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Global wealth inequality on WID.world: estimates and imputations

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WORLD INEQUALITY LAB

WID.WORLD
THE SOURCE FOR GLOBAL INEQUALITY DATA

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Abstract

This technical note describes the imputation procedures used to construct a global wealth inequality estimates on the World Inequality Database and the sources used. Estimates are available on www.wid.world.

1 Imputation of Wealth Aggregates

We first describe the procedure followed to build aggregate wealth series. Our benchmark estimates are based on Blanchet, Bauluz, et al., 2021. These series provide wealth aggregates for a very large set of countries, based on official national accounts, International Monetary Fund data, BIS data on Locational Banking Statistics, OECD Pension Wealth data, Foreign Asset Liabilities and other sources. In order to provide wealth series for the world as a whole, i.e. every country in the world, we rely on a series of imputations.

1.1 Clustering of Countries

For some imputation purposes, we will create groups (clusters) of countries with similar characteristics. We group countries into four clusters. To construct these clusters, we take all of the World Bank's WDI indicators that are comparable across countries (i.e. we exclude indexes or indicators in local currency) and that are available for more than 75% of countries. Then we compute pairwise distances between countries based on the average Euclidean distance of each country's rank for each WDI indicators available for the pair of countries. We perform a k-mean clustering into four groups based on this distances. This gives us the following four country groups:

- Argentina, Australia, Austria, Belarus, Belgium, Bulgaria, Canada, Channel Islands, Chile, China, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong SAR China, Hungary, Iceland, Ireland, Israel, Italy, Japan, South Korea, Latvia, Lithuania, Luxembourg, Netherlands, New Zealand, Norway, Poland, Portugal, Puerto Rico, Romania, Russia, Singapore, Slovakia, Slovenia, Spain, Sweden, Switzerland, Ukraine, United Arab Emirates, United Kingdom, United States
- Albania, Algeria, Armenia, Azerbaijan, Bahrain, Bolivia, Bosnia & Herzegovina, Botswana, Brazil, Colombia, Costa Rica, Cuba, Dominican Republic, Ecuador, Egypt, El Salvador, Fiji, Gabon, Georgia, Guatemala, Guyana, Honduras, Indonesia, Iran, Iraq, Jamaica,

Jordan, Kazakhstan, North Korea, Kuwait, Kyrgyzstan, Lebanon, Libya, Malaysia, Mauritius, Mexico, Moldova, Mongolia, Morocco, Namibia, Nicaragua, North Macedonia, Oman, Panama, Paraguay, Peru, Philippines, Qatar, Saudi Arabia, Serbia, South Africa, Sri Lanka, Suriname, Syria, Tajikistan, Thailand, Trinidad & Tobago, Tunisia, Turkey, Turkmenistan, Uruguay, Uzbekistan, Venezuela, Vietnam, Palestinian Territories, Kosovo

- Afghanistan, Angola, Bangladesh, Benin, Bhutan, Burkina Faso, Burundi, Cambodia, Cameroon, Central African Republic, Chad, Comoros, Congo - Kinshasa, Congo - Brazzaville, Côte d'Ivoire, Djibouti, Equatorial Guinea, Eritrea, Eswatini, Ethiopia, Gambia, Ghana, Guinea, Guinea-Bissau, Haiti, India, Kenya, Laos, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mozambique, Myanmar (Burma), Nepal, Niger, Nigeria, Pakistan, Papua New Guinea, Rwanda, São Tomé & Príncipe, Senegal, Sierra Leone, Solomon Islands, Somalia, South Sudan, Sudan, Tanzania, Timor-Leste, Togo, Uganda, Vanuatu, Yemen, Zambia, Zimbabwe
- American Samoa, Andorra, Antigua & Barbuda, Aruba, Bahamas, Barbados, Belize, Bermuda, British Virgin Islands, Brunei, Cape Verde, Cayman Islands, Curaçao, Dominica, Faroe Islands, French Polynesia, Gibraltar, Greenland, Grenada, Guam, Isle of Man, Kiribati, Liechtenstein, Macao SAR China, Maldives, Malta, Marshall Islands, Micronesia (Federated States of), Monaco, Montenegro, Nauru, New Caledonia, Northern Mariana Islands, Palau, Samoa, San Marino, Seychelles, Sint Maarten, St. Kitts & Nevis, St. Lucia, Saint Martin (French part), St. Vincent & Grenadines, Tonga, Turks & Caicos Islands, Tuvalu, U.S. Virgin Islands, Anguilla, Montserrat, Taiwan

1.2 Notations

A balance sheet is a set of k variables, indexed by $j \in \{1, \ldots, k\}$. There is one balance sheet by country $i \in \{1, \ldots, n\}$, and by year $t \in \{t_{\min}, \ldots, t_{\max}\}$. Let $T = t_{\max} - t_{\min} + 1$. Overall, we have $N = n \times k \times T$ variables. We will use y_{itj} to denote the value of variable j in year t and in country i.

The vector $\boldsymbol{y}_{it} = (y_{it1}, \ldots, y_{itk})'$ contains all k variables for country i in year t. The vector $\boldsymbol{y}_i = (\boldsymbol{y}'_{it_{\min}}, \ldots, \boldsymbol{y}'_{it_{\max}})'$ contains all k variables for all years for country i. Finally, the vector $\boldsymbol{y} = (\boldsymbol{y}'_1, \ldots, \boldsymbol{y}'_n)'$ contains all variables for all years and all countries.

The components of $\boldsymbol{y}$ are not linearly independent. Within a given country and a given year, the variables are related to one another by a set of m accounting identities. Therefore, for each country i and each year t, we have:

$$\mathbf{M}\boldsymbol{y}_{it} = \mathbf{0} \tag{1}$$

where $\mathbf{M}$ is $m \times k$ matrix, filled with the values $\{0, 1, -1\}$ whose rows correspond to accounting identities.

1.3 Estimation of Average Wealth Trends

We start by nonparametrically estimating average trend for every component of wealth within clusters of countries.

Let c be the number of country clusters. For all $i \in \{1, \ldots, n\}$, let $c_i \in \{1, \ldots, c\}$ be the cluster to which country i belongs. For the central prediction, we run the following linear regression:

$$y_{itj} = \beta_{0tj} + \beta_{c_i tj} + e_{itj} \tag{2}$$

where e_{itj} is the prediction error. In itself, the above regression is severely overparametrized. The key to our approach will be to regularize the parameters $\beta_{0tj}, \beta_{1tj}, \dots, \beta_{ctj}$ towards solutions with desirable properties. This is a flexible framework that allows us to not impose strong parametric assumptions (such as linear trends) while still getting robust estimates.

We will introduced three regularization terms:

- First, we penalize the value of the second derivative for every trend. This favors smooth and linear evolutions. We penalize the value:

$$\sum_{j,t} w_j(\beta_{0,t-1,j} - 2\beta_{0,t,j} + \beta_{0,t+1,j})^2 + \sum_{c_i,j,t} w_j(\beta_{c_i,t-1,j} - 2\beta_{c_i,t,j} + \beta_{c_i,t+1,j})^2$$

- Second, we penalize differences in trends between the common trend (β_{0tj}) and the cluster-specific trends ($\beta_{c_i tj}$). This favors similar trends across regions:

$$\sum_{i,t,j} w_j(\beta_{0tj} - \beta_{c_i tj})^2$$

- Third, we penalized the average value fo country-specific trends: this favors similar levels wealth across country clusters:

$$\sum_{i,j} w_j \left(\frac{1}{T} \sum_t \beta_{c_i tj} \right)^2$$

In each case w_j is a scaling factor inversely proportional to the average value of the variable. We determine the adequate degree of regularization by running a leave-one-country cross-validation.

We then run the regularized regression (2) with the appropriate equality constraints on the parameters (to ensure that accounting equations are satisfied) and also inequality constraints (to ensure that components that should be nonnegative are nonnegative). We solve that problem using the software OSQP (Stellato, Banjac, Goulart, Bemporad, et al., 2020; Stellato, Banjac, Goulart, and Boyd, 2019). The wealth levels are always expressed as a fraction of net national income.

1.4 Imputation of Country-Specific Values

We use the predictions from the regression above to fill in missing wealth components whenever they arise. For countries with no data, we use the predictions without any modification.

For countries where the balance sheets are partially observed, we combine the observed data with the imputations as follows. First, we use the trends from the predictions to extend to the entire period of interest the series that are only observed for part of the period. For components that are not observed at all, we use the impute the prediction directly. Then, we adjust all the imputed values so that they satisfy all the accounting identities.

To that end, we solve the following quadratic optimization problem. We minimize the difference between the original imputed values y_{itj} and the adjusted values z_{itj}, with an additional penalization for the first difference of adjusted values $z_{itj} - z_{i,t-1,j}$, to make sure that resulting series are sufficiently smooth. That is:

$$\forall i \qquad \min_{z_{itj}} \sum_{t,j} w_j (y_{itj} - z_{itj})^2 + w_j \rho (z_{itj} - z_{i,t-1,j})^2$$

subject to accounting identities constraints and nonnegativity constraints. For our estimation, we set $\rho = 10\ 000$. We solve that problem using the software OSQP (Stellato, Banjac, Goulart, Bemporad, et al., 2020; Stellato, Banjac, Goulart, and Boyd, 2019). To limit rare problems where the imputed wealth is problematically small, we winsorize the bottom 10% of values by components.

1.5 2020 public wealth correction

2020 benchmark estimates from Blanchet, Bauluz, et al., 2021 for public wealth aggregates tend to underestimate the drop incurred by massive increases in government debt during the global pandemic. We thus use IMF World Economic Outlook 2020 estimates of government debt to correct public wealth in each available country. These estimates are more up to date than those available in our benchmark series for 2020. If the ratio of our measure of government debt to the IMF's gross government debt measure is pretty stable over time, we divide the 2020 IMF value by the 2015-2019 average ratio. If a clear trend is present in the ratio of the two measures, we predict the 2020 ratio with a simple linear regression on years 2015-2019. We then add to public wealth the difference between our initial debt estimates and the correction using IMF data, which in most cases is much higher, resulting in a drop in public wealth levels. In parallel, the same amount is deducted from private wealth.

1.6 2021 aggregate wealth estimation

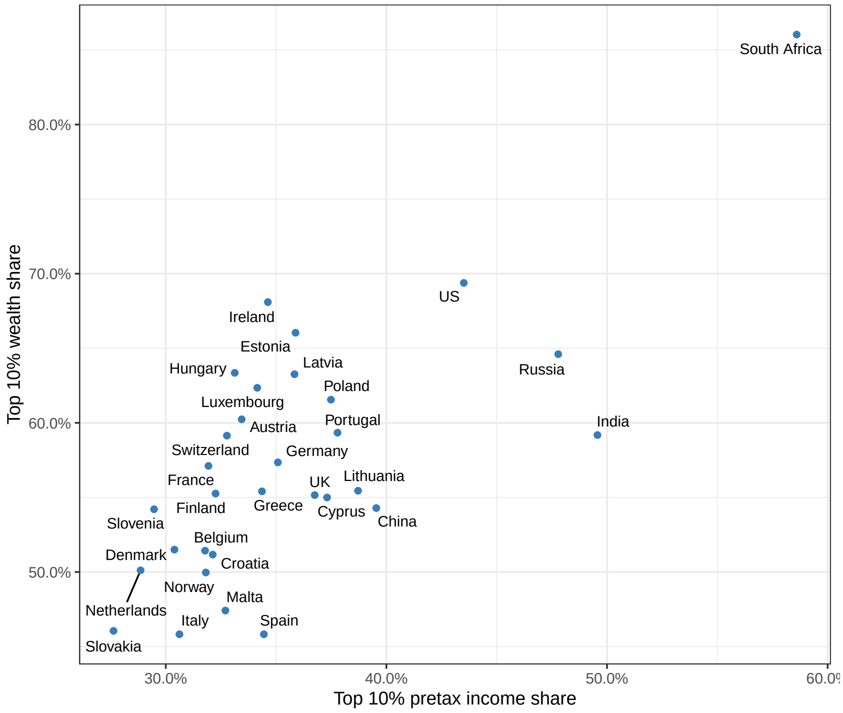
We estimate 2021 aggregate wealth levels using 2016-2019 growth rates. From available financial quarterly accounts, we observed that aggregate wealth growth between Q1 2021 and Q1 2019 is close to the average annual growth rate of wealth between 2016 and 2019. We therefore estimate Q1 2021 aggregate wealth levels in 2021 using known 2019 values and the estimate average growth rate between 2016 and 2019. These estimations are unsatisfactory and will be improved when more recent balance sheets and quarterly financial accounts are released – but they provide a first plausible aggregate wealth level for 2021 in the absence of better information.

2 Imputation of Wealth Distribution

2.1 Imputation of the Full Distributions

Our raw distributional wealth estimates are based on and on other countries available (Blanchet and Martinez-Toledano, 2021) and on the World Inequality Database as of July

2021. We describe the methodology followed to impute wealth inequality estimates for other countries below. for missing countries below. Our imputation method for the distribution of wealth rests on the observation that wealth inequality is highly correlated with income inequality, as shown in figure 1.



Source: Author's estimates based on the World Inequality Database. *Note:* Each country's data point refers to the average top 10% share over all the years for which both income and wealth inequality are observed.

Figure 1: Correlation Between Wealth and Income Inequality

We estimate the distribution of wealth in a given country i using a weighted average of the wealth distribution of other countries for which it is observed. To exploit the correlation of figure 1, we give more weight to countries that have a similar level of income inequality.

We first normalize the wealth distribution to one in every country. Then, we calculate a_{itp}, the average normalized wealth of the g-percentile p in country i in year t as:

$$a_{itp} = \frac{\sum_{j,s} \frac{1}{h} K\left(\frac{r_{ti} - r_{jt}}{h}\right) a_{jsp}}{\sum_{j,s} \frac{1}{h} K\left(\frac{r_{it} - r_{js}}{h}\right)}$$

where $r_{js} \in [0, 1]$ is the position of country j in year s in the ranking of all countries and all years in terms of top 10% income share, and where K is a standard gaussian kernel.

The key parameter of that equation is the bandwidth h, which determines the degree of smoothing. We use a leave-one-country-out cross-validation procedure to determine an optimal bandwidth $h = 0.24$.

2.2 Correction with Forbes Ranking

The set of estimates produced at this stage tend to under estimate the number of billionaires as compared to Forbes data in most countries. In order to recover the number of Forbes billionaires, we rescale the top of the distribution with Forbes data, assuming that aggregate wealth is unchanged and the distribution within the non-billionaire group is unchanged. By doing so we are able to produce series that are consistent with rich lists. In certain countries on WID.world, available estimates already take into account rich lists: in these cases we do not correct the series.

The above method increases the gap between the top of the distribution and the rest, even though the global middle 40% remain relatively unaffected by the changes. Both at the country and the global level, the upward trend of the top 0.001% share is reinforced, with a peak following the Covid-19 global pandemic.

Forbes data

We harmonize historical billionaire sources published by Forbes between 1988 and 2021. We collapse each individual billionaires by country of reference, and exclude those whose country cannot be matched to the WID data. We obtain a dataset with a number of billionaires and their total net wealth in each country between 1988 and 2021.
In our benchmark series, we compute the total net worth of billionaires (before Forbes correction) and the fraction of individuals above 1 billion dollars using cumulative distribution functions and tools available in the gpinter pareto interpolation package[1]. We use the most recent exchange rate and price index available to express all country-series in market exchange rate dollars (or MER euros).

Correction

In most cases, WID.world benchmark series estimate less billionaire wealth than Forbes. In cases where WID.world billionaire wealth is lower than Forbes, we add to the 127th g-percentile of each country the difference between the theoretical and Forbes total wealth of billionaires. We leave WID.world benchmark series unchanged otherwise. In cases where we add the difference between Forbes and WID.world benchmark series, the same amount is subtracted proportionately to each group of the bottom 99.999% to keep aggregate wealth constant and to keep the relative shares inside the rest of the distribution unchanged. In practice, the gap is usually small as compared to the total wealth of the bottom 99.999% and only has very minor impacts on the wealth of these groups.
The exact formula of the correction applied to each bracket average is the following: we first take out the added Forbes worth from the whole distribution.

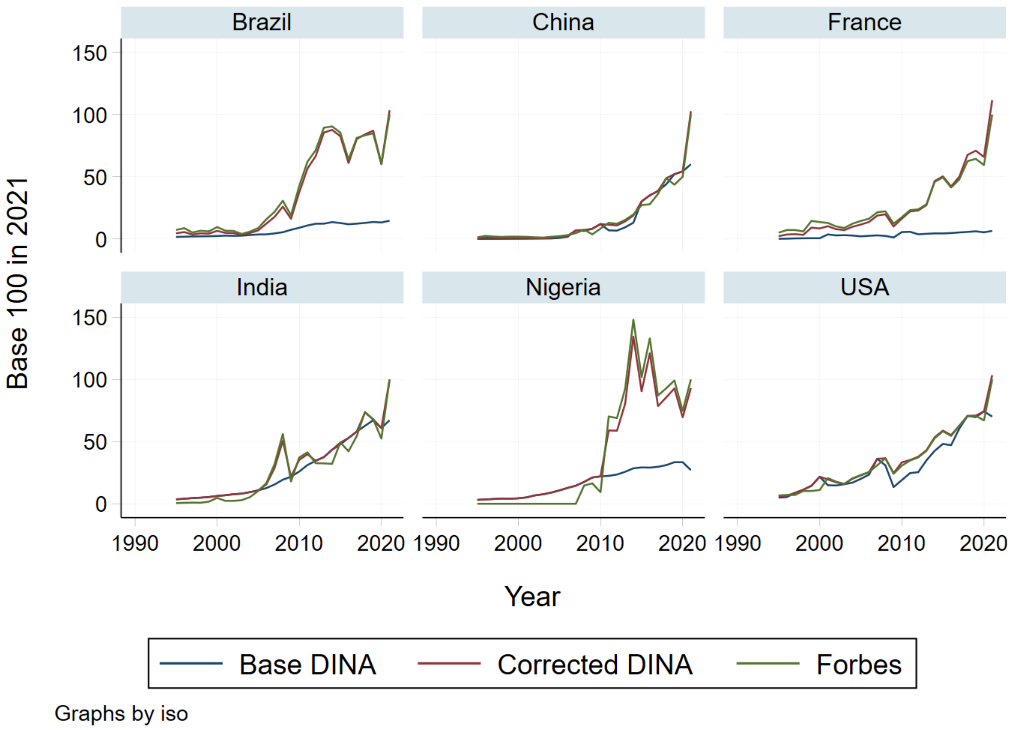
$$a_{corr} = a \times \frac{1 - max(\frac{w_{Forbes} - w_{WID}}{n_{Forbes}}, 0) \times n_{Forbes}}{w_{tot}} \tag{3}$$

Where a is the bracket average of each percentile, w_{Forbes} and w_{WID} are respectively the Forbes and WID estimates of billionaire wealth, n_{Forbes} is the Forbes number of billionaires,

[1] The distributions are fitted using generalized Pareto interpolation, for which an online tool (`https://wid.world/gpinter/`) as well as an eponymous R package have been designed. For details on the procedure see Blanchet, Garbinti, et al., 2018.

and w_{tot} is aggregate wealth in the country. Note that a_{corr} is necessarily smaller than a since we want the correction of the top wealth to be upwards only. We then add the amount of wealth that was subtracted from the distribution back to the 127th g-percentile only:

$$a_{corr} = a_{corr} + max(\frac{w_{Forbes} - w_{WID}}{n_{Forbes}}, 0) \times \frac{n_{forbes}}{pop_{tot}} \quad \text{if} \quad p = 99.999 \tag{4}$$



Source: Author's estimates based on wealth distribution imputations and Forbes historical data.

Figure 2: Wealth of billionaires in selected countries, 1995-2021

From this modified distribution, we compute new shares and bracket averages after fitting them through gpinter again in order to ensure that the general fit of the distribution corresponds to the top correction. The corrected number of billionaires is computed using the same technique as before, multiplying the fraction of individuals beyond the billionaires threshold by country population in each year. Examples of the correction are given in Figure 2. We then aggregate the country series by re-ranking all g-percentiles in a single distribution, which allows us to observe global trends.

Adjustments within the top 0.001%

This first correction yields better approximations of the global worth and number of billionaires, but national and regional figures remain uneven (See columns 3-4 of Table 1). We thus proceed to a second correction, which takes place mostly within the 127th g-percentile instead of adjusting the whole of the distribution of each country. For each country, we compute various thresholds at 1, 10, 100 millions as well as 1, 10 and 100 billions. After computing the top average of wealth at these thresholds, we rescale the total wealth and number of billionaires to match Forbes data.

This shifts wealth from lower brackets to the upper brackets in the case where billionaires were underestimated, while wealth is redistributed to the millionaires if the converse is true. The former case is of little effect on the general distribution, since wealth can be concentrated at its upper end instead without needing any change below (any increase in the top average of a group leaves untouched the lower brackets). The latter is of more consequence, because multimillionaires can usually spill outside of the last g-percentile, and an upwards reevaluation of their wealth induces a re-ranking problem in the top 1%. Fortunately, this issue is limited to a very small number of country and of little magnitude, and can be solved cases by explicitly restricting changes to thresholds included in each country's 127th g-percentile. This correction is illustrated at the regional level alongside base data and the former correction in Table 1. Overall, this allows for estimates of the very top of the distribution to be much closer to reality than in our benchmark series, which can then be used in various wealth tax scenarios.

Region	Uncorrected		1st correction		2nd correction		Forbes	
	N.	Worth	N.	Worth	N.	Worth	N.	Worth
East Asia	722	3024	865	3621	838	3446	837	3446
Europe	279	2622	334	3139	499	2418	498	2419
Latin America	75	512	90	613	105	419	104	447
MENA	36	238	43	285	75	182	74	182
North America	1056	5006	1264	5994	835	4822	834	4822
Russia & Central Asia	48	385	58	461	133	586	132	630
Sub-Saharan Africa	13	52	15	62	11	52	11	52
South & South-East Asia	119	902	142	1080	260	991	260	1075
World	2345	12741	2807	15256	2750	13069	2750	13072

Table 1: Worth ($ bn) and number of billionaires across the world, 2021

3 List of countries imputed

We provide in this section a list of imputed countries for both wealth aggregates and wealth distribution series depending on the availability of wealth data.

3.1 Wealth Aggregates

To provide wealth aggregates series for all countries around the world, we have clustered countries in five groups depending on the availability of data for financial and non-financial assets of the private and the public sectors. The later are the four main asset groups over which we assume if a country has sufficient data to estimate the net market-value national wealth.

- Countries with wealth data available for all asset groups:
  Australia, Canada, China, Czech Republic, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Korea, Mexico, Netherlands, Norway, Russian Federation, Spain, Sweden, Switzerland, Taiwan, Thailand, United Kingdom, USA.
- Countries with wealth data available for at least two asset groups:
  Albania, Austria, Barbados, Belarus, Belgium, Bhutan, Bolivia, Brazil, Bulgaria, Chile,

Colombia, Congo, Costa Rica, Croatia, Cyprus, Dominican Republic, El Salvador, Estonia, Ethiopia, Georgia, Greece, Hungary, Iceland, India, Indonesia, Israel, Jordan, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Luxembourg, Macedonia, Malta, Micronesia, Moldova, New Zealand, Poland, Portugal, Romania, Serbia, Singapore, Slovakia, Slovenia, South Africa, Turkey, Ukraine, United Arab Emirates, Uruguay.

- Countries heavily imputed with data available only for one asset group:
  Afghanistan, Angola, Armenia, Bangladesh, Bosnia and Herzegovina, Burkina Faso, Cameroon, Central African Republic, Chad, Equatorial Guinea, Gabon, Iraq, Kosovo, Lesotho, Mauritania, Mauritius, Mongolia, Morocco, Mozambique, Myanmar, Nepal, Nigeria, Oman, Pakistan, Paraguay, Peru, Samoa, Sao Tome and Principe, Seychelles, Sierra Leone, Sri Lanka, Suriname, Swaziland, Tajikistan, Tunisia, Uganda, Vanuatu.
- Countries heavily imputed with data available only for few asset sub-components:
  Algeria, Andorra, Anguilla, Antigua and Barbuda, Argentina, Aruba, Azerbaijan, Bahamas, Bahrain, Belize, Benin, Bermuda, Botswana, British Virgin Islands, Brunei Darussalam, Burundi, Cabo Verde, Cambodia, Cayman Islands, Comoros, Cote d'Ivoire, Cuba, Curacao, Djibouti, Dominica, DR Congo, Ecuador, Egypt, Eritrea, Fiji, French Polynesia, Gambia, Ghana, Greenland, Grenada, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Hong Kong, Iran, Isle of Man, Jamaica, Kenya, Kiribati, Kuwait, Lao PDR, Lebanon, Liberia, Libya, Liechtenstein, Madagascar, Malawi, Malaysia, Maldives, Mali, Marshall Islands, Montenegro, Montserrat, Namibia, Nauru, New Caledonia, Nicaragua, Niger, North Korea, Palau, Palestine, Panama, Papua New Guinea, Philippines, Puerto Rico, Qatar, Rwanda, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and Grenadines, San Marino, Saudi Arabia, Senegal, Sint Maarten (Dutch Part), Solomon Islands, Somalia, South Sudan, Sudan, Syrian Arab Republic, Tanzania, Timor-Leste, Togo, Tonga, Trinidad and Tobago, Turkmenistan, Turks and Caicos Islands, Tuvalu, Uzbekistan, Venezuela, Viet Nam, Yemen, Zambia, Zimbabwe.
- Countries with full imputation with no data available:
  American Samoa, Guam, Macao, Monaco, Northern Mariana Islands, US Virgin Islands.

3.2 Wealth distributions

We provide a list of countries to differentiate between countries with distributional financial accounts and imputed countries. The wealth distribution for missing countries were imputed based on income inequality data.

- Countries with distributional financial accounts (see Blanchet and Martinez-Toledano, 2021 and working papers available on WID.world); these countries represent 75.5% of global household wealth in 2021:
  Austria, Belgium, China, Croatia, Cyprus, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, India, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Russian Federation, Slovakia, Slovenia, South Africa, South Korea, Spain, Switzerland, USA, United Kingdom.
- Countries with wealth distribution imputed on income inequality data using the methodology described in this document; these countries represent 24.5% of global household wealth:
  Afghanistan, Albania, Algeria, Angola, Argentina, Armenia, Australia, Azerbaijan, Ba-

hamas, Bahrain, Bangladesh, Belarus, Belize, Benin, Bhutan, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Brunei Darussalam, Bulgaria, Burkina Faso, Burundi, Cabo Verde, Cambodia, Cameroon, Canada, Central African Republic, Chad, Chile, Colombia, Comoros, Congo, Costa Rica, Cote d'Ivoire, Cuba, Czech Republic, DR Congo, Djibouti, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea , Eritrea, Ethiopia, Gabon, Gambia, Georgia, Ghana, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Iceland, Indonesia, Iran, Iraq, Israel, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Korea, Kuwait, Kyrgyzstan, Lao PDR, Lebanon, Lesotho, Liberia, Libya, Macao, Madagascar, Malawi, Malaysia, Maldives, Mali, Mauritania, Mauritius, Mexico, Moldova, Mongolia, Montenegro, Morocco, Mozambique, Myanmar, Namibia, Nepal, New Zealand, Nicaragua, Niger, Nigeria, North Korea, North Macedonia, Oman, Pakistan, Palestine, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Qatar, Romania, Rwanda, Sao Tome and Principe, Saudi Arabia, Senegal, Serbia, Seychelles, Sierra Leone, Singapore, Somalia, South Sudan, Sri Lanka, Sudan, Suriname, Swaziland, Sweden, Syrian Arab Republic, Taiwan, Tajikistan, Tanzania, Thailand, Timor-Leste, Togo, Trinidad and Tobago, Tunisia, Turkey, Turkmenistan, Uganda, Ukraine, United Arab Emirates, Uruguay, Uzbekistan, Venezuela, Viet Nam, Yemen, Zambia, Zimbabwe.

3.3 Improving our series

We stress at the outset that our current wealth inequality estimates remain unsatisfactory. We will improve them as soon as we access better country-level household wealth surveys and tax data. Our Inequality Transparency Index (see www.wid.world/transparency) presents a detailed evaluation of the quality of income and wealth statistics country by country. Ultimately, improving wealth inequality series requires more collaboration between the different actors of the inequality data ecosystem (including national and international statistical agencies, tax authorities and research institutions).

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