (3).

After considering the lower bound x_{min}, both estimation methods, OLS with adjusted rank as well as ML estimates for the Pareto coefficient $\alpha_{OLSxmin}$ and α_{ML} respectively, move closer to the value of 1.5 which is assumed by theory and previous experiments. The estimates for α_{ML} yield more conservative than those obtained for $\alpha_{OLSxmin}$, which is expected (Clauset et al. 2009).

All four estimators show a similar pattern. The estimated exponent is not volatile but decreases sightly throughout the observed period. This indicates that overall inequality indeed increases. An exception represents the year 2009 after the last financial crisis. Here, the exponent jumps up in all series, but returns to its previous decreasing path after a few years. This being said, $\alpha_{OLSxmin}$ as well as α_{ML} increase again after reaching an all time low in 2011 while α_{OLS} as well as α_{OLSadj} remain stable.

	(1) obs.	(2) α_{OLS}	(3) α_{adj}	(4) x_{min}	(5) obs.	(6) $\alpha_{OLSxmin}$	(7) α_{ML}	(8) p-value$_{OLSxmin}$	(9) p-value$_{ML}$
2001	538	1.343	1.365	2.8	173	1.624	1.57	0.000	0.465
		(0.007)	(0.0832)			(0.175)	(0.162)		
2002	472	1.350	1.375	1.6	292	1.486	1.39	0.0012	0.010
		(0.007)	(0.0895)			(0.123)	(0.165)		
2003	476	1.381	1.406	2.0	207	1.576	1.47	0.025	0.129
		(0.007)	(0.0911)			(0.155)	(0.129)		
2004	587	1.354	1.374	1.7	355	1.511	1.4	0.001	0.008
		(0.008)	(0.0802)			(0.113)	(0.151)		
2005	691	1.345	1.363	1.9	365	1.551	1.43	0.000	0.008
		(0.008)	(0.0733)			(0.115)	(0.166)		
2006	792	1.343	1.359	2.1	381	1.576	1.42	0.000	0.002
		(0.008)	(0.0683)			(0.114)	(0.127)		
2007	946	1.297	1.310	1.8	582	1.455	1.34	0.000	0.000
		(0.007)	(0.0602)			(0.085)	(0.150)		
2008	1,124	1.256	1.267	2.2	571	1.457	1.33	0.000	0.032
		(0.006)	(0.0534)			(0.086)	(0.094)		
2009	792	1.373	1.390	2.8	233	1.690	1.53	0.000	0.035
		(0.007)	(0.0699)			(0.157)	(0.116)		
2010	1,009	1.293	1.306	2.8	362	1.604	1.46	0.000	0.020
		(0.006)	(0.0581)			(0.119)	(0.183)		
2011	1,207	1.266	1.277	2.2	563	1.453	1.31	0.000	0.002
		(0.006)	(0.0520)			(0.087)	(0.117)		
2012	1,223	1.275	1.285	2.2	601	1.469	1.36	0.013	0.019
		(0.006)	(0.0520)			(0.085)	(0.071)		
2013	1,425	1.252	1.261	2.5	611	1.488	1.37	0.000	0.001
		(0.006)	(0.0472)			(0.085)	(0.164)		
2014	1,653	1.256	1.265	2.6	685	1.477	1.38	0.002	0.007
		(0.005)	(0.0440)			(0.080)	(0.069)		
2015	1,823	1.265	1.273	3.5	511	1.558	1.43	0.000	0.101
		(0.004)	(0.0421)			(0.097)	(0.092)		

Table 3: Estimation results for the Pareto coefficients of total wealth for the years 2001 to 2015. Columns (1) to (3) report the unbounded estimation results, where column (2) reports the unadjusted OLS estimates and column (3) the rank adjusted estimates. Column (4) reports the values of the lower bounds x_{min}. Columns (6) and (7) report the estimates using OLS with adjusted rank as well as ML. Columns (8) and (9) report the receptive p-values of the goodness-of-fit test.

In a next step the sample is decomposed into self-made wealth and inherited wealth. The results are displayed in table 4. Only the estimates for $\alpha_{OLSxmin}$ as well as α_{ML} are presented, since the examination of the total sample has proven that ignoring the lower bound leads to insufficient results. Overall, both estimators find a lower Pareto exponent for inherited wealth which points towards the assumption that wealth accumulated through inheritance may indeed be one factor to increase inequality. On average, the reported Pareto exponents for self-made billionaires are above the equivalent from table 3 indicating the opposite. The ML method consistently estimates smaller α's than OLS, except for the first two observations in the self-made subsample. This being said, the values of the exponents move closer together towards the end of the time series. The inequality in the self-made subsample seems to increase since the exponents decrease on average as has been visualised in figure 10. On the contrary, the values for the inherited subsample estimated with ML increase again after 2010. Overall, the estimates for the self-made subsample react quite similarly to the shock of the crisis and move parallelly over the whole series. In the subsample with inherited wealth only, α_{ML} reacts strongly to the crisis. It increases sharply in 2009 and then quickly decreases again. The values for $\alpha_{OLSxmin}$ remain mostly constant over the observed period and seem to be unaffected from the shock of the crisis.

5.2 Goodness-of-Fit Test

Columns (8) and (9) of table 3 as well as columns (4), (6), (10) and (11) of table 4 report the p-values of a goodness-of-fit test, to test whether the data actually obeys a power law. The test consists of two parts: firstly, the fit of the empirical data resulting from the KS statistic is estimated as in section 4.1. Secondly, a Monte Carlo (MC) study is used to generate data from a power law model with the respective estimated α and x_{min} from the real data. M synthetic samples are created such that $MC : 1, ..., M$ where $M = 2500$ in order to produce reliable p-values up to two digits behind the decimal point (Clauset et al. 2009). Each sample is individually fitted to its own model such that it is possible to calculate M KS statistics. The p-value reports the fraction of events in which the KS statistic of the fitted data is larger than the KS statistic of the empirical data (Clauset et al. 2009).

For reasons of completeness it should be mentioned, that the method developed by Clauset et al. (2007) also creates non power law data for values smaller than the lower limit x_{min} in order to ensure unbiasedness of the p-value. Data is generated proportionally to the ratio of values below and above the lower bound of the real data by applying a semi parametric bootstrap.[9]

A p-value of at least 0.1 is desired which implies that at least in ten percent of all simulations, the KS statistic of the synthetic data is larger than the KS statistic of the empirical data. Clauset et al. (2009) show that 0.1 is a good minimum threshold to aim for. In addition, at least 100 observations are required for the statistic to hold. In case the number of observations lies below this threshold, the test cannot effectively identify a power law behaviour in the data (Clauset et al. 2009). Large p-values in combination with a low n should there-

[9] For a more detailed explanation see Clauset et al. (2007) and Clauset et al. (2009).

	self-made						inherited					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	x_{min}	obs.	$\alpha_{OLSxmin}$	p-value	α_{ML}	p-value	x_{min}	obs.	$\alpha_{OLSxmin}$	p-value	α_{ML}	p-value
2001	2.5	62	1.740	0.011	1.451	0.168	3.0	61	1.517	0.002	1.690	0.042
			(0.313)		(0.118)				(0.275)		(0.295)	
2002	2.8	50	1.756	0.000	1.534	0.267	2.2	59	1.472	0.030	1.499	0.151
			(0.351)		(0.143)				(0.271)		(0.228)	
2003	3.1	44	1.911	0.025	1.471	0.968	2.0	56	1.525	0.007	1.451	0.131
			(0.407)		(0.177)				(0.288)		(0.216)	
2004	3.3	69	1.839	0.001	1.538	0.552	2.0	72	1.621	0.001	1.426	0.048
			(0.313)		(0.144)				(0.270)		(0.336)	
2005	2.1	86	1.817	0.248	1.478	0.328	1.9	88	1.607	0.001	1.343	0.004
			(0.277)		(0.135)				(0.242)		(0.343)	
2006	3.2	118	1.863	0.043	1.562	0.722	1.3	92	1.590	0.000	1.254	0.011
			(0.243)		(0.153)				(0.234)		(0.114)	
2007	1.9	162	1.721	0.061	1.430	0.043	1.5	113	1.544	0.000	1.245	0.002
			(0.191)		(0.113)				(0.205)		(0.140)	
2008	2.8	224	1.604	0,007	1.425	0.300	1.9	128	1.507	0.000	1.265	0.013
			(0.152)		(0.117)				(0.188)		(0.151)	
2009	2.9	94	1.864	0,000	1.604	0.294	2.4	75	1.612	0.009	1.499	0.052
			(0.272)		(0.155)				(0.263)		(0.181)	
2010	2.8	180	1.678	0,000	1.511	0.563	1.2	124	1.574	0.000	1.122	0.000
			(0.177)		(0.158)				(0.200)		(0.220)	
2011	2.1	229	1.599	0,001	1.362	0.002	1.6	140	1.521	0.000	1.185	0.000
			(0.149)		(0.105)				(0.182)		(0.202)	
2012	2.2	221	1.630	0.000	1.399	0.027	2.2	139	1.500	0.000	1.305	0.010
			(0.155)		(0.102)				(0.180)		(0.145)	
2013	1.95	270	1.587	0,062	1.345	0.011	2.6	166	1.547	0.000	1.317	0.000
			(0.137)		(0.076)				(0.170)		(0.233)	
2014	2.7	311	1.538	0.000	1.416	0.025	2.4	193	1.504	0.000	1.317	0.003
			(0,123)		(0.072)				(0.153)		(0.260)	
2015	2.7	349	1.552	0.000	1.405	0.198	2.7	214	1.520	0.000	1.365	0.275
			(0,118)		(0.093)				(0.147)		(0.136)	

Table 4: Estimation results of sample decomposition into self-made and inherited wealth for $\alpha_{OLSxmin}$ and α_{ML} from 2001 to 2015. Columns (1) to (6) report the results for the self-made subsample and columns (7) to (12) for the inherited subsample. Columns (1) and (7) report the estimated values for the respective lower bounds, columns (2) and (8) the observations included in each subsample. Columns (3) and (9) report the estimation results for the Pareto exponent using OLS with adjusted rank, while columns (5) and (11) report the estimation results for the Pareto exponent using ML. Columns (4), (6), (10) and (11) report the p-values obtained from the goodness-of-fit test.

fore not be trusted, as this strongly indicates towards a small sample bias (Clauset et al. 2009).

Overall, the OLS method – for which the goodness-of-fit test shows no significance (except for the self-made subsample in 2005) – is clearly outperformed by the ML estimate. Thus, accounting for the lower bound as well as the rank cannot save the linear approach, at least in this setup. The significance of α_{ML}, however, is also low or not significant. This is consistent with previous results for the *Forbes World Billionaires List* (Ogwang 2013, Brzezinski 2014, Capehart 2014). Only three out of 15 years are reported as significant for total wealth, depicted in column (9) of table 3. For the subsamples of self-made as well as inherited wealth the goodness-of-fit test reports ten and respectively three years as significant. Thus, the significance level when only observing self-made billionaires seems to increase. This result, however, should be considered with caution as the number of observations has decreased once again. Indeed, in eight out of those eleven significant years, the number of observations drops below the threshold of 100 and the test statistic remains inconclusive for these periods. From the remaining four years an extra ordinary high p-value of 0.722 in 2006 in combination with only 117 observations strongly points to a small sample bias. This intuition is underlined by the fact that in all (sub)samples significance decreases as the sample size increases except in 2015. Despite these unsatisfactory results, it cannot be completely ruled out that the underlying wealth data is Pareto distributed as has been done before, especially since other distributions have performed even worse when studying top wealth shares (Clauset et al. 2009).

Figures 11, 12 and 13 (in appendix A) visualise the fitting process for all years and the respective subsamples. The fit is depicted for all $x \geq x_{min}$ where the blue dots project the CCDF of the wealth variable on a log log scale. The red dashed line shows the synthetic fit of the estimated power law. All fits become noisy towards the upper end of the distribution. Overall, it seems that the noise of the tail as well as the straightness of the fit are positively connected to the significance level. Accordingly, the graphs for self-made wealth in figure 12 are much closer to a straight line and have less noisy tails. The fits for inherited wealth in figure 13, on the contrary, have a larger curvature and exhibit more noise in the tail, which breaks away sharply, in some cases close to a vertical line (e.g. in 2003, 2009, or 2012). This pattern is consistent for all observed periods as well as all (sub)samples and agrees with the p-values from tables 3 and 4. Here, the majority of the years of the self-made subsample are reported as significant. However, earlier years perform better than later years and indeed the noise in later years is larger. Under the assumption that low significance is caused by the upper tail, one could state that the noise is caused by the top performers. Recalling table 1, the significance decreases as self-made billionaires climb to the very top of the list indicating that the especially noisy upper end of the distribution may be causing low significance. This being said, alternative interpretations are equally possible such as the argument of the straightness of the fit as well as that significance decreases as the number of observations increases. Finally recall, that fitting through eye balling does not allow to make final judgements (Clauset et al. 2009).

5.3 Social Mobility in the Forbes List

To measure yearly mobility, matching year pairs of the logged wealth variable are created. Figure 8 plots the mobility estimated from one minus the rank correlation. Overall, three points are striking: First, overall mobility ranges from 0.05 to around 0.23 in total, and decreases in all (sub)samples which is also indicated by the linear fit of total mobility (black dotted line). Second, mobility of inherited billionaires (green line) is lower than for self-made billionaires (red line) throughout the time series except once between the years 2004 and 2005. Third, the last financial crisis seems to have especially disturbed the subsample of self-made billionaires while the line of inherited stayed comparatively stable. However, more inherited wealth was destroyed as stated in section 3.

Figure 9 presents the mobility measures calculated from the trace method. As for the rank correlation some similarities can be identified. The yearly mobility on average decreases, but fluctuates more than in the rank correlation. Again, the mobility increases around the year 2009. The average mobility of self-made billionaires (0.466) lies above the one for the inherited subsample (0.448). The average transition rate of the total sample is 0.458, a result that is higher than those found in earlier studies. For top wealth shares in Sweden, Hochguertel & Ohlsson (2011) find an average transition rate of 0.386 measured over 40 years from 1965 to 2005. Compared to the rank correlation, the measured mobility is much higher, ranging from around 0.3 to over 0.6, although a causal comparison between both methods is not possible. In addition, a higher mobility rate of the self-made subsample is not as consistent as in figure 8. Large changes in mobility occur at the beginning of the observation period and in particular after 2008. Whether these disturbances are caused by upwards or downwards

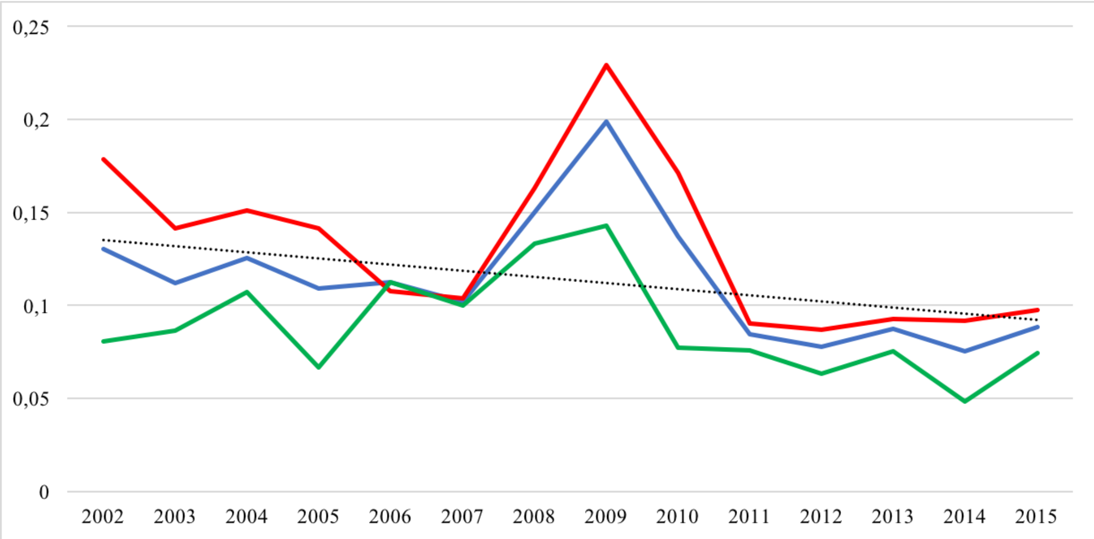

Figure 8: Mobility between year pairs 2001-2015 estimated from the Rank Correlation. The blue line represents average mobility of the total sample, the red line for self-made only and the green line for inherited only. The black dotted line is the linear fit for total mobility.

mobility cannot be identified from the trace alone. This inability to identify the direction of mobility is one of the main points of criticism in the literature (Schluter & Trede 2003, Fields 2010).

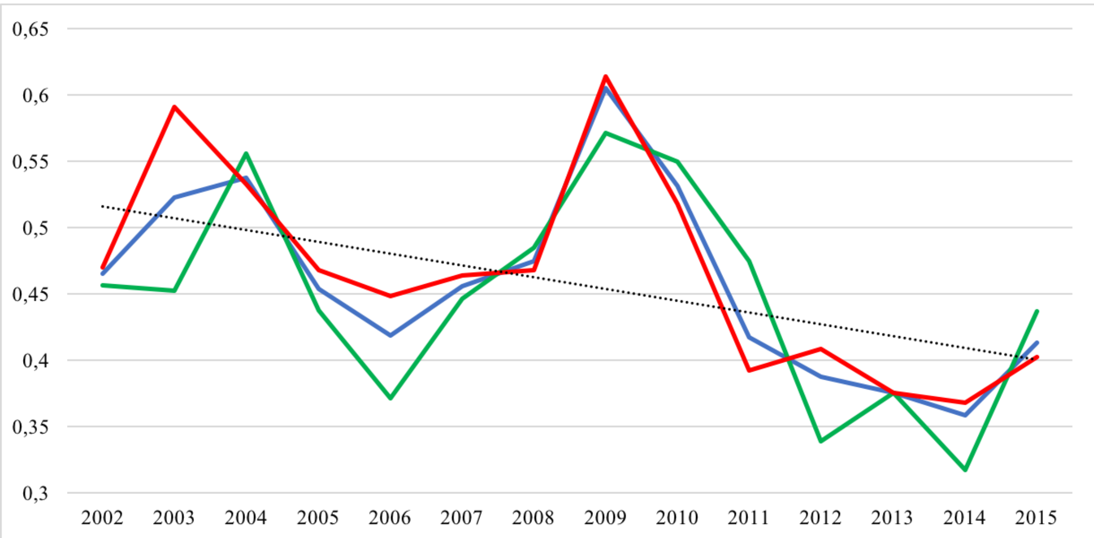

Figure 9: Mobility between year pairs 2001-2015 using the trace method. The blue line represents average mobility of the total sample, the red line for self-made only and the green line for inherited only. The black dotted line is the linear fit for total mobility.

To further study the direction of mobility, it is required to look at the transition matrices directly, which are presented in tables 9 and 10 (in Appendix B). They show that the middle quintiles exhibit more mobility than the first and the last fifth. Especially, the mobility of inherited billionaires is particularly low at the upper and lower end, but higher in the middle quintiles of self-made billionaires. In general, most movements are created through deviation to the neighbouring quintiles above or below. Larger jumps are rare, but when they occur the direction tends to be upwards. Between 2002 to 2003 figure 9 illustrates an increase for self-made billionaires (red line) which is driven mainly by extra ordinary large movements in the middle quintiles, but in addition over proportionally many large downwards movements can also be identified. In the following year inherited billionaires exhibit larger mobility but here an upwards trend is found. In the years following the shock after 2008, fewer individuals than usual keep their position. A pattern can be identified that many individuals move more than one quintile down, but the movement is reversed in the following year pointing to a swift recovery of some individuals. In general, self-made billionaires are affected more. In addition, it may seem that the first quintile remains relatively stable from 2008 to 2009. This is actually not the case, since at the same time the number of billionaires in the list reduces. However, this cannot be detected by the transition matrix.

	(1) ML	(2) OLSxmin
total	0.004	0.003
self-made	0.004	0.008
inherited	0.005	0.002

Table 5: Shorrocks Index of mobility over the period from 2001 to 2015. Values of zero imply no social mobility and values of one perfect mobility.

The Shorrocks Index measures mobility by comparing long-run inequality with the weighted mean of short-run inequalities. Here, the Gini coefficient is used as a measure of inequality. It is calculated twice, once with the estimates $\hat{\alpha}_{ML}$ and once with $\hat{\alpha}_{OLSxmin}$. The results are presented in table 5. Overall, the Shorrocks Index returns extremely low levels of mobility as well as inconclusive results when distinguishing between self-made and inherited wealth.
Especially the results presented in column (1) of table 5 which are obtained from using $\hat{\alpha}_{ML}$ do not reflect previous outcomes. Here, self-made wealth does not exhibit a higher mobility than inherited wealth. On the contrary, column (2) reports a higher mobility for self-made wealth than for inherited wealth. However, the validity of this result is questionable since the estimates of $\hat{\alpha}_{OLSxmin}$ show weak signs of robustness for appropriately fitting a power law to the data.

The results obtained from the Shorrocks Index in this context are poor due to the fact that the overall inequality in the observed years remains stable resulting in little variation between long-run and short-run mobility. Hence, a time series of 15 years does not seem long enough to make robust predictions about the development of mobility in the long run.

5.4 Discussion and Limitations

When accounting for the lower bound, the Pareto exponent of the wealth distribution takes values close to 1.5 as found in the literature. α_{ML} yields more conservative results which lie around 1.4, compared to $\alpha_{OLSxmin}$. The unadjusted measures clearly underestimate α and thus overestimate the level of wealth inequality. For the 15 years observed in the sample, a slight downwards trend can be identified indicating that inequality is indeed increasing. Decomposing the data into an inherited and a self-made subsample reveals that the estimated exponent is constantly lower for the inherited wealth than for self-made wealth.

Before further interpretations can be made it is important to underline that in general, the data does not show a good sign of robustness to the assumption that the upper tail of the wealth distribution actually follows a Pareto distribution. This result is in line with previous research where data is taken from the *Forbes 400* (Clauset et al. 2009, Chan et al. 2017) as well as the *Forbes World Billionaires* (Ogwang 2013, Brzezinski 2014, Capehart 2014, Vermeulen 2014). Benhabib & Zhu (2008) as well as Boehl & Fischer (2017) suggest a double Pareto distribution and Chan et al. (2017) a beta Pareto distribution. Brzezinski (2014) argues that other distributions are better at fitting wealth data at the upper tail as well as that available tests fail to successfully distinguish between different distributions.

However, this should not be the end of the discussion, as many factors indicate that the result is biased due to measurement errors in the data. Capehart (2014) points out the existing rounding errors in Forbes data since wealth is only reported as low as hundred millions USD. Under the assumption that wealth is continuously distributed, the fit smooths out the jumps between each step. Another problem could be that insignificance is caused by different levels of inequality for different countries resulting in a non Paretian behaviour on a global perspective (Ogwang 2013). In fact, some authors manage to improve data quality and even retrieve significant results when accounting for these biases (Capehart 2014, Vermeulen 2014). In addition, Clauset et al. (2009) argue that compared to other distributions, the fit of the Pareto distribution still performs best even though they clearly reject that wealth is described by a power law after all and question its functional form. To this point of discussion may be added, that an ML estimator only performs well under the assumption of asymptotic normality. Given the most likely case of existing measurement errors in the sample, this assumption is violated and the estimator is consequently biased. Low significance reported in the goodness-of-fit test may therefore not be caused by choosing the wrong distribution but by the fact that the estimator is not a good estimator for estimating this kind of data. In reality, the strong assumptions of the ML approach are easily violated which is a common point of critique for this method (Verbeek 2012).

The distributions and their fits presented in figures 11, 12 and 13 highlight that inherited and self-made wealth show a different behaviour. Especially self-made wealth seems to better follow the assumptions of a Pareto distribution. However, the drivers behind these findings remain undetected. The goodness-of-fit test is inconclusive for many significant years due to small sample sizes and significance seems to decrease as the sample size increases. In addition, the later years of self-made wealth have noisier tails. This is not the case for the last year of the time series. Whether this is an outlier cannot be identified with only 15 observations. As the tails of self-made wealth become noisy, inequality of self-made wealth successively converges towards inherited wealth. This is especially the case in the years after 2010 and by the end of the observation period both exponents are close together. As shown in figure 10 the α_{ML} for self-made wealth yields 1.41 and the inherited one 1.36.

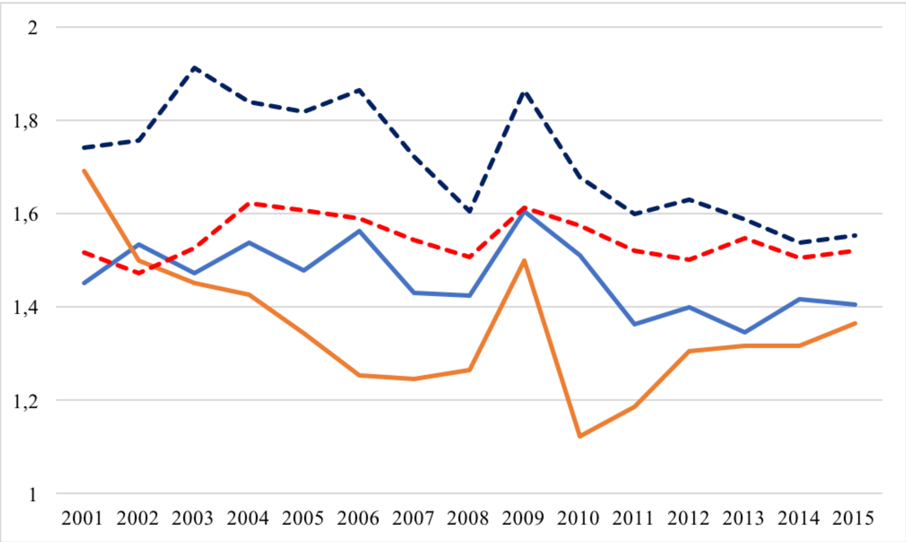

Figure 10: Pareto coefficients, decomposed into self-made and inherited wealth from 2001 to 2015. Blue shades present estimates for the self-made subsample, red shades for the inherited subsample. The dotted lines are estimates obtained from $\alpha_{OLSxmin}$, the solid lines present the estimates for α_{ML}.

Given this argumentation, the findings presented here do not allow to ultimately rule out the Pareto distribution. In particular in the self-made subsample, significance is reported too often to simply call it luck. Based on the findings, one can therefore carefully confirm the first hypothesis. Indeed, the distribution of inherited wealth exhibits higher levels of inequality than self-made wealth. However, results do not show a good sign of robustness. The theoretical assumptions for measuring wealth inequality are based on the Pareto distribution for which the data returns only low significance.

The rank correlation as well as the trace method give a similar picture in two ways. The overall mobility rate is decreasing and the average social mobility of inherited wealth is lower than for self-made wealth. The latter is, however, less clearly identified by the trace method. Kopczuk et al. (2010) report similar numbers for rank correlations after one year. This should raise some questions whether the variation after one year is enough to effectively observe mobility. The trace index, on the contrary, reports relatively larger mobility rates although it is difficult to directly compare the results with other findings (Hochguertel & Ohlsson 2011).
The self-made series of the rank correlation is more volatile than the inherited. Mobility in the inherited subsample seems to be particularly affected by the shock in 2009, a results that contradicts with the findings from the transition matrices. Here, self-made billionaires experienced more mobility. Such differences in the behaviour of the two subsamples cannot be identified in the results from the trace index as the results are not as clear. In addition, the transition matrices reported in tables 9 and 10 show that quintiles one and five exhibit much lower mobility than the middle quintiles. The results seem quite similar with usual results of measuring social mobility (Charles & Hurst 2003, Clark & Cummins 2015). However, one should keep in mind that only a very small proportion of the population is observed and that there cannot be a poverty trap when observing billionaires.
Measuring mobility by applying the Shorrocks Index produces very low mobility rates. The results from the separation into inherited and self-made subsamples remain inconclusive. This can be explained by the low variation in the yearly inequality levels α_t which are used to calculate the Gini coefficients. Averaging them produces a long-run mobility rate which is close to the yearly rates. Hence, 15 years are clearly not long enough to create enough variation to measure any speed of convergence to equilibrium equality. Given theses circumstances, the second hypothesis can be approved: for the periods observed, both short-run measures of mobility return on average higher mobility rates for self-made wealth than for inherited wealth.

Little more can be identified from using non-parametric measures only, although there is some research on more elaborated indices (Schluter & Trede 2003, Fields 2010). In section 2 it was shown that wealth accumulates as an autoregressive process and λ exhibits positive autocorrelation. Although these assumptions are not formally proven at this point, it is reasonable to assume that a variable that "accumulates over time" follows a trending relationship (Benhabib et al. 2011). Therefore, linear models are likely to fail in such a model setup. Nevertheless, they are popular to estimate the wealth elasticity between two generations in the literature on intergenerational wealth mobility (Charles & Hurst 2003, Chetty et al. 2014, Clark & Cummins 2015).
Alternatively, a panel model could be considered. Static panel models are insufficient and more elaborated models are needed to capture the underlying dynamics in the accumulative process of wealth. To find and to properly apply such a model in the given context are beyond the scope of this study but indeed offer an opportunity for further research. A possible solution could be dynamic panel approaches. First attempts can be found in Hochguertel & Ohlsson (2011) as well as Benhabib et al. (2015).

Combining the results from both parts, a connection between mobility and inequality can be identified, in particular in the self-made subsample. Here, inequality increases and mobility decreases. A the same time, the number of self-made billionaires grows faster than the number of inherited billionaires. It seems that once self-made billionaires have taken their rank position, further wealth accumulation increasingly depends on their individual capital returns rates. Consequently, social mobility decreases and wealth inequality increases with the number as well as the time self-made billionaires spend in the upper wealth share.
Last but not least, the reader would wonder why so many variables have been collected and only so few are used. However, the careful reader will have realised that the data quality is not good enough to further pursue into smaller subsamples without fixing some of the problems faced during the analysis. This of course, raises the question: why is the Forbes data so popular? The answer is simple: there are simply little other alternatives available for comparable data on top wealth shares.

6 Conclusion and Outlook

Decomposing the *Forbes World Billionaires List* into self-made and inherited wealth, I was able to identify that inherited wealth exhibits higher levels of inequality than self-made wealth. In the fifteen years observed, inequality increases on average in the total sample as well as in the two subsamples and self-made wealth inequality converges to the level of inherited wealth inequality. In addition, I could show that self-made billionaires also experience higher social mobility, at least in the short run. This being said, a logical and oppositional connection between inequality and mobility can be seen especially from the self-made subsample. Thus, I was able to add some empirical results to the discussion on the drivers of wealth inequality. Despite these findings that are in line with the theory, the data shows weak significance in favour of a Pareto distribution. This is problematic as the analysis of wealth inequality is based on the assumption of Pareto distributed data. Both estimators applied perform poorly in this context. OLS does not seem to be appropriate, to match a Pareto distribution even after adjusting for a lower limit and the rank. Applying ML returns comparatively better results which points to two conclusions: Either the wealth distribution is actually not Paretian and consequently, the ML estimator is misspecified. Alternatively, the data suffers from measurement errors as the individuals have a strong incentive to hide their actual wealth from the public. It follows, that the ML estimator is also biased, since its asymptotic properties are violated. The results that have been found here point to the latter conclusion, since the goodness-of-fit test returns significance too often to completely rule out the Pareto distribution. This is particularly the case for self-made wealth which seems to better obey a power law. Depicting the fit reveals systematic differences between the behaviour of inherited and self-made wealth. These findings should be a motivation for future research to further collect and study the tail behaviour of wealth. Since good quality data on wealth is extremely difficult to find, data mining methods could be applied to improve the quality of existing data, such as *rich lists*. Having said this, it lies within the nature of studying human behaviour that some laws of nature cannot be reproduced to complete satisfaction. Instead it may be handy to accept the results at hand as a sufficient approximation in order to continue to speak of the wealth distribution to be Paretian.

Concerning the results on social mobility, only non-parametric approaches were used. The rank correlation as well as the the trace index find that self-made billionaires experience higher social mobility than billionaires who obtained their fortunes from inheritance. The results from the trace index are less consistent and a look at the transition matrices reveals that the two subgroups indeed react differently at certain points in the time series. In addition, it seems that the first and the fifth qunitile exhibit very little mobility. It should however be noted, that billionaires whose fortunes drop below the threshold of one billion USD drop out of the list, which distort the results. Finally, no long-run dynamics could be identified. The time line exhibits too little variation to successfully measure the development of long-run mobility compared to mobility within each of the observed years. More elaborated approaches are needed to further study mobility. In order to find these, further research must be conducted.

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A Figures

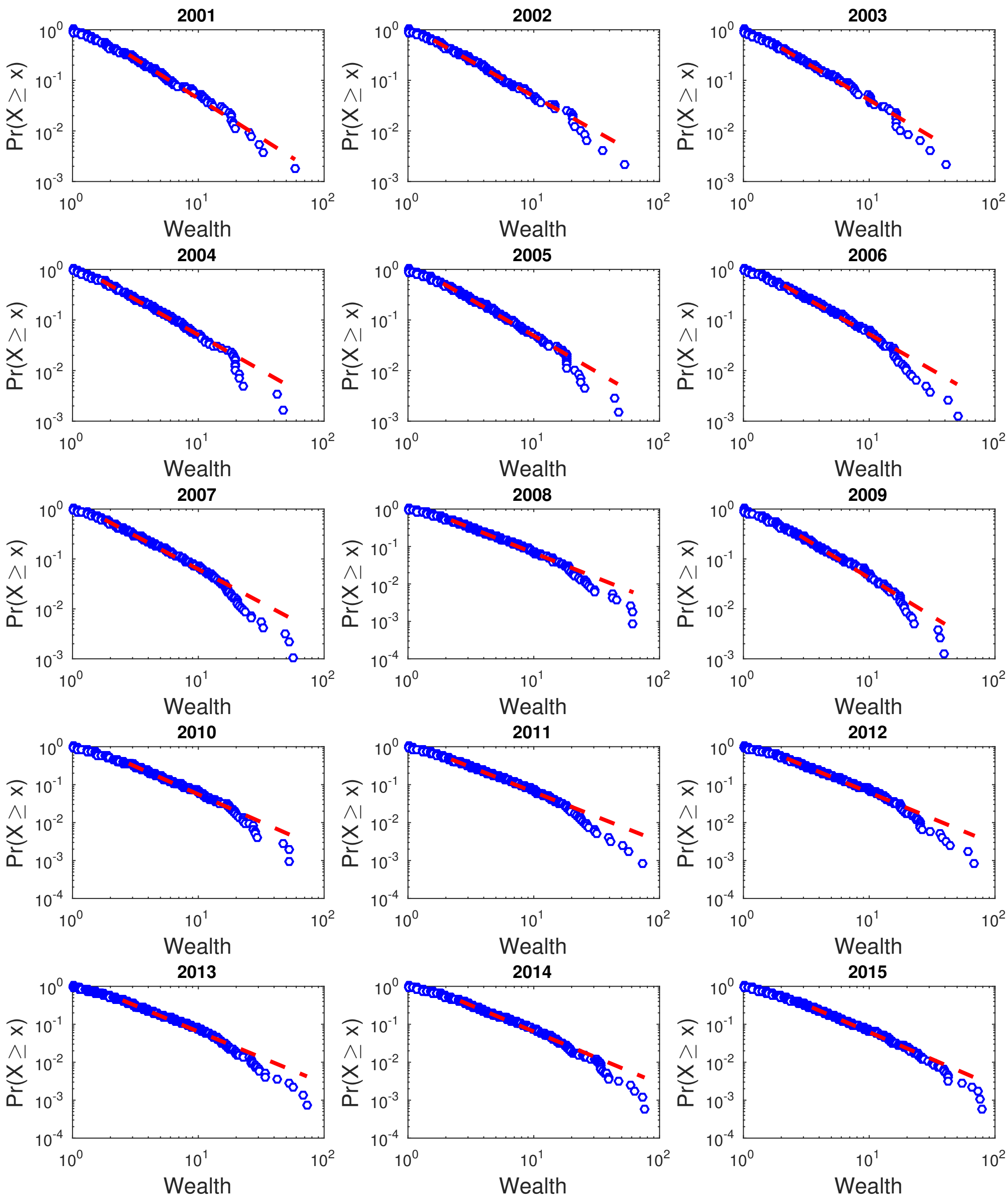

Figure 11: CCDF's and their maximum likelihood power-law fits for total wealth in billion USD for the years 2001 to 2015. Blue dots project the CCDF of the wealth variable on a log log scale. The red dashed line shows the fit of the estimated power law.

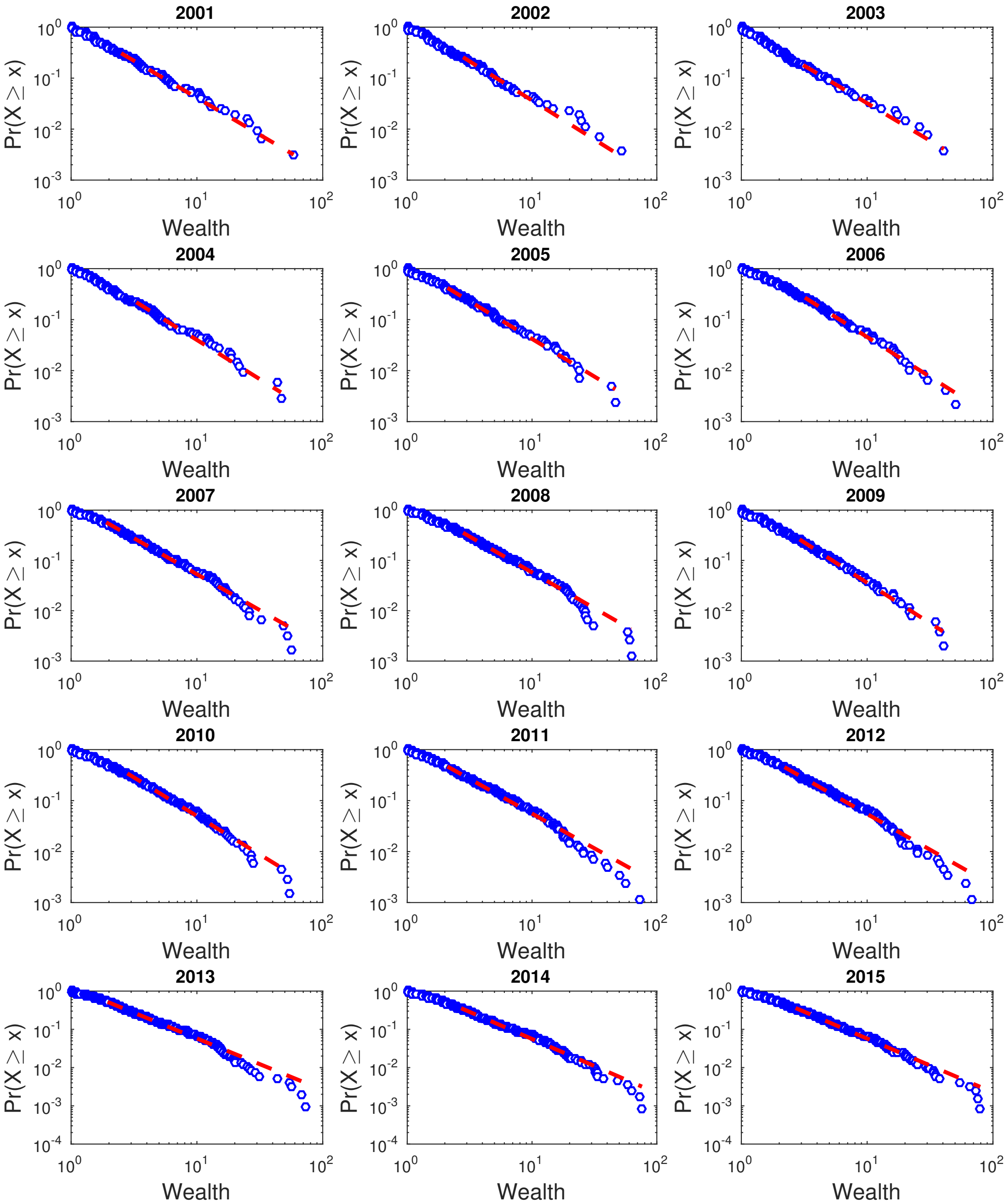

Figure 12: CCDF's and their maximum likelihood power-law fits for self-made wealth in billion USD for the years 2001 to 2015. Blue dots project the CCDF of the wealth variable on a log log scale. The red dashed line shows the fit of the estimated power law.

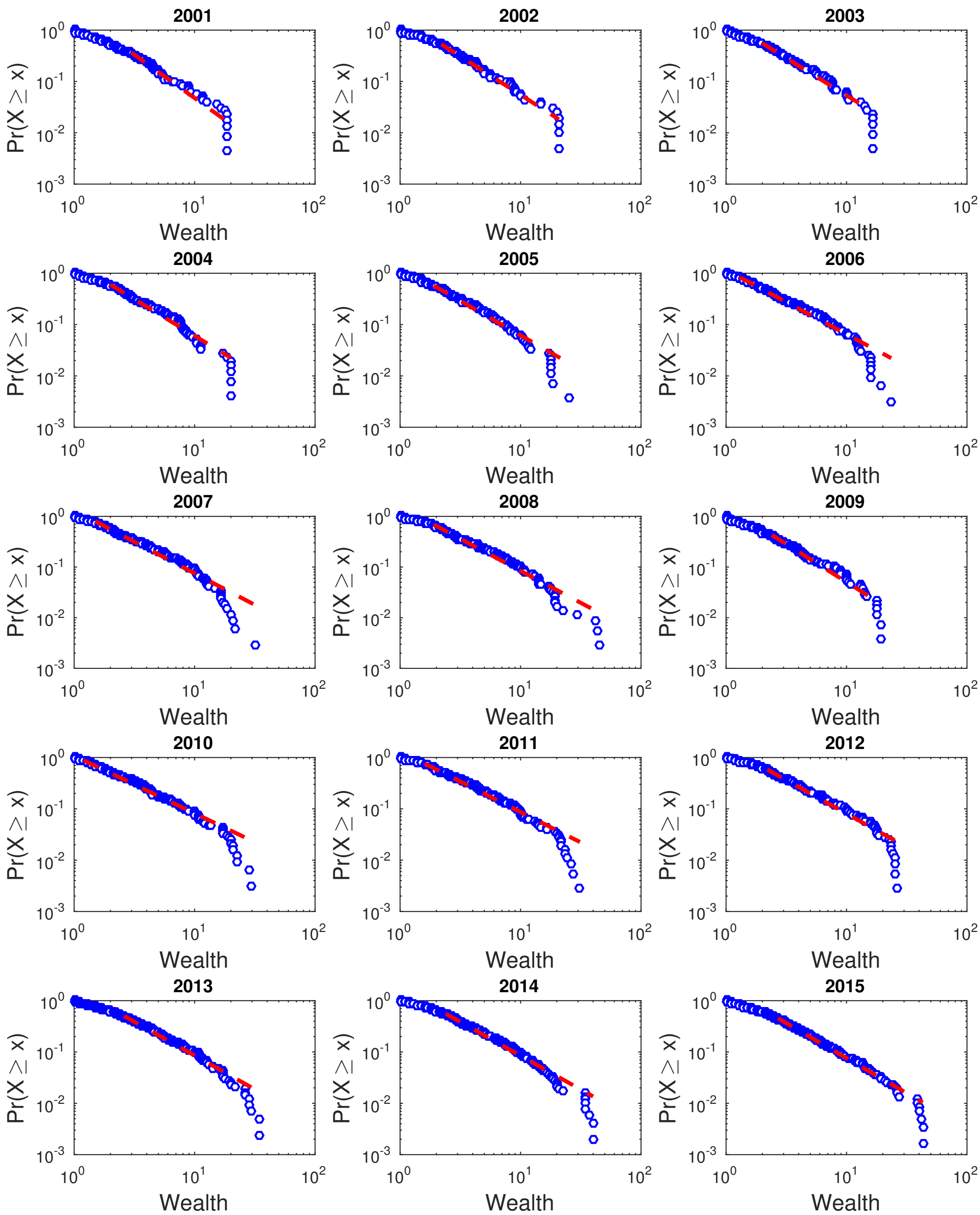

Figure 13: CCDF's and their maximum likelihood power-law fits for inherited wealth in billion USD for the years 2001 to 2015. Blue dots project the CCDF of the wealth variable on a log log scale. The red dashed line shows the fit of the estimated power law.

B Tables

variable name	description
year	year of Forbes list
name	name of individual or family on the billionaires list
rank	rank of individual on the billionaires list, by year
citizenship	billionaire country of citizenship
countrycode	3-digit ISO country code, which corresponds to billionaire's citizenship
networthusbillion	net worth of billionaire, current US dollars
age	billionaire age
gender	variable that is 0 for male billionaires, 1 for female billionaires and 3 for families, couples and jointly reported family members
selfmade	binary variable that is 0 for inherited billionaires and 1 for self-made billionaires
industryaggregates	broad industry categories
industry	industry labels based on Kaplan and Rauh (2013)
generation	categorical variable that divides inherited billionaires by generation
deflator1996	deflator for US economy, using 2009 as base year adjusted to 1996 baseline
realnetworth	real net worth of billionaires, 1996 US dollars
source	Reported source if it was not www.forbes.com

Table 6: Description of variables included in the data base

Industry aggregate	industry	description
Resource related Sectors	Energy, mining and metals	Energy (excluding solar and wind), mining and steel
New Sectors	Computer technology and medical technology	Computer technology, software, medical technology, solar and wind power, pharmaceuticals
Traded Sectors	Consumer goods, non-consumer industrial	Agriculture, consumer goods, shipping and manufacturing
Non-traded Sectors	Retail/restaurant, media and construction	Retail, entertainment, media, telecommunications, construction, restaurants and other service industries
Financial Sectors	Money management, venture capital, hedge funds, private equity/leveraged buyout, real estate and diversified/financial	Banking, insurance, hedge funds, private equity, venture capital, investments, diversified wealth and real estate
Other Sectors	Other	Education, engineering, infrastructure, sports team ownership, unidentified diversified wealth

Table 7: Industry decomposition

	total wealth			self-made wealth			inherited wealth		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	obs.	ρ	$\hat{M}$	obs.	ρ	$\hat{M}$	obs.	ρ	$\hat{M}$
2002	430	0.870	0.465	248	0.822	0.470	182	0.920	0.457
2003	394	0.888	0.523	227	0.859	0.591	167	0.914	0.452
2004	460	0.875	0.538	256	0.849	0.532	204	0.893	0.556
2005	540	0.891	0.453	313	0.859	0.468	227	0.934	0.438
2006	647	0.888	0.418	386	0.892	0.449	261	0.888	0.371
2007	744	0.898	0.456	463	0.896	0.464	281	0.900	0.446
2008	879	0.850	0.474	573	0.837	0.468	306	0.867	0.485
2009	751	0.801	0.605	490	0.771	0.614	261	0.857	0.571
2010	749	0.863	0.531	492	0.829	0.518	257	0.923	0.549
2011	945	0.916	0.417	645	0.910	0.393	300	0.924	0.475
2012	1072	0.922	0.388	751	0.913	0.408	321	0.937	0.339
2013	1152	0.913	0.376	816	0.907	0.375	336	0.925	0.375
2014	1251	0.925	0.359	893	0.908	0.368	358	0.952	0.318
2015	1457	0.912	0.414	1003	0.903	0.403	454	0.926	0.437

Table 8: Results of the rank correlation and the trace index, for the log of total wealth, self-made wealth and inherited wealth by year pairs from 2001/2002 to 2014/2015. All results for the rank correlation in columns (2), (5) and (8) are significant at the 5% level or lower.

			2002			
2001	**1**	**2**	**3**	**4**	**5**	
1	**0.884**	**0.116**	**0.000**	**0.000**	**0.000**	**1.000**
inh.	0.891	0.109	0.000	0.000	0.000	1.000
self.	0.875	0.125	0.000	0.000	0.000	1.000
2	**0.081**	**0.640**	**0.233**	**0.023**	**0.023**	**1.000**
inh.	0.068	0.636	0.250	0.023	0.023	1.000
self.	0.095	0.643	0.214	0.024	0.024	1.000
3	**0.000**	**0.163**	**0.523**	**0.244**	**0.070**	**1.000**
inh.	0.000	0.139	0.500	0.306	0.056	1.000
self.	0.000	0.180	0.540	0.200	0.080	1.000
4	**0.012**	**0.070**	**0.198**	**0.453**	**0.267**	**1.000**
inh.	0.000	0.125	0.292	0.458	0.125	1.000
self.	0.016	0.048	0.161	0.452	0.323	1.000
5	**0.023**	**0.012**	**0.047**	**0.279**	**0.640**	**1.000**
inh.	0.000	0.031	0.063	0.219	0.688	1.000
self.	0.037	0.000	0.037	0.315	0.611	1.000

			2003			
2002	**1**	**2**	**3**	**4**	**5**	
1	**0.833**	**0.154**	**0.000**	**0.013**	**0.000**	**1.000**
inh.	0.864	0.114	0.000	0.023	0.000	1.000
self.	0.794	0.206	0.000	0.000	0.000	1.000
2	**0.169**	**0.532**	**0.234**	**0.052**	**0.013**	**1.000**
inh.	0.128	0.692	0.154	0.026	0.000	1.000
self.	0.211	0.368	0.316	0.079	0.026	1.000
3	**0.012**	**0.136**	**0.506**	**0.235**	**0.111**	**1.000**
inh.	0.000	0.212	0.606	0.121	0.061	1.000
self.	0.021	0.083	0.438	0.313	0.146	1.000
4	**0.000**	**0.048**	**0.371**	**0.371**	**0.210**	**1.000**
inh.	0.000	0.045	0.273	0.409	0.273	1.000
self.	0.000	0.050	0.425	0.350	0.175	1.000
5	**0.000**	**0.021**	**0.031**	**0.281**	**0.667**	**1.000**
inh.	0.000	0.034	0.069	0.276	0.621	1.000
self.	0.000	0.015	0.015	0.284	0.687	1.000

			2004			
2003	**1**	**2**	**3**	**4**	**5**	460
1	**0.822**	**0.156**	**0.011**	**0.000**	**0.011**	**1.000**
inh.	0.827	0.135	0.019	0.000	0.019	1.000
self.	0.816	0.184	0.000	0.000	0.000	1.000
2	**0.138**	**0.564**	**0.277**	**0.011**	**0.011**	**1.000**
inh.	0.118	0.588	0.294	0.000	0.000	1.000
self.	0.163	0.535	0.256	0.023	0.023	1.000
3	**0.036**	**0.169**	**0.482**	**0.265**	**0.048**	**1.000**
inh.	0.030	0.182	0.455	0.212	0.121	1.000
self.	0.040	0.160	0.500	0.300	0.000	1.000
4	**0.015**	**0.075**	**0.254**	**0.418**	**0.239**	**1.000**
inh.	0.000	0.136	0.409	0.364	0.091	1.000
self.	0.022	0.044	0.178	0.444	0.311	1.000
5	**0.000**	**0.016**	**0.095**	**0.325**	**0.563**	**1.000**
inh.	0.000	0.022	0.109	0.326	0.543	1.000
self.	0.000	0.013	0.088	0.325	0.575	1.000

			2005			
2004	**1**	**2**	**3**	**4**	**5**	
1	**0.870**	**0.111**	**0.009**	**0.009**	**0.000**	**1.000**
inh.	0.912	0.070	0.000	0.018	0.000	1.000
self.	0.824	0.157	0.020	0.000	0.000	1.000
2	**0.084**	**0.654**	**0.243**	**0.019**	**0.000**	**1.000**
inh.	0.018	0.636	0.345	0.000	0.000	1.000
self.	0.154	0.673	0.135	0.038	0.000	1.000
3	**0.010**	**0.149**	**0.396**	**0.376**	**0.069**	**1.000**
inh.	0.000	0.158	0.500	0.263	0.079	1.000
self.	0.016	0.143	0.333	0.444	0.063	1.000
4	**0.011**	**0.056**	**0.180**	**0.562**	**0.191**	**1.000**
inh.	0.032	0.032	0.161	0.548	0.226	1.000
self.	0.000	0.069	0.190	0.569	0.172	1.000
5	**0.015**	**0.000**	**0.044**	**0.237**	**0.704**	**1.000**
inh.	0.000	0.000	0.000	0.348	0.652	1.000
self.	0.022	0.000	0.067	0.180	0.730	1.000

			2006			
2005	**1**	**2**	**3**	**4**	**5**	
1	**0.823**	**0.131**	**0.015**	**0.023**	**0.008**	**1.000**
inh.	0.839	0.081	0.016	0.048	0.016	1.000
self.	0.809	0.176	0.015	0.000	0.000	1.000
2	**0.138**	**0.698**	**0.147**	**0.009**	**0.009**	**1.000**
inh.	0.077	0.673	0.212	0.019	0.019	1.000
self.	0.188	0.719	0.094	0.000	0.000	1.000
3	**0.040**	**0.151**	**0.603**	**0.183**	**0.024**	**1.000**
inh.	0.000	0.111	0.711	0.133	0.044	1.000
self.	0.062	0.173	0.543	0.210	0.012	1.000
4	**0.009**	**0.070**	**0.193**	**0.500**	**0.228**	**1.000**
inh.	0.000	0.020	0.140	0.580	0.260	1.000
self.	0.016	0.109	0.234	0.438	0.203	1.000
5	**0.000**	**0.025**	**0.081**	**0.193**	**0.702**	**1.000**
inh.	0.000	0.019	0.058	0.212	0.712	1.000
self.	0.000	0.028	0.092	0.183	0.697	1.000

			2007			
2006	**1**	**2**	**3**	**4**	**5**	
1	**0.877**	**0.110**	**0.007**	**0.007**	**0.000**	**1.000**
inh.	0.905	0.063	0.016	0.016	0.000	1.000
self.	0.855	0.145	0.000	0.000	0.000	1.000
2	**0.148**	**0.644**	**0.178**	**0.030**	**0.000**	**1.000**
inh.	0.184	0.592	0.163	0.061	0.000	1.000
self.	0.128	0.674	0.186	0.012	0.000	1.000
3	**0.007**	**0.230**	**0.507**	**0.209**	**0.047**	**1.000**
inh.	0.000	0.189	0.491	0.283	0.038	1.000
self.	0.011	0.253	0.516	0.168	0.053	1.000
4	**0.000**	**0.053**	**0.233**	**0.440**	**0.273**	**1.000**
inh.	0.000	0.048	0.222	0.492	0.238	1.000
self.	0.000	0.057	0.241	0.402	0.299	1.000
5	**0.000**	**0.012**	**0.073**	**0.206**	**0.709**	**1.000**
inh.	0.000	0.000	0.075	0.189	0.736	1.000
self.	0.000	0.018	0.071	0.214	0.696	1.000

			2008			
2007	**1**	**2**	**3**	**4**	**5**	
1	**0.843**	**0.145**	**0.006**	**0.000**	**0.006**	**1.000**
inh.	0.797	0.189	0.014	0.000	0.000	1.000
self.	0.878	0.112	0.000	0.000	0.010	1.000
2	**0.092**	**0.620**	**0.252**	**0.031**	**0.006**	**1.000**
inh.	0.113	0.585	0.226	0.057	0.019	1.000
self.	0.082	0.636	0.264	0.018	0.000	1.000
3	**0.016**	**0.164**	**0.503**	**0.219**	**0.098**	**1.000**
inh.	0.015	0.031	0.615	0.292	0.046	1.000
self.	0.017	0.237	0.441	0.178	0.127	1.000
4	**0.012**	**0.102**	**0.199**	**0.476**	**0.211**	**1.000**
inh.	0.017	0.150	0.250	0.433	0.150	1.000
self.	0.009	0.075	0.170	0.500	0.245	1.000
5	**0.005**	**0.031**	**0.062**	**0.241**	**0.662**	**1.000**
inh.	0.000	0.000	0.111	0.259	0.630	1.000
self.	0.007	0.043	0.043	0.234	0.674	1.000

			2009			
2008	**1**	**2**	**3**	**4**	**5**	
1	**0.780**	**0.133**	**0.053**	**0.007**	**0.027**	**1.000**
inh.	0.841	0.127	0.016	0.000	0.016	1.000
self.	0.736	0.138	0.080	0.011	0.034	1.000
2	**0.197**	**0.547**	**0.139**	**0.066**	**0.051**	**1.000**
inh.	0.217	0.587	0.130	0.022	0.043	1.000
self.	0.187	0.527	0.143	0.088	0.055	1.000
3	**0.031**	**0.276**	**0.319**	**0.209**	**0.166**	**1.000**
inh.	0.019	0.308	0.346	0.192	0.135	1.000
self.	0.036	0.261	0.306	0.216	0.180	1.000
4	**0.000**	**0.027**	**0.383**	**0.315**	**0.275**	**1.000**
inh.	0.000	0.047	0.375	0.219	0.359	1.000
self.	0.000	0.012	0.388	0.388	0.212	1.000
5	**0.000**	**0.033**	**0.033**	**0.316**	**0.618**	**1.000**
inh.	0.000	0.028	0.028	0.222	0.722	1.000
self.	0.000	0.034	0.034	0.345	0.586	1.000

Table 9: Transition matrices of log wealth position between year pairs 2001 - 2009. Each element of the matrix indicates the probability that a billionaire belongs to the qth quintile of the distribution in the following year, given that they belong to the qth quintile of the distribution from the previous year. Along one row the entries sum to one. The qintiles are then separated according to self-made and inherited billionaires which is presented below the bold entries for total log wealth.

			2010			
2009	**1**	**2**	**3**	**4**	**5**	
1	**0.810**	**0.184**	**0.007**	**0.000**	**0.000**	**1.000**
inh.	0.750	0.250	0.000	0.000	0.000	1.000
self.	0.855	0.133	0.012	0.000	0.000	1.000
2	**0.132**	**0.550**	**0.291**	**0.026**	**0.000**	**1.000**
inh.	0.115	0.538	0.327	0.019	0.000	1.000
self.	0.141	0.556	0.273	0.030	0.000	1.000
3	**0.029**	**0.196**	**0.420**	**0.304**	**0.051**	**1.000**
inh.	0.000	0.167	0.333	0.438	0.063	1.000
self.	0.044	0.211	0.467	0.233	0.044	1.000
4	**0.014**	**0.049**	**0.153**	**0.444**	**0.340**	**1.000**
inh.	0.000	0.056	0.194	0.444	0.306	1.000
self.	0.019	0.046	0.139	0.444	0.352	1.000
5	**0.012**	**0.030**	**0.107**	**0.201**	**0.651**	**1.000**
inh.	0.000	0.000	0.053	0.211	0.737	1.000
self.	0.018	0.045	0.134	0.196	0.607	1.000

			2011			
2010	**1**	**2**	**3**	**4**	**5**	
1	**0.872**	**0.122**	**0.005**	**0.000**	**0.000**	**1.000**
inh.	0.866	0.134	0.000	0.000	0.000	1.000
self.	0.876	0.116	0.008	0.000	0.000	1.000
2	**0.104**	**0.699**	**0.162**	**0.029**	**0.006**	**1.000**
inh.	0.085	0.661	0.237	0.017	0.000	1.000
self.	0.114	0.719	0.123	0.035	0.009	1.000
3	**0.035**	**0.139**	**0.515**	**0.262**	**0.050**	**1.000**
inh.	0.068	0.136	0.373	0.356	0.068	1.000
self.	0.021	0.140	0.573	0.224	0.042	1.000
4	**0.000**	**0.038**	**0.204**	**0.489**	**0.269**	**1.000**
inh.	0.000	0.048	0.242	0.484	0.226	1.000
self.	0.000	0.032	0.185	0.492	0.290	1.000
5	**0.000**	**0.005**	**0.046**	**0.194**	**0.755**	**1.000**
inh.	0.000	0.000	0.019	0.264	0.717	1.000
self.	0.000	0.007	0.056	0.168	0.769	1.000

			2012			
2011	**1**	**2**	**3**	**4**	**5**	
1	**0.896**	**0.085**	**0.014**	**0.000**	**0.005**	**1.000**
inh.	0.855	0.118	0.026	0.000	0.000	1.000
self.	0.919	0.066	0.007	0.000	0.007	1.000
2	**0.083**	**0.685**	**0.204**	**0.028**	**0.000**	**1.000**
inh.	0.068	0.743	0.189	0.000	0.000	1.000
self.	0.092	0.655	0.211	0.042	0.000	1.000
3	**0.005**	**0.172**	**0.586**	**0.192**	**0.044**	**1.000**
inh.	0.000	0.062	0.708	0.185	0.046	1.000
self.	0.007	0.225	0.529	0.196	0.043	1.000
4	**0.005**	**0.029**	**0.190**	**0.533**	**0.243**	**1.000**
inh.	0.000	0.019	0.192	0.596	0.192	1.000
self.	0.006	0.032	0.190	0.513	0.259	1.000
5	**0.004**	**0.004**	**0.043**	**0.199**	**0.749**	**1.000**
inh.	0.000	0.000	0.056	0.204	0.741	1.000
self.	0.006	0.006	0.040	0.198	0.751	1.000

			2013			
2012	**1**	**2**	**3**	**4**	**5**	
1	**0.916**	**0.079**	**0.004**	**0.000**	**0.000**	**1.000**
inh.	0.951	0.049	0.000	0.000	0.000	1.000
self.	0.897	0.096	0.007	0.000	0.000	1.000
2	**0.094**	**0.673**	**0.179**	**0.036**	**0.018**	**1.000**
inh.	0.129	0.686	0.143	0.000	0.043	1.000
self.	0.078	0.667	0.196	0.052	0.007	1.000
3	**0.009**	**0.191**	**0.595**	**0.167**	**0.037**	**1.000**
inh.	0.000	0.268	0.535	0.155	0.042	1.000
self.	0.014	0.153	0.625	0.174	0.035	1.000
4	**0.000**	**0.042**	**0.234**	**0.603**	**0.121**	**1.000**
inh.	0.000	0.040	0.200	0.640	0.120	1.000
self.	0.000	0.043	0.244	0.591	0.122	1.000
5	**0.000**	**0.015**	**0.029**	**0.245**	**0.711**	**1.000**
inh.	0.000	0.000	0.047	0.266	0.688	1.000
self.	0.000	0.019	0.024	0.239	0.718	1.000

			2014			
2013	**1**	**2**	**3**	**4**	**5**	
1	**0.911**	**0.069**	**0.016**	**0.004**	**0.000**	**1.000**
inh.	0.891	0.089	0.020	0.000	0.000	1.000
self.	0.925	0.055	0.014	0.007	0.000	1.000
2	**0.093**	**0.713**	**0.169**	**0.021**	**0.004**	**1.000**
inh.	0.093	0.680	0.213	0.013	0.000	1.000
self.	0.093	0.728	0.148	0.025	0.006	1.000
3	**0.008**	**0.163**	**0.613**	**0.188**	**0.029**	**1.000**
inh.	0.016	0.129	0.677	0.161	0.016	1.000
self.	0.006	0.174	0.590	0.197	0.034	1.000
4	**0.000**	**0.011**	**0.195**	**0.592**	**0.202**	**1.000**
inh.	0.000	0.000	0.169	0.678	0.153	1.000
self.	0.000	0.014	0.202	0.568	0.216	1.000
5	**0.000**	**0.008**	**0.024**	**0.231**	**0.737**	**1.000**
inh.	0.000	0.000	0.033	0.164	0.803	1.000
self.	0.000	0.010	0.021	0.253	0.716	1.000

			2015			
2014	**1**	**2**	**3**	**4**	**5**	
1	**0.892**	**0.101**	**0.007**	**0.000**	**0.000**	**1.000**
inh.	0.894	0.106	0.000	0.000	0.000	1.000
self.	0.890	0.098	0.012	0.000	0.000	1.000
2	**0.095**	**0.670**	**0.204**	**0.017**	**0.014**	**1.000**
inh.	0.077	0.625	0.260	0.019	0.019	1.000
self.	0.105	0.695	0.174	0.016	0.011	1.000
3	**0.021**	**0.146**	**0.582**	**0.197**	**0.054**	**1.000**
inh.	0.014	0.216	0.581	0.162	0.027	1.000
self.	0.024	0.115	0.582	0.212	0.067	1.000
4	**0.000**	**0.047**	**0.267**	**0.437**	**0.248**	**1.000**
inh.	0.000	0.023	0.233	0.360	0.384	1.000
self.	0.000	0.056	0.280	0.466	0.198	1.000
5	**0.003**	**0.006**	**0.056**	**0.169**	**0.766**	**1.000**
inh.	0.000	0.013	0.065	0.130	0.792	1.000
self.	0.004	0.004	0.053	0.181	0.757	1.000

Table 10: Transition matrices of log wealth position between year pairs 2009 to 2015. Each element of the matrix indicates the probability that a billionaire belongs to the qth quintile of the distribution in the following year, given that they belong to the qth quintile of the distribution from the previous year. Along one row the entries sum to one. The qintiles are then separated according to self-made and inherited billionaires which is presented below the bold entries for total log wealth.