IARIW 2022

IARIW 2022

Monday 22 - Friday 26 August

The Sky and the Stratosphere: Concentrated Wealth in India During the 'Lost Decade'

Ishan Anand

O.P. Jindal Global University
ishan.jsr@yahoo.com

Rishabh Kumar

UMass Boston
Rishabh.Kumar@umb.edu

Paper prepared for the 37th IARIW General Conference

August 22-26, 2022

Session 7D-2: Dynamics of the Wealth Distribution around the World III

Time: Friday, August 26, 2022 [16:00-17:30 CEST]

Abstract

Recently released official survey data show a decline in wealth inequality (measured by the Gini) and wealth concentration (shares of the top fractiles) over 2012-2018. We investigate a puzzling detail – the rich hold equities, whose prices increased over 2012-2018, while the middle class holds precious metals, whose prices declined over the same period. The survey predicts the richest Indian to be worth Rs 244 million in 2018; according to glossy magazine covers, the richest Indian has, in fact, a net worth of Rs 2,560 billion. We correct this series using data from named rich lists and find that the decline in wealth inequality is more modest. More strikingly, *we find a sharp increase in wealth concentration*, with the share of the Top 0.001 percent doubling in size – as of 2018, the wealth of the richest 7000 (approx.) Indians exceeds the wealth of the poorest 50 percent.

Keywords: Wealth inequality, wealth concentration, Rich lists, Pareto distribution, Top shares, Gini, India, HNWI, elite distress

1 Wealth inequality in India

We use a recently released wealth survey by India's official statistical agency to produce an estimate of wealth inequality up to 2018. Our estimates are the latest calculations on wealth distribution in India using actual data (others have extrapolated from past estimates). We ask three main questions. Was there an increase in wealth inequality? Do survey results potentially undercount the rich? And, if so, can official estimates be "corrected" using supplementary information?

Our calculations show that wealth inequality in India appears to have decreased for the first time since computerized wealth surveys became available in 1991. The Gini coefficient for wealth, while extremely high (0.65-0.70) in context of other measures like consumption inequality, [1] is lower in 2018 than it was in 2012 (the year of the last survey). In fact, the data suggests a sharp reversal in wealth inequality, down to levels[2] prevalent a few decades prior. The central factor behind the decline in wealth inequality is negative wealth growth over this period for everyone *above* the 90th percentile. In most economies of the twenty first century, the share of wealth in the top decile tends to be high, and wealth is usually more concentrated than incomes due to inheritance and portfolio composition. Accordingly, when the wealth of the rich goes down, average wealth and wealth inequality both tend to reduce; this is the case we find for India in our estimates from the survey.

[1] The Gini coefficient for monthly per capita consumer expenditure obtained from the last available NSS Consumer Expenditure Surveys for 2011-12 was 0.375.

[2] Our estimate of per-adult Gini from the survey is close to the per-capita Gini for 1991 estimated in other studies.

In isolation, these findings are within the realms of possibility. But, such a decline in wealth at the top needs to be scrutinized against actual economic policies and developments in this period, and a potential undercounting of the rich. Because wealth tends to be highly concentrated, missing the actual rich can present an inaccurate picture about the level and distribution of wealth. We live in an era where public interest in the lives and fortunes of the wealthy is high: there are magazines and websites dedicated to ranking the wealthiest persons across the planet. Thus, society tends to be informed about how wealthy elites such as superstar athletes, film stars and industrialists really are. Based on these factors, one can check the upper tail of the survey data, and compare it to information available in named rich list data. We do this crosscheck using data from Forbes and the Hurun rich list and find a huge gap between the richest individuals in the survey, and the least wealthy occupants of named rich lists. Even including a few individuals from the rich list would change the distribution of wealth. Indeed, such corrections have been done before on Indian data, for example in Bharti (2018). In our research, we mobilize the largest number of observations available (in the hundreds) from these rich lists and "fill in" a corrected upper tail.

Our revised estimates show that while wealth inequality still decreases a little bit between 2012 and 2018, there is an increase in wealth concentration at the top, with the share and magnitude of wealth of the Top 0.001 percent doubling during this period; the sky (the rich) is closer to the ground, but the distance between the sky and the stratosphere (the super rich) has gone up. In fact, *the Top 1 percent in India now has a lower share than equivalent groups in other countries, while the Top 0.001 percent has a share that is only surpassed by the* *same fraction in Russia.* To be sure, we show in our calculations that while one can be termed "rich" according to the statistical position in a distribution, few Indians are actually rich compared to the rest of the world. This matters a lot in setting up the aggregate picture of distribution in what is basically a poor country.

There are important implications of our research. There is a lot of interest, but also a lot of uncertainty about distributional statistics in India for the period after 2011-12. According to the country's former economic advisor – Arvind Subramanian – official GDP is overestimated by 2-3 percent (Subramanian, 2019). Secondly, results from consumption surveys conducted by the official statistical authorities (used for poverty headcount calculations) for 2017-18 were suppressed[3] in 2019 due to apparent inconsistencies. Meanwhile, there is no tradition of conducting household level income surveys in India. The gist is that over this rather important period in Indian economic development, there are no systematic estimates of the level and distribution of economic welfare in the world's largest democracy. Our wealth estimate serves as one possible measure for this period that is often referred to as a "lost decade" (Mehra, 2019; Subramanian and Felman, 2022).

1.1 Related literature on wealth inequality in India

Our paper is related to an emerging new literature on wealth inequality in India. Studies that have focused on India's wealth distribution find extremely high and

[3] A leaked news report about the consumption survey allegedly showed that mean consumption in India declined for the first time in decades. This data was not made public "in view of data quality issues"

rising levels of disparity, particularly in the post-liberalization period (Anand and Thampi, 2016). The distribution of asset and net worth across socio-religious groups remains heavily skewed, and historically deprived groups face disproportionate disadvantage (Zacharias and Vakulabharanam, 2011; Bharti, 2018; Tagade et al., 2018). In recent years, rural-urban and within-urban inequality has increased sharply and metropolitans areas show heavy wealth concentration and high disparities (Vakulabharanam and Motiram, 2018). Thus, on aggregate, wealth inequality has cumulated and exacerbated initial inequalities within a highly diverse population. Recognizing the limitations of the sample surveys, economists have also used rich-lists to exclusively study the super-rich. Jayaraj and Subramanian (2018) find that the wealth of the top 100 richest families in India was equivalent to nearly one-fifth of India's GDP in 2017.

2 Macroeconomic data

The focus of our paper is on distributional data; however, we utilize several macroeconomic series for normalization and price adjustments across time. We briefly summarize them in this section.

We use macroeconomic series covering 2012-2018 on prices (assets and output), State and National Gross Domestic Product (GDP), and the stock market. We collected several prices series from the Reserve Bank of India's (RBI) database online. Our main deflator is the Consumer Price Index[4] (CPI), calculated separately

[4]Given the absence of a genuine wealth deflator, previous studies have used either the Consumer Price Index and the Wholesale Price Index. In this paper we use the new CPI series (base

for rural (CPI-R) and urban (CPI-U) residents. We also use Gold (per 10 grams) and Silver prices (per gram) from transactions on the Mumbai market. Our series on equity prices were collected from the online tool developed by the Federal Reserve of St Louis (FRED). We also used the same source for obtaining total stock market capitalization (publicly listed companies only). All our monetary aggregates are adjusted to 2012 prices using CPI.

3 Wealth survey and findings

3.1 Definitions used

We define wealth as the monetary sum of all assets net of liabilities of each observational unit. That is, for unit i:

$$\text{wealth}_i = \sum \text{non-financial assets}_i + \sum \text{financial assets}_i - \text{debt}_i \qquad (1)$$

The sum of wealth across all units (N) gives the annual estimate of total personal wealth:

$$\sum_i^N \text{wealth}_i = \text{net personal wealth} \qquad (2)$$

We define wealth on a per adult basis, with equal split across all adults in a household. We do not cap the split on spousal basis alone; if a household has 4 adults, then total wealth W will be represented as $W/4$ in our data. The control population (N) is the total adult population of India in each year.

We estimate aggregate wealth inequality using the Gini index which uses Lorenz curves to show the cumulative share of wealth held by a fraction of the population.

year 2012=100).

As is standard, the index ranges between 0 and 1, with 0 representing full equality (everyone has the same wealth) and 1 representing the extreme upper limit of inequality (one person owns all wealth).

Since wealth tends to be concentrated (more so than income), an aggregate inequality measure does not necessarily reflect interpersonal variations due to the super-rich – the upper tail of wealth distribution. For instance, if there is redistribution between the fourth (60-80th percentile) and 2nd quintile (20-40th percentile), the Gini may go down, but there may be an increase in the amount of wealth held by (say) the Top 2-3 percent. These dynamics are important in discussing extreme wealth inequality. Accordingly, we use wealth shares for every decile (0-10, 10-20 so on) but split the top decile into five subgroups, increasing in wealth: p90-99, p99-p99.9, p99.9-p99.99, p99.99-p99.999 and p99.999-p100 (the Top 0.001 percent). As we will show, changes within the top percentile (p99-p100) are crucial to understanding wealth in India.

3.2 Unit-level wealth data: official surveys

We use household level data pertaining to two rounds of the All-India Debt and Investment Survey (AIDIS). These were conducted during the 70th (January - December 2013) and 77th (January - December 2019) round of the National Sample Surveys. AIDIS contains information on household debt, quantity and value of physical and financial assets such as land, buildings, livestock, transport equipment, agricultural machinery, non-farm business equipment, cash and deposits, bullion and ornaments, mutual fund and shares. Information on assets and liabilities of households was collected as on 30 June 2012 in the 70th round and 30 June

2018 in the 77th round. The NSO adopted a stratified two-stage sample design for the surveys. The first-stage units for the surveys were census villages for rural areas and blocks for urban areas. The second stage sampling units for rural and urban areas were households.

Limitations of AIDIS data have been discussed extensively in the literature (Jayadev et al., 2007; Subramanian and Jayaraj, 2009), and many of these issues are also relevant for the most recent round of the survey. The AIDIS data likely suffer from under-reporting of wealth and under-sampling of the wealthy, which may lead to underestimating wealth inequality levels. Additionally, the lack of a genuine wealth deflator remains an ongoing concern. Regarding valuation, the report published by the NSO states: "The concepts and definitions followed in the AIDIS of 77th Round and 70th Round are similar except for valuation of buildings." In the 70th round, the value of buildings was recorded per guideline values. That is, surveyors could consult local officials to ascertain the value of the building. In the 77th round, the values of buildings were recorded "as per the market price prevailing in the locality."

An important development in the 77th round is the possibility of underestimation of the urban population. The urban share of total estimated population in the 77th round of AIDIS is 30.8 percent, which is lower than the urban population share (33.5 percent) on 1 March 2018 as per the official population projection. Additionally, the wealth survey data suggest a decline in urban population in 2018 against the 2012 estimate. Wealth in urban India tends to be higher on average, and rising urban inequality is itself an important historical driver of wealth inequality (Vakulabharanam and Motiram, 2018). Accordingly, an underestimation of urban population in the 77th round of AIDIS is likely to bias total wealth downwards in 2018.

3.3 Distribution results from surveys

In most basic terms, the summary from the official surveys is: *wealth inequality in India declined between 2012 and 2018.* We estimated a decline of almost 5-6 Gini points with the Gini index estimated at 0.718 for 2012, and 0.661 in 2018. Strikingly, our estimates show that wealth per adult (in real terms) fell during this period. In 2012, average wealth per adult amounted to Rs 512,832, compared to Rs 457,070 in 2018; a drop of nearly 11 percent over six years. Lower inequality and wealth decline are only possible if these losses are concentrated among the upper classes – we analzye this hypothesis by constructing growth incidence curves (GIC) which track wealth growth[5] across the wealth distribution. Figure 1 presents our results. The vertical axis measures per annum growth rates in each decile, percentile or sub-percentile (within the Top 1 percent). Usually, increasing inequality shows up as a continuously rising GIC while inequality reduces when the curve is sloping down. We confirm the upper-class wealth loss hypothesis, with wealth growth being positive (though declining slightly) up to the 90th percentile and turning increasingly negative[6] going up to the 99.999th percentile. Wealth losses are particularly large within the top percentile, all the way up to the

[5]These curves are anonymous, that is, in the absence of longitudinal information on households we are unable to say if the same households occupy a particular ranking in 2012 and 2018.

[6]The sharpest decline occurs in the bottom decile (0-10) – the poorest became further indebted, with a 35 percent negative growth in their average wealth. However, the size of this debt is too small to make any significant difference to the distribution of wealth.

super-rich (Top 0.001 percent), ranging 2 percent to nearly 16 percent per annum negative growth for intermediate fractiles.

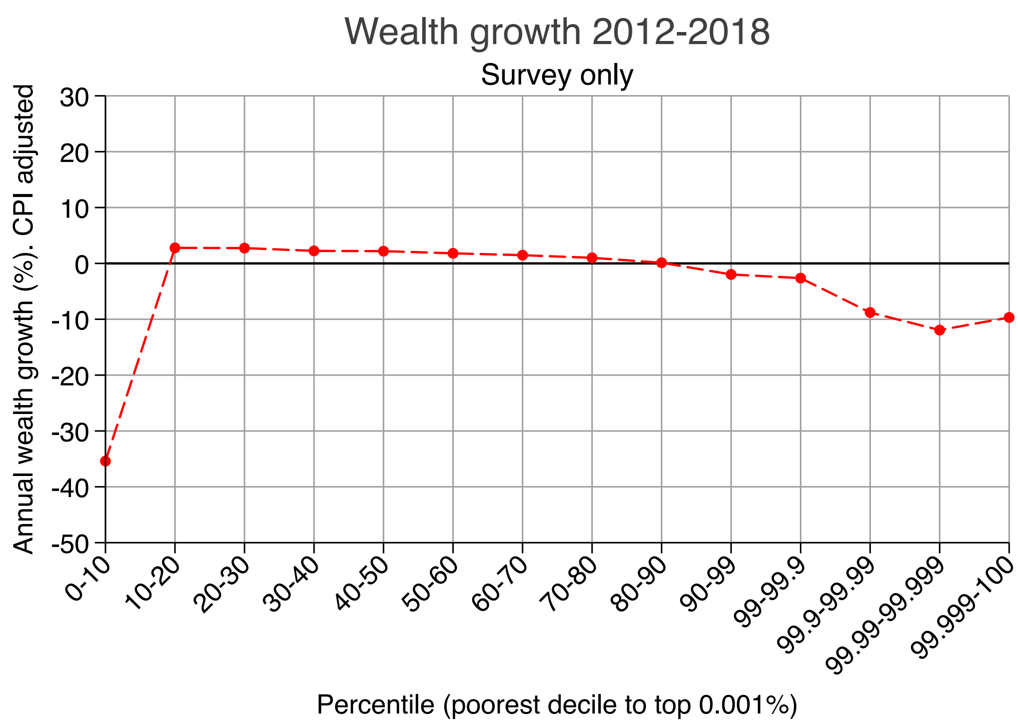

Figure 1: Wealth growth incidence calculated from official surveys.

3.3.1 Distribution of wealth

Survey data for 2018 suggest that the Top 1 percent owned about 18 percent of the total wealth, the Top 5 percent owned around 39 percent, and the Top 10 percent owned around 52 percent. The survey data points to a seven-percentage point fall in wealth share of the Top 1 percent and an eight percentage point fall in the wealth share of the Top 5 percent and the Top decile between 2012 and 2018. This is in sharp contrast to the results from earlier rounds of the wealth surveys, which show increasing concentration of wealth among the Top 10 percent Anand and Thampi (2016). The fall in wealth share of the Top decile is puzzling given other evidence of further consolidation among the rich in recent years.

3.3.2 Composition of wealth

Survey data suggests that household wealth in India is largely dominated by real estate. The combined share of land and building in total assets was over 90 percent in both rounds of the survey. Financial assets (shares, mutual funds, deposits) accounted for 3.4 percent of total assets in 2012 and its share increased to 6.9 percent in 2018. The share of other production capital (livestock, agricultural machinery, non-farm business and transport equipment) remained close to 4 percent in both rounds. The share of debt in total household wealth increased marginally from 3.5 percent in 2012 to 4 percent in 2018. Table 1 shows the composition of household wealth by wealth groups. Real estate is the dominant asset class across groups. Metal is an important component of wealth for the bottom 50 percent, but not so much for the rich. The share of equity in total wealth for the Top 1 percent was only 0.2 percent in both rounds, perhaps indicating an underestimation of financial assets in the sample survey data. Household debt, as a proportion of total wealth, is much higher for the bottom 50 percent in comparison to other groups.

Year	Group	Real Estate	Production capital	Equity	Other Fin	Metals	Debt
2012	0-50	89.8	8.5	0.0	5.2	11.8	-15.5
	50-80	88.9	5.2	0.0	3.8	6.2	-4.1
	80-95	91.6	4.1	0.1	3.8	3.8	-3.3
	95-99	92.7	3.3	0.2	3.5	2.6	-2.2
	99-100	96.2	1.8	0.2	1.8	1.0	-1.0
	Overall	92.4	3.8	0.1	3.3	3.8	-3.5
2018	0-50	89.1	8.1	0.0	9.3	9.5	-15.9
	50-80	87.7	4.6	0.0	7.7	4.5	-4.5
	80-95	90.7	3.7	0.0	6.2	2.7	-3.3
	95-99	91.2	3.2	0.1	6.3	1.7	-2.4
	99-100	91.8	2.4	0.2	5.8	0.8	-1.1
	Overall	90.2	3.9	0.1	6.8	3.1	-4.1

Table 1: Composition of wealth by wealth ranking. Rows sum to 100 percent. Reading: *In 2018, the bottom 50 percent of the adult population (ranked by net wealth) held 89 percent of its wealth in the form of real estate (land and buildings)*

3.3.3 Decomposing wealth inequality: states, sector and caste

We decompose the Gini coefficient of wealth into between-group and within-group components for states, sector and caste. This decomposition of Gini into between and within components produces an overlapping index when the subgroup wealth range overlaps. We focus on the between and within group components alone. The results of Gini decomposition presented in Table 2 show the relative contribution (percentage share) of between and within group components in total inequality. The within-group component accounts for a substantial amount of total inequality for all three decompositions. Between-caste inequality accounted for 9.5 percent of total inequality in 2012, which came down marginally in 2018. Between sector (rural/urban) inequality accounted for 4.5 percent in 2012 and came down further in 2012. Similarly, the between group inequality among states also reduced in 2018. The results of the decomposition analysis show there are significant heterogeneities within castes, rural and urban areas, and states, that are driving the overall wealth inequality.

	Year	Within-group (%)	Between-group (%)
Caste	2012	90.5	9.5
	2018	91.1	8.9
Sector	2012	95.5	4.5
	2018	97.2	2.8
State	2012	89.0	11.0
	2018	92.7	7.3

Table 2: Gini decomposition. The residual due to overlap has been excluded

4 Reduction in wealth..or underestimating the rich?

Do redistributive policies explain the destructive equalization of wealth? Remember, our wealth estimates are pretax; so the leveling of wealth for the upper class cannot be explained as redistributive taxation. Public policy in India has largely avoided delving into the issue of wealth inequality (Shetty, 2018). In fact, if

	(1)	(2)	(3)	(4)	(5)	(6)
	Real estate	Production capital	Equity	Metals	Other Fin	Debt
2012						
0-50	6.756	15.42	1.896	21.54	10.87	30.89
50-80	17.72	25.16	2.978	29.79	21.17	21.84
80-95	27.43	29.65	12.62	27.49	31.64	26.55
95-99	21.39	18.06	41.24	14.42	22.33	13.67
99-100	26.70	11.71	41.27	6.761	13.99	7.059
2018						
0-50	8.782	18.27	1.585	26.83	12.19	34.40
50-80	21.71	26.05	4.954	31.72	25.39	24.52
80-95	30.31	28.24	11.47	25.77	27.84	24.38
95-99	20.57	16.29	24.46	10.94	18.90	12.03
99-100	18.62	11.14	57.53	4.737	15.67	4.669

Computed from survey data only

Table 3: Share in total assets by wealth ranking. Columns sum to 100 percent. Reading: *In 2018, the bottom 50 percent of the adult population (ranked by net wealth) owned 1.584 percent of total equities in India.*

anything, direct taxes on Indian wealth were abolished in 2015 after becoming effectively defunct for several decades. The general direction of tax policy in India since the mid 1980s has been pro-rich, with previous tax codes on inheritance, wealth and Top incomes, either dismantled or reduced via lower Top marginal rates (Kumar, 2020). We rule out redistribution through taxation.

A second possible explanation of reduction in Top wealth shares is asset price collapse, especially in the asset held by the rich. As we showed in Table 3, equities are concentrated among the rich, and precious metals like gold and silver are held more prominently by the rest of the distribution – especially, below the 90th percentile. For a price based explanation, we should expect a divergence between gold/silver and equity prices, with the former going up. What we see, over 2012-2018, is in fact the opposite. Figure 2 shows that equity prices went up by 40 percent in real terms (2012=100), while gold and silver prices (real) went down by a factor of 25-50 percent. Therefore, prices speak to the opposite – a decline in asset prices for the poor and an increase in asset prices for the rich.

Another possible explanation is the phenomena of "elite distress" – that is, a hostile environment for the broad upper class, which is reflected in wealth losses. We have some evidence, based on investigative reporting, which also has some basis in the economic environment. There was a noticeable slowdown in economic growth after an incubation period following the 2008 financial crises. These effects took the form of a credit crises in the financial sector (especially infrastructure banks), partly provoked by a downturn in global economic conditions (Subramanian and Felman, 2019). As a result, the balance sheets of prominent businesses which relied on credit became insolvent and incidences of default increased. Several ultra-rich Indians began to exit the country; some visible industrialists left to escape prosecution for defaulting, while others left for more lucrative destinations to park their wealth. For instance, two prominent businessmen – Nirav Modi and Vijay Mallya, worth billions of dollars, both escaped India around this period, to avoid repayments to banks. More reasons offered include politi-

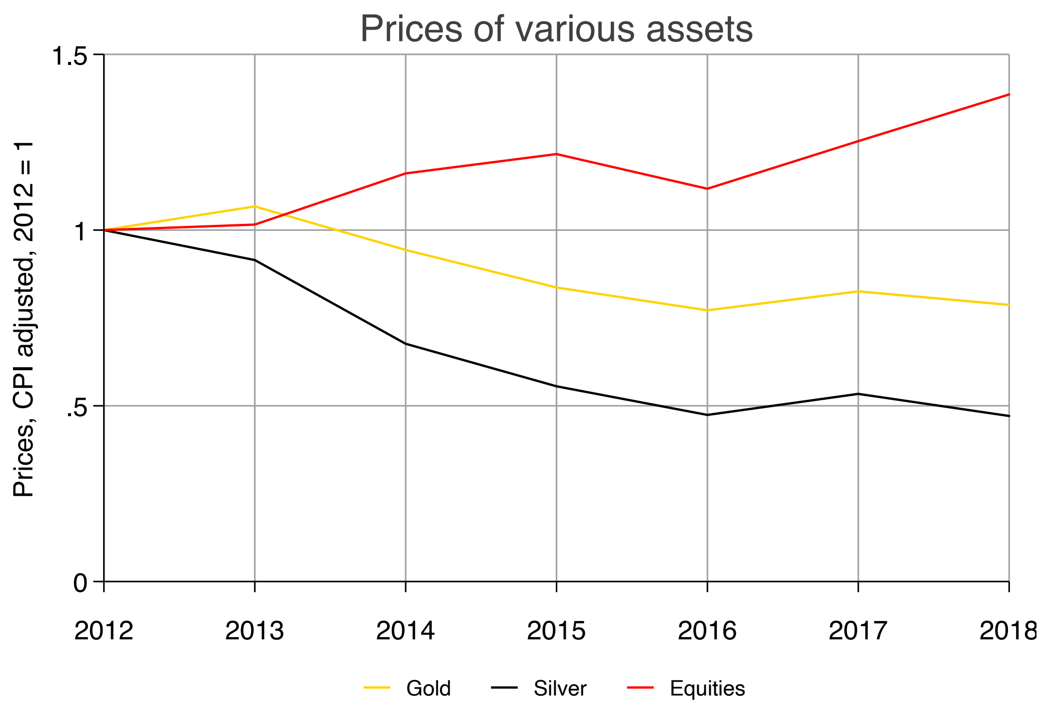

Figure 2: Price indices of metals and equities

cal vendettas and crackdowns on illicit wealth. Modi and Mallya were prominent figures, and made the news but the effect was pronounced across the "dollar millionaire" class with India accounting for the largest population of high net worth individuals emigrating abroad[7] between 2014 and 2018.

[7]India produced the largest number of elite migrants after 2014. For example, Morgan Stanley estimated that 2.1 percent of India's "dollar millionaires" left in 2017 alone (double the figures for China). See https://www.businesstoday.in/latest/economy-politics/story/at-least-23000-dollar-millionaires-have-left-india-since-2014-report-247217-2018-03-20

An exit of the rich to foreign countries rationalizes at least some of the losses in wealth shown in the upper part of the distribution, which was shown previously in Figure 1. If some of the upper tail vanishes, then new entrants to these positions would be Indians who would not have been as rich in the first place. However, anecdotes alone do not justify the universality of elite distress. The news media also featured regular instances of large corporate acquisitions, market capitalization and consumption of luxury goods and services. For example, the spending of India's richest individual (Mukesh Ambani[8]) on a wedding[9] made international headlines.

The point is that to rationalize the rise or fall of the elite classes, we need to verify trends in time using systematic evidence. Here, we are helped by the fact that the prominence of the rich makes them a topic of curiosity in popular rankings. Based on such named estimates of wealth, we are able to assess the length of the upper tail and compare it to official survey evidence. Do the surveys accurately capture the net worth of the richest? The answer is basically no. For example, in 2018, Mukesh Ambani (the richest man in India) was worth Rs 2,560 billion. The survey shows that the highest ranked Indian is worth only (sic) Rs 244 million. Such discrepancy is not unusual because sampling strategies like topcoding, under-reporting as well as high rates of nonresponse among the rich

[8]https://fortune.com/2018/07/13/asia-richest-man-mukesh-ambani/

[9]See "Must Reads: India's richest man throws the wedding to end all weddings, with Beyonce and Hillary in attendance" LA Times, Dec 13, 2018. https://www.latimes.com/world/la-fg-india-ambani-wedding-20181213-story.html

misrepresent[10] the wealthy anyway. What is concerning, from a statistical sense, is the amount of wealth that is potentially missed when the gap is so large. Wealth is by its nature concentrated and distributed at the top with a fat-tailed power law (Sinha, 2006). The upshot is not that the survey underestimates the richest, but that the size of wealth in the extreme upper tail is crucial in determining the mean and variance of the distribution of wealth in the first place (Mandelbrot and Taleb, 2010). Without the actual rich, there is little we realistically know about wealth.

4.1 Correcting wealth using rich lists

To account for the missing upper tail, we combine data from the survey with unit level wealth estimates in named *rich lists* for 2012 and 2018. Our methodology is in keeping with a new tradition amongst economists interested in computed top wealth shares in countries[11] with imperfect survey data. The main advantage[12] of these lists is that they give us at least some idea about the actual super-rich, who because of their influence and positioning are prominent enough to be non-anonymous anyway. Using public knowledge of their holdings, and interviews, publishers estimate a dollar value of their net worth. For India, Gandhi and Walton (2012) produced a series on billionaire wealth using Forbes lists for the 1990s and

[10]Some surveys like the US Survey of Consumer Finances uses strategies like oversampling tax returns to fill this gap. Some issues on this topic are discussed in Bricker et al. (2016)

[11]For example, Novokmet et al. (2018) used rich lists to supplement survey data for Russia; Piketty et al. (2019) did the same for China

[12]There are shortcomings to this method too. Atkinson (2006) cites the extent of public knowledge, valuation of assets like art, visibility of assets versus debt and citizenship. In response, newer lists have become more transparent to improve the quality of rich lists.

2000s. Sinha (2006) used a similar list (Business Standard) to fit a power law. Bharti (2018) used 15-46 members on the Forbes to correct the upper tail of the 2002 and 2012 wealth survey.

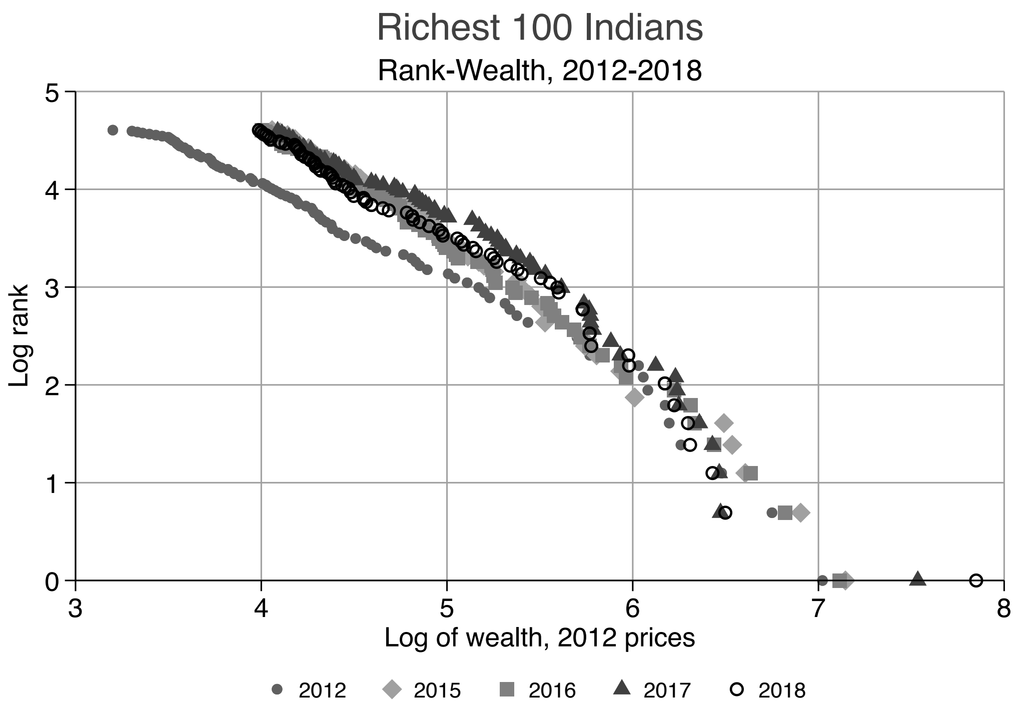

Figure 3: Scatter of rank and wealth (2012 prices) for the super rich computed using Forbes and Hurun rich list

We collected lists of named top wealth holders for 2012 and 2015-2018 from various websites that publish this information. Our list for 2012 was downloaded from Forbes Magazine's website and for 2015-2018, we web-scraped the Hurun India rich list. Forbes has a long history of ranking the richest individuals but recently Hurun has entered the luxury publication market and produces larger rich lists for their upscale clientele. To our knowledge, these data on the rich contains the largest annual number of observations (numbering in the hundreds) for India. We converted all dollar amounts using annually averaged exchange rates and adjusted nominal wealth using CPI. A sample from our list is presented in Figure 3, showing the rank-wealth scatter of the richest 100 Indians. This plot confirms a power law relationship ($R \propto w^{-a}$) between rank (R) and wealth (w); a well known statistical regularity in the wealth distribution. Accordingly, on a log-log scale, the data should collapse linearly ($\log R \propto -a \log w$), with slope $-a$. We note a horizontal shift in the data in time, both for the full set of observations, and the 100th ranked wealth holder. The implication is thus that the members of this list became significantly wealthier between 2012 and 2018.

An important feature of the rich list is that it reestablishes the relationship between the wealthy and the stock market. Although not all members of the super-rich own equities in publicly listed companies (though most do), much of their wealth is held in shares of large corporations. Figure 4 shows the evolution of average wealth for the richest 100 Indians moves in sync with stock market capitalization (normalized against GDP). In 2012, the average wealth of the 100 richest was approximately Rs 125 billion. Following the market, this number swelled to nearly Rs 200 billion in 2017, before declining slightly to Rs 180 billion in 2018. This association shows that surveys miss important dynamics at the top, especially the correlation between equity prices and wealth.

How far apart are the rich lists, in scale, to the upper tail of the survey? To test these differences, we compared our rich list data against the Top 5 percent of samples from the survey, ranked on wealth and with sampling weights applied to

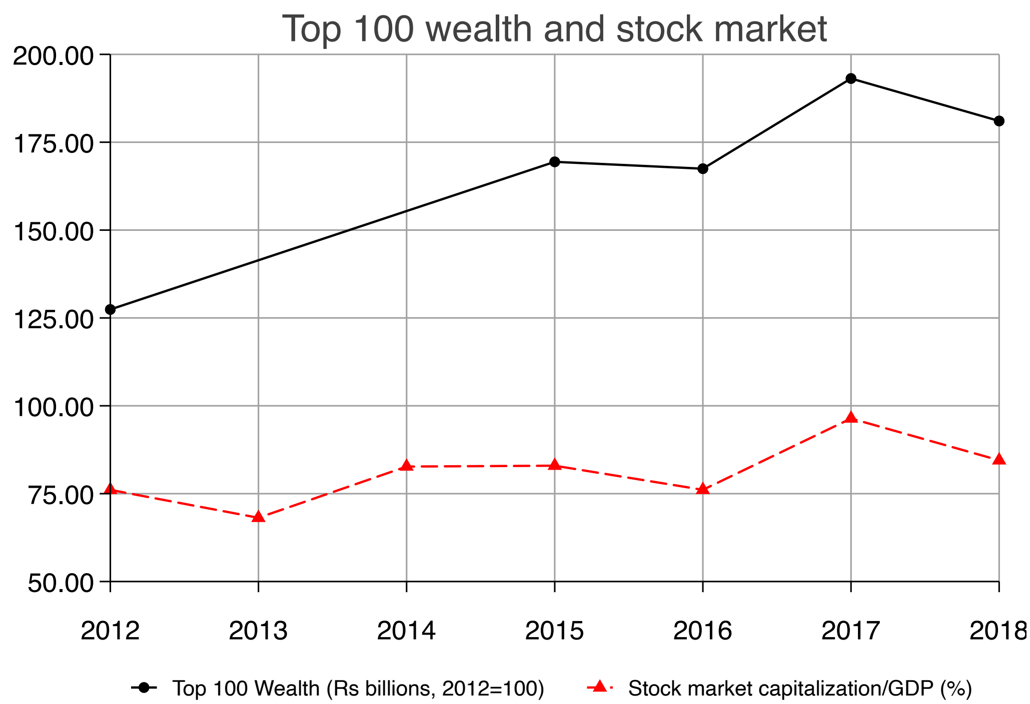

Figure 4: Average wealth of the Top 100 richest Indians versus stock market capitalization, 2012-2018

scale to adult population. On these data, we ran the regression:

$$\log rank_i = b_0 + b_1 \log wealth_i + u_i \tag{3}$$

Where the coefficient $\hat{b}_1$ in Eqq 3 estimates $-a$ in the linearized power law relationship given by $\log R \propto -a \log w$, with lower absolute values implying thicker upper tails, and therefore more inequality within the sample. Table 4 shows our results; both datasets agree very well with the power law ($R^2 > 0.97$). In both years, 2012 and 2018, we get significantly lower estimates of b_1 for the rich list

(1.04 and 0.90) compared to the survey upper tail (1.66 and 1.80). Naturally, comparing a list of billionaires will produce different tails than the survey but the key distinction we observe is that *the survey shows a reduction in inequality within the upper tail, while the rich list suggests the opposite.* We know already that the wealth on the rich list is a significant amount – more than 8 percent of total wealth on the survey in 2018.

	(1)	(2)	(3)	(4)
	Survey, 2012	Survey 2018	Rich list 2012	Rich list 2018
Log wealth	-1.66***	-1.80***	-1.04***	-0.90***
	(0.01)	(0.00)	(0.04)	(0.01)
Constant	32.84***	34.77***	29.72***	26.82***
	(0.11)	(0.06)	(0.94)	(0.33)
Observations	5000	5000	100	831
Adjusted R^2	0.998	0.999	0.977	0.963

Standard errors in parentheses

Sampling weights used

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Power-law formula fitted to upper tails of survey and rich-list data separately. Wealth adjusted for inflation between 2012 and 2018

A straightforward corollary of these additional data is that the upper tail would be longer and wealth concentrated in the tail would increase if the rich list was appended to survey data. Importantly, we are interested in observing if the coefficients on the upper tail decline (inequality in the upper tail increases) once both data are combined. We analyzed these implications by running the regression on Eqq 3 again, but this time on the upper tail of the appended[13] dataset. Table 5 shows our results; once again the fit is good, but we obtain estimates of b_1 which are smaller in absolute value than the survey alone. For example, in a larger sample mix for 2018 (column 2), we get $\hat{b}_1 = -1.10$ compared to the original 1.80 in the survey, by itself. The combination retains the decline in b_1 shown earlier; thus our combined dataset shows that inequality within the rich increased over 2012-2018.

With changes due to inclusion of the richest Indian apparent, we re-estimated the distribution of wealth for 2012 and 2018. Our estimation strategy is different to relatable corrections[14] to survey data, such as at WID (Novokmet et al., 2018; Bharti, 2018). We keep wealth on the survey intact and add units from the rich list on top, thus making a correction beyond the highest estimates of wealth on the former dataset. Basically, the richest adults on the survey fall in rank and

[13]In our joint dataset, we retained the sampling weights for the survey sample. That is, the samples are reprsentative. For the rich list, we allocated a weight of 1 when a single person is listed, and 2 when the list includes the word "and." For example "firstname1 lastname1 and firstname2 lastname1" would carry a weight of 2. Basically, billionaires only represent their actual self.

[14]A conventional strategy in these cases is to pick a percentile $p*$ at some wealth level w^* and apply the parameter a from the combined datasets to scale up all wealth greater than w^*. For example, say the power law fits above p95, and the newly estimated scaling parameter is 1.5. Then, using Pareto interpolation and extrapolation, one can calculate average wealth for p95, p99 and so on, while computing wealth shares for cumulative top fractiles (Top 5 percent, Top 1 percent). The assumption in these cases is that wealth is under-reported by the same factor for the entire population above the threshold w^*.

	(1)	(2)	(3)	(4)
	2012L	2018L	2012S	2018S
Log wealth	-1.37***	-1.10***	-1.36***	-1.05***
	(0.02)	(0.01)	(0.03)	(0.02)
Constant	28.52***	24.69***	28.37***	23.91***
	(0.35)	(0.21)	(0.44)	(0.23)
Observations	10099	10830	8099	8830
Adjusted R^2	0.976	0.948	0.969	0.936

Standard errors in parentheses

Sampling weights used

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Power-law formula fitted to upper tails of combined survey and rich-list data. Wealth adjusted for inflation between 2012 and 2018. L (S) refers to larger (smaller) samples

are replaced by a synthetic population supplied from the rich list. Total wealth, also increases. Our strategy makes no assumptions on under-reporting (bypassing potentially heterogenous rates of non-response/under-reporting) in the survey and assumes simply that the survey is unable to capture the actual rich, who we then populate backwards from the rich list. We interpolate precise fractiles using the Stata plug-in `pshare` described in Jann (2016). Our method has clear shortcomings: if rates of nonresponse/under-reporting are an increasing function of wealth size, then our estimates are biased downward as wealth rank increases. Alternatively, if nonresponse/under-reporting are present but orthogonal to wealth size, then our estimate of total wealth of the rich is biased downward. Either way, our results should be understood as a lower bound on the actual size and share of wealth of India's rich.

4.2 Rising wealth concentration, decline in total inequality

We next present our revised estimates of India's wealth distribution. Table 6 shows the wealth share at different points of the distribution, comparing across the survey and our corrections. In line with expectations from our methodology, the share of the Top 5 percent goes up (relative to the survey) from 38.6 percent to 44 percent for 2018; they make little difference to the 2012 distribution. We note that the corrections still show a decline in the wealth share of the Top 5 percent – down just over 4 points from 49 percent in 2012.

Table 7 lists our estimates of wealth shares cumulatively for the top decile, zoomed in all the way to the Top 0.001 percent – the richest 7000 individuals[15] in India. We observe a continuous decline through to the 99.999th percentile, same as the survey, with the difference being the decline is reduced (5 percent versus 8 percent in the survey) by adding very wealthy individuals from the rich list. But once our corrections begin to take hold within the top percentile, wealth shares

[15] Sample surveys typically underestimate actual population estimates from censuses. Our count of 7000 is based on the survey and rich list, but might in fact reflect a higher count when scaled to the census-type population

		Wealth share (%)	
		Survey	Corrected with rich lists
2012	Bottom 50 percent	6.95	6.69
	50-80th percentile	18.42	17.75
	80-95th percentile	27.67	26.65
	Top 5 percent	46.96	48.91
2018	Bottom 50 percent	8.88	8.09
	50-80th percentile	22.32	20.33
	80-95th percentile	30.16	27.47
	Top 5 percent	38.64	44.11

Table 6: Share of wealth, 2012-2018 computed using surveys and corrected with rich lists.

adjust sharply upwards. The last row shows this clearly; the survey suggests a measly 0.34 percent in the hands of the Top 0.001 percent which we now revise up to 9.19 percent. Further, instead of a decline over 2012-2018, our estimates point to a doubling of wealth shares of the Top 0.001 percent in time. Comparing across Tables 6 and 7 highlights the stark differences in wealth ownership at the absolute top against the bottom half of the population when the rich are more adequately captured in the data. The reason this difference is worth pointing out – we already know that the bottom half of the distribution is, by definition, poor – is due to the magnitudes involved. At 9.19 percent, the wealth of the richest 7000 individuals is more than the wealth of the poorest 350 million Indians.

		Wealth share, cumulative (%)	
		Survey	Corrected with rich lists
2012	Top 10 percent	60.16	61.63
	Top 1 percent	25.64	28.38
	Top 0.1 percent	12.04	15.28
	Top 0.01 percent	4.94	8.44
	Top 0.001 percent	0.72	4.37
2018	Top 10 percent	52.43	56.67
	Top 1 percent	18.30	25.57
	Top 0.1 percent	5.45	13.86
	Top 0.01 percent	1.68	10.43
	Top 0.001 percent	0.34	9.19

Table 7: Cumulative wealth shares, 2012-2018 computed using surveys and corrected using rich lists

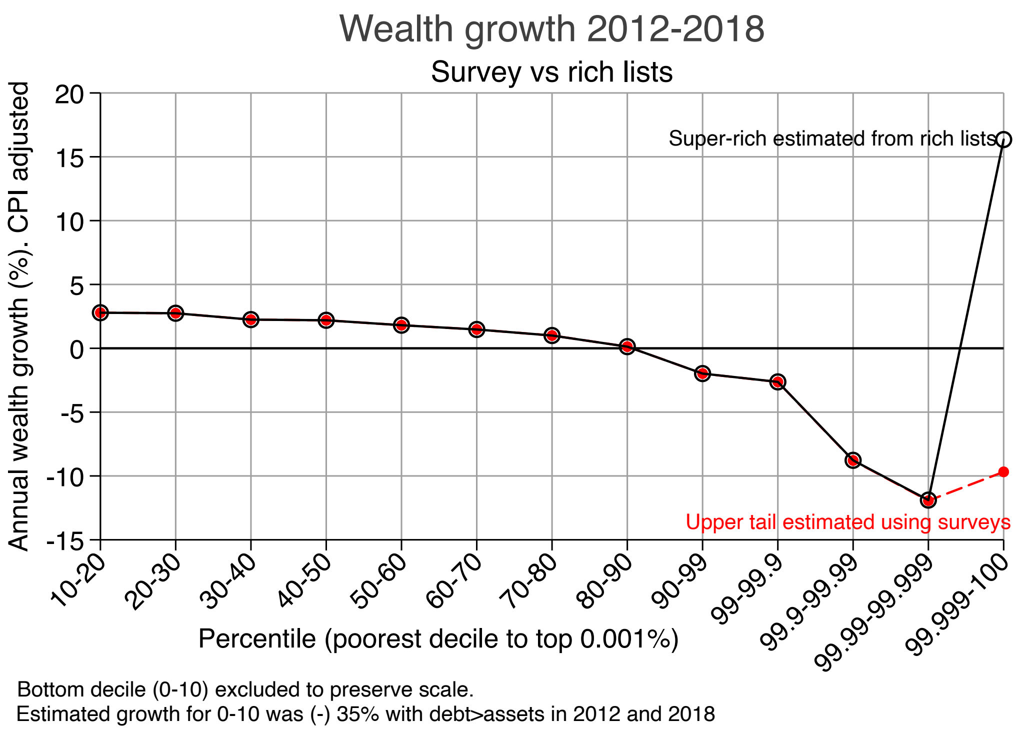

Figure 5: Corrected growth incidence curve, 2012-2018

Our revised data still show a fall in per-adult wealth over 2012-2018. But, our adjustments blunt the size of decline to 5 percent (from approximately 10 percent in the survey). How do our corrections distribute the rate of wealth growth? We recomputed growth incidence across the distribution to dynamically assess our revised wealth share figures; the result is presented in Figure 5 with a comparative series from the original survey. The added rich make little difference to the overall distribution – the poor half of the population had modest growth of 1 or 2 percent per annum, which is basically inconsequential as an episode because their shares remain below 10 percent of total wealth anyway. Rates of wealth growth decline with size of wealth, again turning negative for most the disaggregated top decile. The difference is that the plummeting curve changes course sharply at the 99.999th percentile. What appeared as a (-) 10 percent decline in wealth, is now a 16 percent positive growth rate (the highest of any subgroup) for the Top 0.001 percent – unambiguously different from elite distress in material terms, delivering an average wealth of Rs 4.6 billion in 2018 (see Appendix A). By definition, few are members of this class, while most (bottom 50 percent) have little wealth despite positive growth. Those with significant wealth and population shares have negative wealth growth (the upper class, outside the Top 0.001 percent) thus dragging mean wealth per adult down in 2018.

4.2.1 Trends in time and across countries

We place our findings in a slightly longer context, comparing our estimates with trends in wealth inequality in India since 1990. Figure 6 shows the evolution of the Gini coefficient (left panel) and Top 1 percent wealth share (right panel) using comparable estimates from Anand and Thampi (2016) and WID (Bharti, 2018). Due to differences[16] in underlying data and methodology, these estimates differ in levels but for us what matters is the trend. Simply stated, wealth inequality in India increased continuously after 1990, and the official surveys suggest a near return to the lowest levels of inequality ever since, producing an inverse U-shaped time series over 1990-2018. Based on these data alone, the interpretation would be a complete reversal of wealth inequality during India's high-growth decades (1990-

[16] Anand and Thampi (2016) use only survey data, and compute wealth on a per-capita basis while Bharti (2018) uses survey and rich-lists with Pareto corrections for a larger fraction of the upper tail. WID has extended the latter (by extrapolation) to 2016.

2010) along with a first instance of declining Gini, across estimations put together by different authors. However, our corrections show that the decline, while still present, is more a return to the mid-2000s. Either way, the Gini (0.65-0.7) is much higher than estimates from consumption surveys[17] and the share of the Top 1 percent at around 25 still represents significant wealth concentration. Focusing on the share of the Top 0.001 percent, Figure 7 shows that our estimate of the pronounced increase is roughly in line with other estimates of concentration since the late 2000s. The survey is in another universe of modest elites, quite clearly. Thus, at the absolute top, there is no trend towards reversal back to the 1990s and more a persistence of high wealth concentration.

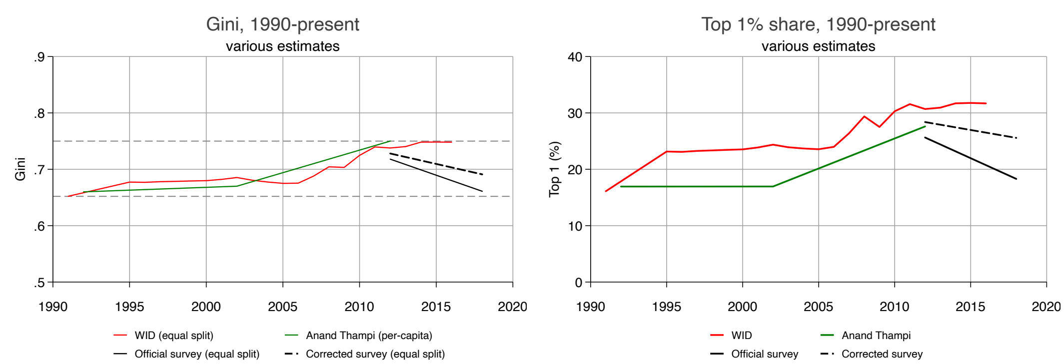

Figure 6: Evolution of Gini coefficient and Top 1 percent wealth shares: 1990-2018

We turn next to how these trends compare with inequality in other countries: is wealth more or less concentrated in India, relative to other countries? To com-

[17]Consumption Ginis are in the range of 0.35-0.40 according to the World Bank. See https://data.worldbank.org/indicator/SI.POV.GINI?locations=IN

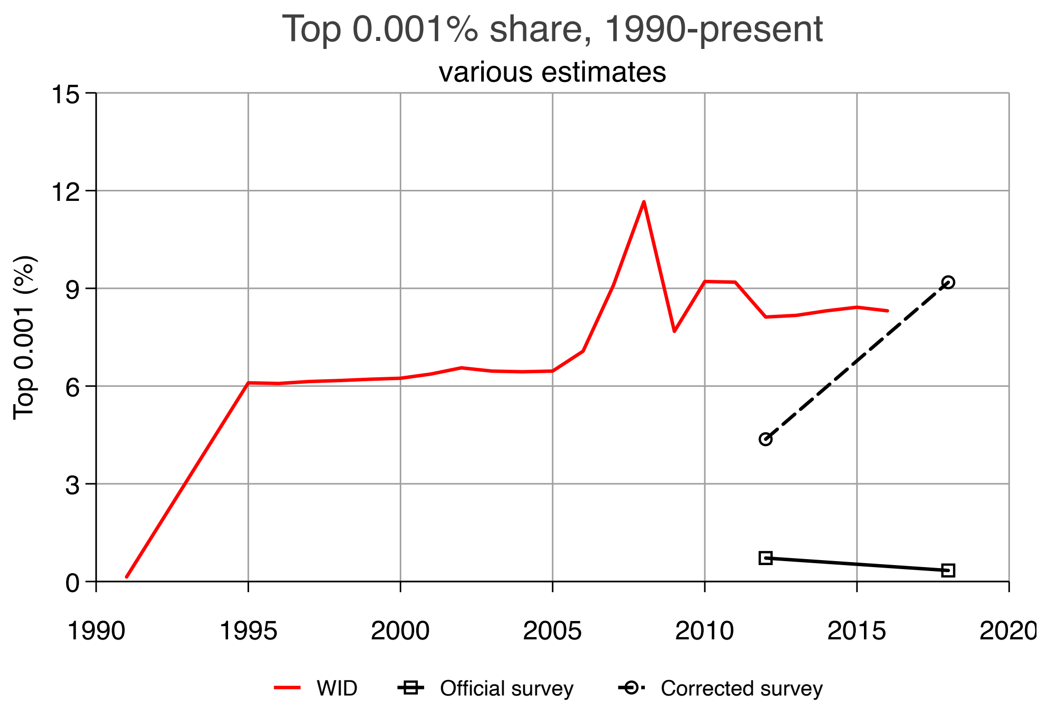

Figure 7: Top 0.001 percent wealth shares

pare, we avoid the "top-desensitized" Gini and instead compare two groups across countries/regions: the Top 1 percent (the rich) and the Top 0.001 percent (the ultra rich). As we saw, in time, wealth shares evolved differently for both. Figure 8 shows that the rich in India were much less rich in 2018, relative to those in other large countries like China, Russia and the US, and in fact our estimate of the Top 1 percent share puts India below the average for the World and Asia. For the ultra rich, the story is the opposite – India's top 0.001 percent went from wealth shares roughly at US levels of concentration (the lowest in our set) in 2012, to higher than the Chinese, Asian or World average in 2018, falling short only to Russia's post-soviet oligarchs (Novokmet et al., 2018).

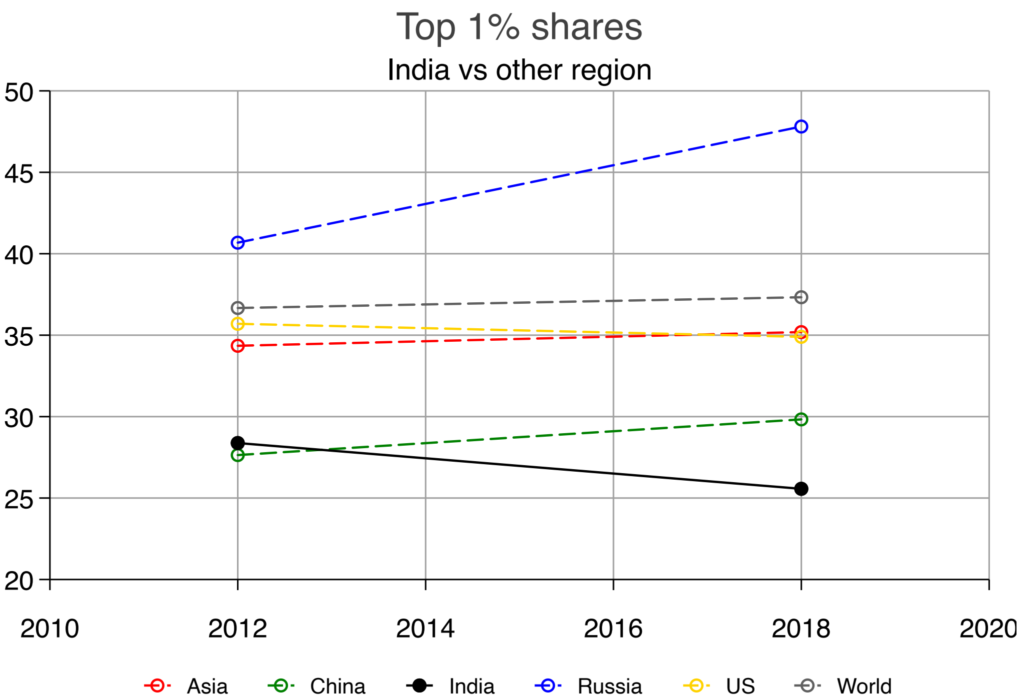

Figure 8: Top 1 percent wealth shares, compared to other countries/regions

How big is the gap between India's rich and poor, from a global perspective? On wealth shares alone, there is little more we can say (one can be globally poor, but rich in a very poor country). Rather, because we already know that India's mean income constrains it to the lower to lower-middle class of the world, most Indians are not rich (Lakner and Milanovic, 2016). But at the same time a few Indians are as rich as the richest individuals in the world (thus featuring in global rich lists). To fix ideas, we converted averages across the distribution to US dollar amounts and normalized them with flows of US per-capita GDP in 2012 and 2018.

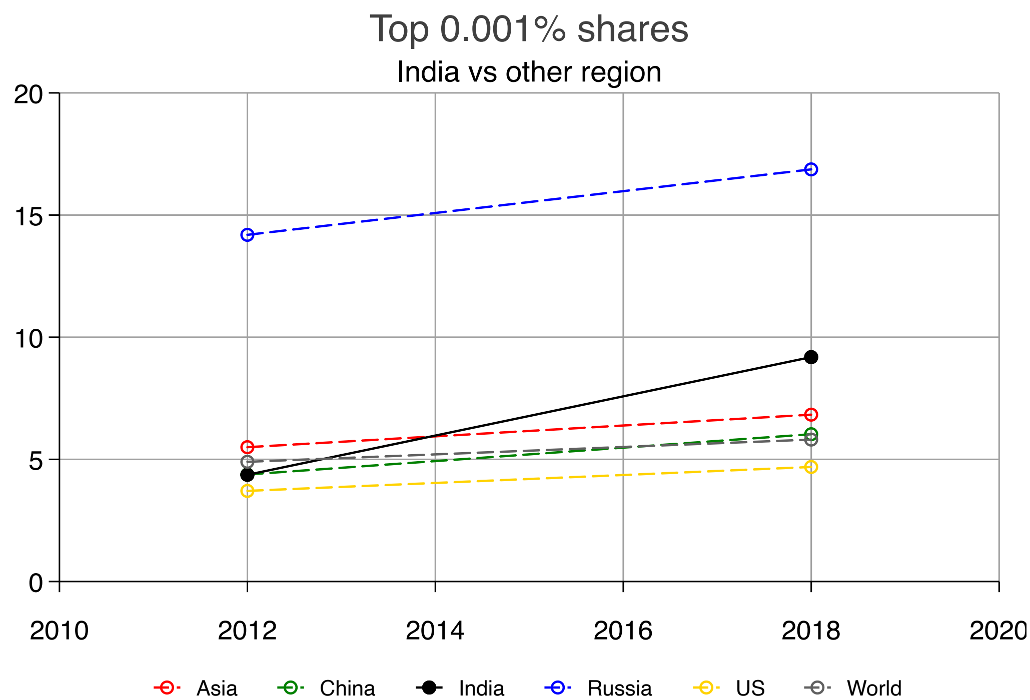

Figure 9: Top 0.001 percent wealth shares, compared to other countries/regions

The resulting estimate measures years worth of average living standards[18] in an advanced economy, afforded to Indians of different strata. Table 8 shows that differences are stark. While we expected most Indians to be poor, even India's upper class is unable to afford a year worth of US income; average wealth in the top decile, excluding the top 1 percent, was worth 0.7 years in 2012, and declined slightly to 0.58 years in 2018. The Top 0.001 percent, on the other hand, are very rich even by American standards, with the ability to afford 1,546 years in

[18]Since our intention is to measure wealth as if it was buying American living standards, we do not convert to PPP dollars.

Average wealth, in USD (nominal)

		Wealth, 000 USD	Years of US p.c. income
2012	Bottom 50 percent	1.33	0.03
	50-90th percentile	7.90	0.15
	90-99th percentile	36.85	0.71
	99-99.9th percentile	145.20	2.81
	99.9-99.99th percentile	757.77	14.68
	99.99-99.999th percentile	4,515.34	87.50
	Top 0.001 percent	43,579.57	844.53
	Richest 100	2,429,952.24	47,090.27
2018	Bottom 50 percent	1.72	0.03
	50-90th percentile	9.35	0.15
	90-99th percentile	36.68	0.58
	99-99.9th percentile	138.10	2.19
	99.9-99.99th percentile	405.25	6.43
	99.99-99.999th percentile	1,461.65	23.18
	Top 0.001 percent	97,508.88	1,546.19
	Richest 100	3,876,287.44	61,465.93

Table 8: Average wealth expressed in US dollars and normalized by US per capita GDP

2018. Needless to say, the ability to migrate out and live off of wealth is limited to a few thousand individuals in India – a fraction of the Top 1 percent. Our normalization exercise shows that wealth differences in India are exceptionally large. All but a fraction of a fraction are poorer in wealth than a year's worth of US per-capita income. Remembering that a fraction of 1 percent still means numerous individuals in a population of more than 700 million adults, there are also many Indians who are richer[19] than most of America.

5 Concluding remarks

We wish to assert that in our view, the timing and quality of survey data are suspect. Our results should be interpreted with these suspicions in mind. The most obvious quality issue is that these surveys simply do not account for the actual rich. Potentially, the actual growth of the rich has surpassed the methodology used by the survey making it more representative of the vast majority, but not the actual rich (who would hold a very significant fraction of wealth). We adjusted for this by supplementing these data but we stress that given our methodology, our estimates of the rich are likely biased downwards. Simply by bridging the lines between the rich in two different datasets, we were able to reverse what appeared otherwise as a decline in wealth for Indians in the Top 0.001 percent. Although we do not know why, the timing of release is also a puzzle. In previous years, wealth surveys were conducted and released on a decennial basis (1991-92, 2002, 2011-12). However, this iteration was released within six years of the last publication. One explanation might be public pressure after the demonetization of currency in 2016. However, the official statistical body did not release the consumption survey for the same year (compared to wealth, that survey was due to be published

[19] At a 5 percent rate of return, this magnitude of wealth would give capital income equal to 77 times the average income of the US, easily putting these individuals in the Top 0.01 percent of the US income distribution

at that time). From the perspective of transparency, we hope the reason is not that a decline in wealth inequality is more politically favorable than a decline in mean consumption. These are important topics that should be addressed by the concerned authorities, and likely the focus of future research.

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Appendices

A Supplementary Tables

Average wealth, Rs 100K (CPI adjusted)

		Survey	Corrected with rich lists
2012	Bottom 50 percent	0.71	0.71
	50-90th percentile	4.22	4.22
	90-99th percentile	19.67	19.67
	99-99.9th percentile	77.50	77.50
	99.9-99.99th percentile	404.28	404.45
	99.99-99.999th percentile	2,405.77	2,410.03
	Top 0.001 percent	3,700.00	23,260.29
	Richest 100		1,296,970.00
2018	Bottom 50 percent	0.81	0.81
	50-90th percentile	4.42	4.42
	90-99th percentile	17.33	17.33
	99-99.9th percentile	65.24	65.26
	99.9-99.99th percentile	191.05	191.49
	99.99-99.999th percentile	682.94	690.68
	Top 0.001 percent	1,551.52	46,076.47
	Richest 100		1,831,686.00

Table 9: Average wealth, 2012-2018 computed using surveys and corrected using rich list data.