Dynamics of income inequality under disequilibrium: The case of India

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Abstract:

Income inequality is one of the most significant socio-economic challenges confronting India, with potentially long-lasting implications for the future of its democracy and society. In this work, we explore income inequality in India, without assumptions of equilibrium, and illustrate the nature and direction of re-distribution within the income distribution in a dynamic sense. Given that both mean income and income inequality show a rising trend post the Industrial Revolution, we argue that such a process is appropriately modeled using Geometric Brownian Motion (GBM). Specifically, we use the mechanism of GBM with a reallocation parameter (which indicates the nature of re-distribution occurring in the income distribution) proposed by Berman et al. We find that since the mid-1990s, reallocation is negative, meaning that incomes are exponentially diverging, indicating that there is a perverse re-distribution of resources from the poor to the rich. It has been well known that static inequality is rising in India, but the assumption has been that while the rich may be benefiting more than proportionally from economic growth, the poor are also better off than before. The surprising finding from our work is that the nature of income inequality is such that we have moved from a regime of progressive to regressive re-distribution. Essentially, continued impoverishment of the poor is directly spurring multiplicative income growth of the rich. We characterize these findings in the context of increasing informality of the workforce in the formal manufacturing and service sectors, as well as the possible evolution of negative net incomes of the agriculture workforce in India. Significant structural changes may be required to address this phenomenon.
1. Introduction

We live in a time characterized by increasing anxiety about income and wealth inequality (Ribeiro, 2013; Oncu, 2013; Lyster, 2016; Kohut, 2011). Prior to the Industrial Revolution, mean incomes in most countries were stagnant for many centuries (Alvarez-Nogal and Prados de la Escosura, 2013), but inequality waxed and waned over time as a consequence of idiosyncratic forces such as wars, discovery of new lands, and epidemics (Milanovic, 2016). The rise and fall of inequality around an essentially fixed mean income illustrates the fact that there was no systematic relationship between inequality and...
especially the early 1990s, inequality has shown a sustained and steep increase, resulting in the top 10% (1%) earning 56% (21%) of income in 2015 (Chancel and Piketty, 2017a).

While Chancel and Piketty (2017a) provide a measure of the instantaneous levels of income inequality at different points in time, we propose to explore the dynamics of income distributions suggested by these inequality measures, and their time scales for convergence. We seek to do this without assuming stationary limit distributions in the long-time limit (as is commonly done) (Benhabib et al., 2017; Piketty and Saez, 2013; Nardi et al., 2015) because this assumption presupposes that convergence to stationary distribution occurs within time scales relevant to redistributive policy changes. This speed to convergence is of critical importance in evaluating any model’s validity (Atkinson, 1969). For instance, we know from Indian income tax data that significant changes in effective top marginal tax rates occurred every 5 to 7 years between 1970 and 2000, though there appears to be lesser variance between 2000 and 2015 - the effective top marginal tax rate was 98% in 1974, 72% in 1980, 50% in 1986, 40% in 1993, and 30% in 1998 (Acharya, 2005). Therefore, the convergence of model income distributions to their asymptotic forms ought to be seen against such time scales. In this context, there has been emerging work on studying income and wealth distributions to understand the underlying dynamics of change, without a particular focus on asymptotic form (Gabaix et al., 2015; Berman and Shapira, 2017; Berman et al., 2017).

In order to contemplate appropriate models to simulate income growth over time, it is useful to go back to the systematic nature of the relationship between mean income and income inequality post the Industrial revolution (Milanovic, 2016; Piketty, 2014), with both average income and income inequality, on average, rising over time. Given this framing of income dynamics, we argue that income evolution is perhaps best studied as a multiplicative growth process following Geometric Brownian Motion (GBM), which obtains a broadening log-normal distribution over time. There have been models that simulate economic quantities such as stock prices, wealth and income as GBM (Gabaix et al., 2015; Berman et al., 2017; Bouchaud and Mezard, 2000; Vasicek, 1977). In this work, we propose to use the methodology of Berman et al. (2017), who analyze wealth dynamics under disequilibrium - specifically by not assuming the ‘ergodic’ hypothesis that rescaled wealth converges to a stationary distribution. Essentially, it models wealth (or in our case, income) as a noisy multiplicative process following GBM and also incorporates a reallocation parameter \( \tau \) to model the transfer of wealth between individuals. The reallocation parameter in this model can be understood as a consolidated measure of reallocation in the economy, including all taxes and other rede distributive mechanisms. Therefore, under this model (called the reallocating GBM or RGBM model), the time-evolution of wealth comprises two mechanisms, namely growth and reallocation, and is modeled using the following stochastic differential equation (Berman et al., 2017):

\[
dx_i = x_i(\mu dt + \sigma dW_i) - \tau(x_i - \langle x \rangle_N)dt
\]  

\( dx_i \) is the change in wealth of individual \( i \) over time period \( dt \). The first term \( x_i(\mu dt + \sigma dW_i) \) is the growth term and the second one \( \tau(x_i - \langle x \rangle_N)dt \) is the reallocation term. In the growth term, the \( \mu dt \) represents systemic growth (economic growth that affects all wealth) while the \( \sigma dW_t \) represents idiosyncratic growth of the particular individual \( i \)’s wealth, with \( dW_i \) specifically being the increment in a Wiener process, which is normally distributed with mean zero and variance \( dt \). \( x_i \) is the wealth of \( i \) at time \( t \), while the parameters \( \mu \) stand for drift and \( \sigma \) for volatility. The reallocation term comprises the reallocation parameter \( \tau \) applied to the net reallocation from individual \( i \), which is the difference between the individual’s wealth and mean wealth (given by \( \frac{1}{N} \sum_{i=1}^{N} x_i \)).

Income inequality time series data for India (1922-2017) was generated by Chancel and Piketty (2017b). We use this data for the period from 1951, when India became a republic, until 2015. Specifically, the dataset provides annual estimates on income of the top 10% of population as
proportion of total national income ($S_{10\%}$) and the income of the top 1% as proportion of the total
national income ($S_{1\%}$).

Our objective is to reproduce the income shares of the top 10% (and 1%) by fitting a time series $\tau(t)$
(the value of the reallocation parameter over time). As per the RGBM algorithm (Berman et al.,
2016), we begin with the initialization of $N$ individual incomes from a log-normal distribution (the
lognormal is a reasonable representation of real-world income and wealth distributions - Clementi and
Gallegati, 2005; Souma, 2001; Brzezinski, 2014), with parameters of the distribution chosen such that
the income of the top 10% of the distribution - $S_{10\%}^{model}(t_0)$ - matches the empirically observed
$S_{10\%}(t_0)$. Once incomes have been initialized, individual incomes are propagated using Eq. 1 for
$\Delta t = 1$ with the value of $\tau$ chosen so as to minimize the difference between $S_{10\%}^{model}(t + \Delta t, \tau)$ and
$S_{10\%}(t + \Delta t)$. This step is repeated till the end of the time-series in 2015 to get a full time series for $\tau(t)$.

Berman et al. (2017) find that the RGBM (with parameters generated from US data) yields three
distinct regimes of behavior based on the nature of reallocation. For $\tau = 0$ or no reallocation, the
RGBM is simply the GBM, which does not converge to a stationary distribution in the long-time
limit, and both mean wealth and wealth inequality increase continually over time. For $\tau > 0$, or
positive reallocation, which we expect to reflect the reality of most modern economies which have
systems of taxation and re-distribution, wealths disperse (which means that inequality may still
increase despite re-distribution) but remain confined around the sample mean $(x)_N$. As $\tau$ increases,
the distribution is more closely held around the mean. This is obvious, because by design, increasing $\tau$
means increasing re-distribution from top of the distribution to the bottom. For $\tau < 0$ or negative
reallocation, wealth is essentially re-distributed from the poor to the rich. In this regime, negative
wealths are possible (meaning no floor for wealth), which at the same time fuels the multiplicative
growth of wealth of those at the top of the distribution. There is no stationary distribution as wealths
diverge exponentially away from the mean - those with wealths below sample mean are pushed into
negative wealth and those above gain exponentially.

Overall, our research objective is two-fold. First, we implement the RGBM model on Indian income
distribution data and attempt to uncover the reallocation regimes of the distribution over time. Second,
we attempt to characterize these findings in the context of specific evidence from the socio-economy
of modern India.

2. Model Implementation and Results

We first estimate the parameters of the income distribution for India, $\mu$ and $\sigma$ (using similar strategies
to the RGBM model for the US - Berman et al., 2016). Chancel and Piketty (2017b) provide data on
average individual incomes in independent India from $t_0 = 1947$. Fitting the evolution of average
individual income over time using a curve of the form $\exp[\mu(t - t_0)]$ yields a value of $\mu = 0.0231$.
We estimate annual $\sigma(t)$ as the standard deviation of daily logarithmic changes of the Bombay Stock
Exchange’s (BSE) benchmark index called the Sensex (BSE, 2019), multiplied by $(250 \text{ per yr})^{0.5}$
(assuming 250 working days per year). These values are averaged and we get a consolidated
$\sigma(Sensex) = 0.2358$. However, the BSE’s benchmark index data is only available from April 1979,
as there is no benchmark prior to this date. Given the fact that India was a largely closed economy
with a dominant public sector until the early 1980s, it is reasonable to expect that volatility of average
income was substantially lower in the period till 1979. For our model, therefore, we use $\sigma = 0.20$.

Using these parameters for drift and volatility in the Indian context, we test the model for positive,
negative, and no reallocation with $\tau = +0.1; 0.0; -0.1$ (other parameters: $N = 1000$, and $x_i(t_0) = 1$
for $i = 1, ..., N$), and find that the results show a distribution confined around the mean for $\tau =$
+0.1 (Figure 1a), standard GBM for $\tau = 0.0$ (Figure 1b), and exponentially diverging distribution (with negative incomes) for $\tau = -0.1$ (Figure 1c); these outcomes are in complete concordance with the regimes observed in simulations using US parameter data (Berman et al., 2016).

Figure 1. Theoretical exploration of reallocation regimes and evolution of instantaneous inequality over time. A: Simulation of incomes for positive reallocation ($\tau = 0.1$). Incomes disperse but stay around sample mean for finite $\tau$. Mean income increases with time. B: Simulation of incomes for zero reallocation ($\tau = 0.0$). This is simply the GBM where incomes follow a log-normal distribution. Mean income and income inequality increase over time. C: Simulation of incomes for negative reallocation ($\tau = -0.1$). Incomes diverge exponentially from the mean, no stationary distribution exists and re-distribution occurs from the bottom to top of distribution. Black lines: Maximum and minimum incomes forming the income envelope. Blue line: Sample mean of incomes. Yellow line: Sample median of incomes. D: Fraction of income belonging to the top $q\%$ of the population ($S_{q\%}$) over time (1951-2015). Blue line: $S_{10\%}$. Red line: $S_{1\%}$.

Figure 1d plots the evolution of instantaneous income inequality (income inequality at specific points in time) in India using the two measures provided in the Chancel and Piketty (2017b) data: $S_{10\%}$ and $S_{1\%}$. This clearly reveals that income inequality (as represented by both $S_{10\%}$ and $S_{1\%}$) shows a downward trend initially followed by a continuous and rapid upward trend over the past two decades.

We execute the RGBM algorithm (as described in Section 1) using actual income distribution data from India (both for $S_{10\%}$ and $S_{1\%}$), for the following parameter values: $N = 10^5$, $\mu = 0.0231$, $s = 0.2$. We find that the reallocation parameter in the case of $S_{10\%}$ (termed $\tau_{10\%}$) is largely positive between 1951 and the early 1990’s, but remains persistently negative from the mid-1990s onwards (Figure 2a, red line). A similar trend is observable when we assess the reallocation parameter for $S_{1\%}$ (termed $\tau_{1\%}$), except that the negative reallocation occurs in the 1980s itself (Figure 2a, blue line). This suggests that for over the past two decades at least, the income distribution has been diverging, which is a significant concern given that it means that income re-distribution has left a progressive regime (reallocation from the rich to the poor) and entered a persistently regressive regime where the income of the poor is being re-distributed to the rich resulting in negative incomes as the bottom of the distribution. The notion of negative incomes has generally been meant to quantify
household or family financial losses in micro and small businesses or agriculture (Chen et al., 1982). We discuss the specific context for negative incomes in India in the Discussion section.

It could be argued that the reallocation described by \( \tau_{10\%}(t) \) and \( \tau_{1\%}(t) \) in Figure 2a shows too much variability on an annual basis and that reallocation policies do not display such sharp changes year on year. In order to address this and smooth the evolution of \( \tau(t) \), we compute the effective reallocation rate as the 10-year moving average of \( \tau_{10\%} \) (termed \( \bar{\tau}_{10\%} \)) and of \( \tau_{1\%} \) (termed \( \bar{\tau}_{1\%} \)). We still find that these effective reallocation rates \( \bar{\tau}_{10\%}(t) \) are positive for close to four decades from 1951 and then become negative from the 1990s. Effective reallocation rates \( \bar{\tau}_{1\%}(t) \) are negative from earlier, the mid-1980s onwards.

Finally, we verify that the effective reallocation rate \( \bar{\tau}_{10\%}(t) \) is still representative of the same income distribution as the simple reallocation rate \( \tau_{10\%} \) and not introducing any other systematic element into the distribution. In order to do this, we use \( \bar{\tau}_{10\%}(t) \) to propagate the initial income distribution (parameter set: \( N = 10^5, \mu = 0.0231, \sigma = 0.2, \tau(t) = \bar{\tau}_{10\%}(t) \)) and compute the resultant \( S_{10\%}^{model}(t) \). Figure 3 plots the temporal evolution of \( S_{10\%}^{model}(t) \) and we see that it shows close alignment with \( S_{10\%}(t) \). Therefore, we argue that the effective reallocation rate is a meaningful measure of the actual re-distribution occurring in the income distribution.
The RGBM model of Indian income dynamics reveals that the income distribution has been in the regime of negative reallocation in the past two decades, and that the wealths of the rich and poor are diverging away from each other exponentially. This essentially means that an individual whose income is lower than the sample mean, will remain in the lower half of the distribution and continue to be further impoverished over time. The perversity of this situation becomes apparent when we consider that the impoverishment of such individuals in the bottom half of the income distribution directly spurs the multiplicative growth in income of individuals in the top half of the distribution. As Berman et al. (2016) state, this becomes an economy of debtors and creditors.

We elicit further proof of this phenomenon by tracking the evolution of mean income of each decile of the population (as generated in the model based on Indian inequality data) over the period 1951 to 2015 (Figure 4a). We find that mean incomes across all deciles appear to increase up until the early 1980s (highlighted by the black dashed line), even as the richer deciles garner disproportionate proportion of overall income - indicating increasing income inequality. However, from the 1990s it is apparent that we enter a fundamentally different regime of divergence, where the mean incomes of the bottom four deciles show a continuous and persistent decline, even as the mean incomes of the top two deciles increase sharply, thus yielding rapid increases in inequality. But, importantly, as this divergence is unfolding, we see that the evolution of mean income of the entire population (dashed pink line) shows an uninterrupted, increasing trajectory over time. The top deciles see their mean incomes diverging rapidly above this mean threshold, while the bottom deciles see their mean incomes diverging below this threshold, with the bottom two deciles even showing negative mean income towards the end of the time frame. These trends are further explicated when we assess the fraction of income owned by each decile over time (Figure 4b). For instance, even in the period when the income share of the top decile decreases (1951-1980), it is clear that the average income of the decile grows monotonically (Figure 4a). More importantly, we find that the bottom decile owns a decreasing share of income from the 1980s, and post 2005 the share becomes negative – which simply means that total income of the bottom decile is negative. The penultimate (9th) decile also sees its share of wealth dropping to zero. This highlights the fact that a substantial portion of the population in the bottom deciles could be trapped in a vicious cycle of negative income.
The continual casualization of the workforce in the formal sector has meant a fraction of contractual employees increase also in the increasingly contractual nature of services through networks of agents who are not directly employed by them (Mehrotra et al., 2012; NSSO, 2015). This has meant excess returns for capital (Milanovic, 2016) (there were nine billionaires in India in 2000, 57 in 2011, and 131 in 2017 as per the Forbes Rich List), while at the same time resulting in an increasing informalization of jobs in the organized sector (Mehrotra et al., 2012; NSSO, 2015). This is obvious not only in the nature of employment in new-age technology companies (such as Uber, Ola, and Amazon among many others) which provide their services through networks of agents who are not directly employed by them (McQuown, 2016), but also in the increasingly contractual nature of employment in the manufacturing sector (where the fraction of contractual employees increased from 16% in 1998-99 to 35% in 2014-15) (Mehrotra et al., 2012; NSSO, 2015). The continual casualization of the workforce in the formal sector has meant a

3. Discussion

It is well recognized fact that economic growth is essential for a nation like India to effectively combat poverty (Roemer and Gugerty, 1997; Fosu, 2017; Adams, 2004). Economic growth has been seen as key to the reduction of poverty in India over the past 25 years (Panagariya and More, 2014; Panagariya and Mukim, 2014), and recognizing that the increased growth may indeed be somewhat inequitably distributed, it is argued that the benefits of growth are not just increasing, but not结婚 increasing, but being (and perhaps continue to be) in a regressive regime of redistribution would follow economic growth (which yielded the inverted-U shape of the Kuznets curve, signifying rising and then falling inequality with rising income), though there is evidence to suggest that lower inequality benefits economic growth and therefore poverty reduction (Fosu, 2017; Lakner et al., 2019; Alesina and Rodrik, 1994). Our finding that for the past two decades we have been (and perhaps continue to be) in a regressive regime of re-allocation in India, where inequality is not just increasing, but that incomes are exponentially diverging over time resulting in a degenerate re-distribution of income from the bottom to the top, challenges the notion that inequality ought not to be an extant concern and underlines the need for a deeper interrogation into the nature of economic growth in India.

The onset of the technology revolution has indeed led to a rise in inequality across the world (Milanovic, 2016), and India appears no exception (Chancel and Piketty, 2017a; Deaton and Dreze, 2002; Sarkar and Mehta, 2010). This has meant excess returns for capital (Milanovic, 2016) (there were nine billionaires in India in 2000, 57 in 2011, and 131 in 2017 as per the Forbes Rich List), while at the same time resulting in an increasing informalization of jobs in the organized sector (Mehrotra et al., 2012; NSSO, 2015). This is obvious not only in the nature of employment in new-age technology companies (such as Uber, Ola, and Amazon among many others) which provide their services through networks of agents who are not directly employed by them (McQuown, 2016), but also in the increasingly contractual nature of employment in the manufacturing sector (where the fraction of contractual employees increased from 16% in 1998-99 to 35% in 2014-15) (Mehrotra et al., 2012; NSSO, 2015). The continual casualization of the workforce in the formal sector has meant a

Figure 4. Temporal evolution of income dynamics by deciles from 1951-2015. A: Mean incomes of each decile vs. Time (in years). Mean incomes of all deciles show an increasing trend from 1951 to 1980, despite increasing inequality. Beyond 1985, mean wealths of deciles show a divergence away from the mean population income, with the deciles above the mean population income showing rapid increases in mean income, while those below showing persistent declines in mean income. Dashed pink line: Mean income of population from 1951 to 2015 shows a continuous increasing trend. Black dashed line: Indicates the point in the early 1980s when the income distribution crossed over from one regime to another. B: Share of income earned by each decile v. Time (in years). We see similar trends as indicated in (A), and post 2005, the share of income earned by the bottom decile is negative, meaning that total income of the bottom decile is negative.
gradual stripping away of job contracts, security and benefits, resulting in diminished possibilities for meaningful worker mobilization and organization (Applebaum and Lichtenstein, 2016).

Nowhere is the stark nature of the India’s extant income distribution more apparent than in the agricultural sector, which employs close to 50% of India’s workforce (DEA, 2018). It is well recognized that agrarian economic distress has been widespread in India since the 1990s (Vakulabharanam and Motiram, 2011; Reddy and Mishra, 2008, Vaidyanathan, 2006). This is manifested in the increasing indebtedness of farmers - over half the nation’s farmers are indebted, and both incidence and extent of indebtedness have been increasing over time (Suri, 2006; Narayananmoorthy and Kalamkar, 2005), primarily on account of increased input costs due to removal of public subsidies, output price volatility, and decline in public investments (Vakulabharanam and Motiram, 2011; Reddy and Mishra, 2008; Suri, 2006). This indebtedness is linked to the increase in numbers of marginal and small-hold farmers and also to the spate of farmer suicides - over 298,000 farmers committed suicide between 1995 and 2012 (Vaidyanathan, 2006; Suri, 2006; Nagaraj et al., 2014; Kennedy and King, 2014). Thus, the inherent volatility underlying agricultural incomes since the 1990s is closely linked to the simultaneously rising levels of smallholder farms and agricultural debt. Essentially, any crop failure in a smallholding or marginal farm – a business loss - would result in a direct income loss to the household (because such farms are not incorporated to benefit from limited liability – in this context, all business liability is personal liability). Combined with high levels of debt, this intertwining of business and personal income, could directly result in negative agricultural incomes that are tending further negative over time. There is previous evidence of negative income observations in agricultural contexts, as in the case of Taiwan in the 1960s and 1970s (Pyatt et al., 1980). Consequently, these trends reveal a real concern that prevailing conditions are leaving increasing fractions of the agricultural sector workforce in India as net debtors in the economic system.

Given this confluence of global and national trends, there is arguably a need for structural interventions to enable a reversal of the extreme inequality evident today. It has been argued that the current tide of rising income inequality can be countered by a number of strategies such as new forms of political mobilization, taxation policies, and universal incomes, among others (Piketty, 2014; Schiller, 2004; Burman, 2014; Skidelsky and Skidelsky, 2012). Schiller (2004), for instance, contends that a progressive tax system is an essential bulwark against income inequality, by ensuring that higher earnings are taxed at higher rates, but that the system does not respond adequately if income inequality rises and become increasingly more extreme (as our work demonstrates in the Indian context). To counter such inequality, he proposes a fundamental reform of the tax system by having taxes indexed to income inequality. This would mean that the system remains progressive, but most importantly, tax rates would endogenously adjust to changes in inequality. Effectively, in scenarios of increasing or extreme inequality, the rate of rise in marginal tax rate on the highest income brackets will reflect the rate of rise in inequality. Burman (2014) further nuances this idea by proposing a progressive tax code integrating inequality indexing with inflation indexing, where losses in tax revenue on account of inflation indexing can be offset by increased tax revenues from inequality indexing. The nature of this offset due to inequality indexing would be that richer tax payers bear more of the burden (and poorer tax payers less) in case of worsening inequality. Piketty (2014) also recommends raising the tax rates on the highest incomes, as well as increasing inheritance taxes. The Universal Basic Income (UBI), where all citizens of a country receive a regular, unconditional sum of money from the government, is also proposed as a counter to inequality. It is argued that since the lion’s share of productivity gains over the past few decades have gone to the richest, a reversal of this trend could fund a modest initial basic income (Skidelsky and Skidelsky, 2012). Given the increasing threat of automation and the further exacerbation of inequality that this trend could represent, a UBI that grows in line with capital productivity would benefit the many instead of privileging the few (Skidelsky and Skidelsky, 2012).
While the details of specific policy proposals to counter income inequality will vary by context, what our work specifically highlights is the need for structural reforms to ensure that the divergence of the income distribution is reversed and we are able to return to a progressive re-distribution regime.

4. Conclusion

We attempt to characterize the dynamics of income inequality in India. Milanovic (2016) shows that the rise of modern capitalism after the Industrial Revolution had a fundamental impact on the nature of the relationship between average income and income inequality. Essentially, both average income and income inequality tend to rise over time and it is only for a brief period in the mid-20th century that we see a decline in income inequality even as average income increases. This is on account of a combination of factors that resulted in the enactment of policies such as progressive taxation aimed at reducing inequality. The advent of the communications and internet revolutions has once again resulted in a continual upward surge in inequality over the past three decades. In the Indian context, we find that income inequality reduces in the period between 1951 and the early 1990s, beyond which it shows continual and significant increase.

Given Milanovic’s characterization of the evolution of income post the Industrial revolution – a period of increasing mean incomes and increasing income inequality - we seek to model income evolution as a multiplicative process following Geometric Brownian Motion (GBM). In doing so, we follow the methodology of Berman et al. (2017), who model the dynamics of wealth distributions without the ‘ergodic’ assumption that rescaled wealth converges to a stationary distribution. Their model termed reallocating GBM or RGBM incorporates a re-distribution term \( \tau \) to the GBM and finds distinct regimes of behaviour for positive reallocation (wealths disperse but remain confined around the mean) and negative reallocation (wealths diverge exponentially away from the mean, no stationary distribution exists).

Applying the RGBM to Indian income inequality data, we find that there are two distinct regimes: between 1951 and 1995 the reallocation is positive (\( \tau > 0 \)) and between 1995 and 2015, the reallocation is distinctly negative (\( \tau < 0 \)). This means that for the past two decades and more, India’s income distribution has been in a regime of perverse, regressive taxation where re-distribution occurs from the poor to the rich. Even in the period between 1951 and 1995 when reallocation is positive, we find that the time scales to equilibrium (stationary distributions) are significantly longer than time scales of policy changes, meaning that assumptions of stationarity in such models are irrelevant. Further work using the RGBM model on alternate measures of income inequality such as the Gini coefficient could help validate our results.

We discuss how the nature of India’s economic growth is closely linked to the nature of income inequality observed over the past two decades in the RGBM model. The increasing informalization of the formal workforce in both new-age tech as well as the manufacturing sector has meant that workers have been left with no avenues for mobilization. The agricultural workforce appears to be the worst hit, with highly volatile incomes (especially of marginal and small farmers) combining with increased indebtedness resulting in the possibility of sustained negative net incomes over time.

Given the current nature of income inequality in India as revealed by the RGBM model, it is important for us to reconsider and suitably reorient extant models of economic growth and taxation so that prosperity is more equitably distributed and any economic re-distribution remains progressive.

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