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Inequality and locational determinants of the distribution of living standards in India

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Inequality and locational determinants of the distribution of living standards in India

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Abstract

Using 2011-12 consumption micro-data, we find that nearly one-third of the variation in living standards in India can be explained by location alone. Consumption levels and locational inequality are positively related. In effect, from an individual's perspective, living standards are higher in richer, but more unequal, locations in India. The central factor behind these findings is the large difference in average consumption levels between rural and urban India and continued divergence in per-capita incomes between rich and poor states. Our results provide a possible explanation for the persistence of economic migration from rural to urban areas within a fast-growing emerging economy. While individuals cannot easily alter specific characteristics like their caste or religion, they have some freedom to change their location to enjoy better living standards.

Keywords: Inequality, Dual-Sector Model, Consumption, Migration, Rural-Urban Gap

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1. Introduction

In 2011-12 the average income in the poorest State in India (Bihar) was around 13% of the corresponding figure for the national capital (New Delhi), measured using per capita State Gross Domestic Product (SGDP). The magnitude of such differences among Indian states rivals differences in per capita incomes between rich and emerging economies – for instance, the 13% differential between average incomes in Bihar and Delhi is close to the ratio of GDP per capita between India and USA in the same year.[2] Delhi is a mostly urban state which serves as the hub of public administration and new industries in its outer regions. Bihar, on the other hand, has a large rural population and provides a large flow of economic migrants to other regions of India. We focus our paper on the extent to which such large within-country locational differences can account for existing inequality in India.[3] Our main question is simple: *how much of the variation in living standards in India can be explained solely based on location?*

As shown in a seminal study by Milanovic (2015), location is a leading explanation of inequality of opportunity on a global scale, because of large between-country differences in per capita incomes. He finds that country of residence and within-country inequality predict greater than 50% of the variation in global incomes. Thus, more than luck or effort expended by individuals or their specific circumstances, their economic outcomes (relative to their global peers) stem from the level and distribution of income within their country.

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[2] Measured using 2011 PPP dollars, according to the World Bank Open Database, India's GDP per capita was 4,493 versus 49,886 for the USA. See: https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.CD?locations=US-IN

[3] See for instance the World Inequality Report (2018) on rising income inequality in India. Anand & Thampi (2016) show that wealth inequality has risen in India between 2002 and 2012. According to Asher et al (2020), intergenerational mobility has remained static since the early 1990s, depending mostly on caste and religion. Vakulabharanam & Motiram (2018) highlight the rise of urban inequality as an important determinant of wealth inequality. Bhalla (2011) presents a strong counterview; using consumption surveys, he suggests weak evidence for rising inequality and points to increase in schooling as evidence for inclusivity in India's economic growth.

We apply this model to India, exploiting the fact that while there is substantial regional variation across states in industrialization and development, internal migration is not constrained by state boundaries. In essence, if location turns out to be an important determinant of living standards, then domestic migration can act as a low-cost option to move up the opportunity ladder.[4] We define *location* as a pair, consisting of a state and its rural or urban subregion, so that for N states, we construct 2N locations. The main reason is that since the 1990s, urban India has grown much more than rural India in terms of average consumption levels. Inequality is also higher in the former (Subramanian & Jayaraj, 2015). Partly this is due to a wider dispersion of consumption – urban regions account for the bulk of India's rich while rural India remains relatively more equal, albeit at lower consumption levels. Moreover, as Deaton & Dreze (2002) have argued, in some states urban growth never took off. Therefore, such inter-state differences have further exacerbated urban inequality.

Using nationally representative survey data on consumption (a proxy for living standards), our main finding is that almost a third of the variation in living standards can be accounted for by location (as defined above). As expected, richer states are associated with higher consumption levels. Strikingly, an individual can (*ceteris paribus*) increase their living standards in the more unequal subregion – i.e. consumption is positively related to the degree of locational inequality. While this last result is especially pronounced for the upper classes, it is statistically significant for every decile of the consumption distribution. One potential explanation maybe the concentration of economic growth in the urban sphere which simultaneously produces higher inequality, approximating a Lewis-Kuznets type process.

[4] The importance of this question was highlighted by developments during the lockdowns imposed due to the Covid-19 pandemic, which forces many urban migrant workers to return to their rural homes. However, within days of a relaxation in intra-state transportation the flow reversed and there was a recovery in rural-to-urban migration. See for instance: https://theprint.in/ilanomics/why-migrant-workers-are-starting-to-return-to-cities-how-this-can-revive-economy-faster/435923/

The basic takeaway is that an economic migrant can (on average) expect to be better off in the lower classes of urban India than in the middle class of rural India. Given that rural India offers much lower living standards on average, a person may be indifferent to their relative class position and prefer the absolute gains emanating despite moving down in the class hierarchy. These estimates explain some of the large flow of inter-state migration – according to the 2017 Economic Survey of India, and the 2011 census, 9 million migrate annually in India and 139 million out of a 1.3 billion strong population[5] are migrants (These are further bolstered by the large swathe of migrant population and its movement during the Covid 19 pandemic). At a more basic level, this paradox of absolute versus relative gains underpins the challenge of inclusive growth in a developing economy.

Our results are constrained by data availability and factors which we have chosen to exclude in order to focus on locational factors. Firstly, our data stop in 2011-12 because this is the year of the last public release of "thick" consumer expenditure surveys conducted by the National Sample Survey Organization (NSSO)[6]. However, from a historical perspective, this captures the most important policy innovation with regard to rural India – namely, the rural job guarantee[7] (MGNREGA). Our results therefore are further enforced by the fact that despite this historic stimulus to rural wages, gains to living standards are higher via migration to an unequal urban area. Secondly, we do not control or account for other important circumstantial factors (such as caste, gender etc.) that could explain a person's consumption levels in India. Our focus is solely on broader regional factors (inequality, industrialization etc.) which cannot be influenced by an individual, similar to Milanovic's global model. Household wealth, human capital and social mobility, for

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[5] See for instance, the World Economic Forum summary of these numbers: https://www.weforum.org/agenda/2017/10/india-has-139-million-internal-migrants-we-must-not-forget-them/

[6] The findings of a more recent 2017/18 NSSO consumption survey were leaked in the press recently, however no microdata is available for public use, hence we have chosen to restrict our data till 2011/12.

[7] The Mahatma Gandhi National Rural Guarantee Act is a rural job guarantee act passed in 2005 and applicable to all districts of India as of 2008. It guarantees every rural household 100 days of annual employment (at minimum wages) in proximity to the household's location.

instance, are strongly influenced by the caste-based organization of society in India (Zacharias and Vakulabharanam, 2011; Asher et al 2020). Individuals cannot select a caste by their own choosing and instead inherit this social ranking at birth. Combined with the factors on which we focus, one could expect that variation in living standards could be predicted even better once these specific circumstances are also taken into account.

In section 2, we briefly explain our concepts and describe our data sources. Sections 3 and 4 discuss our results at the national level, as well as in broader comparison to two other large emerging countries for which household surveys on consumption are available (China, Indonesia).[8] Section 5 concludes.

2. Concepts and Data Sources

Our main cross-sectional data source is the 2011-12 release (68th round) of the NSSO Consumer Expenditure Survey. We use micro-data from this nationally representative survey to calculate annual per capita consumer expenditure using monthly expenditure information – our indicator of living standards. Social scientists have utilized these data (themselves a topic of lively debate) as the chief metric to measure the evolution of inequality in India. The reason for this is that there are no regular surveys on incomes in India. Even the consumer survey is conducted separate from the decennial household asset survey so that one cannot necessarily relate capital accumulation and living standards for the same households.[9] Further, while tabulated income tax data have been employed to study top income shares in India, such data are more suited to studying the upper tails of the income distribution. In 2011, less than 5% of the adult population of India was being captured in income tax returns (Chancel & Piketty, 2019); these data themselves were not

[8] We have compiled all our calculations as reproducible Stata files, available to the interested reader on request.

[9] We are referring to the All India Debt and Investment Survey cosponsored by the Reserve Bank of India (RBI). The RBI also conducts its own consumption surveys although these are based on much thinner sample sizes than the NSSO's own survey.

published by the tax authorities for the decade 2000-2010 when economic growth in India was at its peak. Regardless, one can assert plausibly that consumption is in itself a fair assessment of living standards in India and its distribution approximates the distribution of income for the bulk of the population.[10] One's living standard, as measured by consumption of goods and services, is improved when one has more income to spend. For our purpose, what is more important is that these consumption surveys cover both rural *and* urban India - agricultural incomes in India are not taxed, thus they are not listed in tax data tabulations.

We use the NSSO micro data to compute annual consumption spending per capita by households. We can distinguish households by location, the state as well as whether they are in rural or urban subregions of that state. For both these locational groups, we computed the Gini index of consumption – thus we know, for example, if an individual resides in rural Bihar how much inequality there is in Bihar and rural Bihar. We also collected state-level time series on state GDP from India's official national accounts (NAS) as a proxy for the level of industrialization and the average incomes in that state.

We use the World Bank's PovCalNet database to measure temporal dynamics of consumption.[11] For India, PovCalNet uses the NSSO surveys to merge and standardize distribution information with other worldwide surveys to permit a more consistent measurement of global poverty.[12] Consumption spending figures in PovCalNet are provided only at decile levels of the distribution. Each year of data can be disaggregated at the national, rural or urban level. The advantage of using data in this version is that they

[10] That said, as is the case with most survey data, top-coding and non-response rates limit our knowledge of consumption levels at the upper tail of the population, as substantiated for the case of India in Sundaram and Tendulkar (2003). Moreover, theory suggests that the average propensity to consume increases at a decreasing rate with income because the very rich are able to make savings and simultaneously maintain high living standards. Thus, income inequality tends to be higher than consumption inequality. See for instance such evidence in the US Survey of Consumer Finances (Dynan et al 2004).

[11] See https://worldbank.github.io/povcalnet/

[12] For an excellent introductory review of the PovCalNet database, see Smeeding & Latner (2015)

permit computing decile-wise growth rates over time and comparison with two other high growth, emerging, Asian economies – China and Indonesia. The PovCalNet metric for these two countries is also based on consumption surveys, thereby making comparison appropriate. These consumption data are in 2011 PPP Dollars, jointly covering at least 1983-2011/12 for India, China and Indonesia. PovCalNet further divides these three countries into rural and urban sub-countries owing to their large (particularly rural) populations. Price indices are calculated separately to account for differences in the cost of consumption in urban regions, as opposed to the rural countryside.[13] Thus, any divergence in urban and rural growth reflects more than simply the cost of living such as (say) due to housing rents.

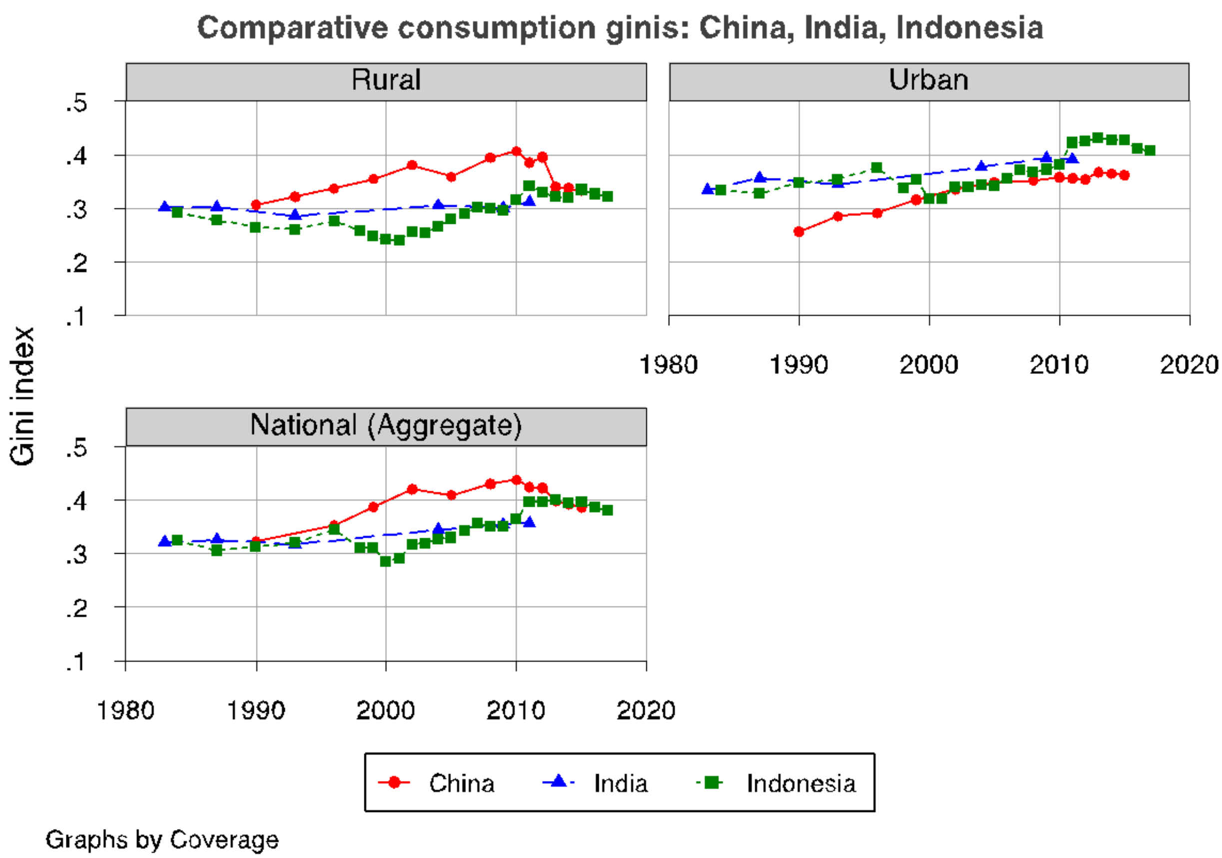
3. A brief summary of the evolution of consumption inequality in India

We first summarize aggregate trends based on the evolution of the Gini index in rural and urban India and compare them with China and Indonesia (Figure 1). Most noticeably, India's Ginis have remained fairly stable and do not display the cyclicality in inequality observed for China and Indonesia. One perspective on this issue is that because India's population is located mostly in rural regions (where consumption Ginis have stayed stable), economic growth has not exacerbated inequality (Bhalla, 2011). In this view, growth and poverty reduction move hand-in-hand, with the former eventually overriding initial inequalities. Furthermore, this view also suggests growth in education, which is far more equally distributed, is the new wealth and it needs to be included in the discussion on wealth inequality (Bhalla S. , 2018). Others have argued that the surveys miss rising consumption in the upper tail, leading to the divergence of consumption estimates in the

[13] See http://iresearch.worldbank.org/PovcalNet/methodology.aspx for the methodology underlying PovCalNet price indices. Because cost of living may be lower in rural India than urban India, the PPP is separately calculated and built into all welfare measures.

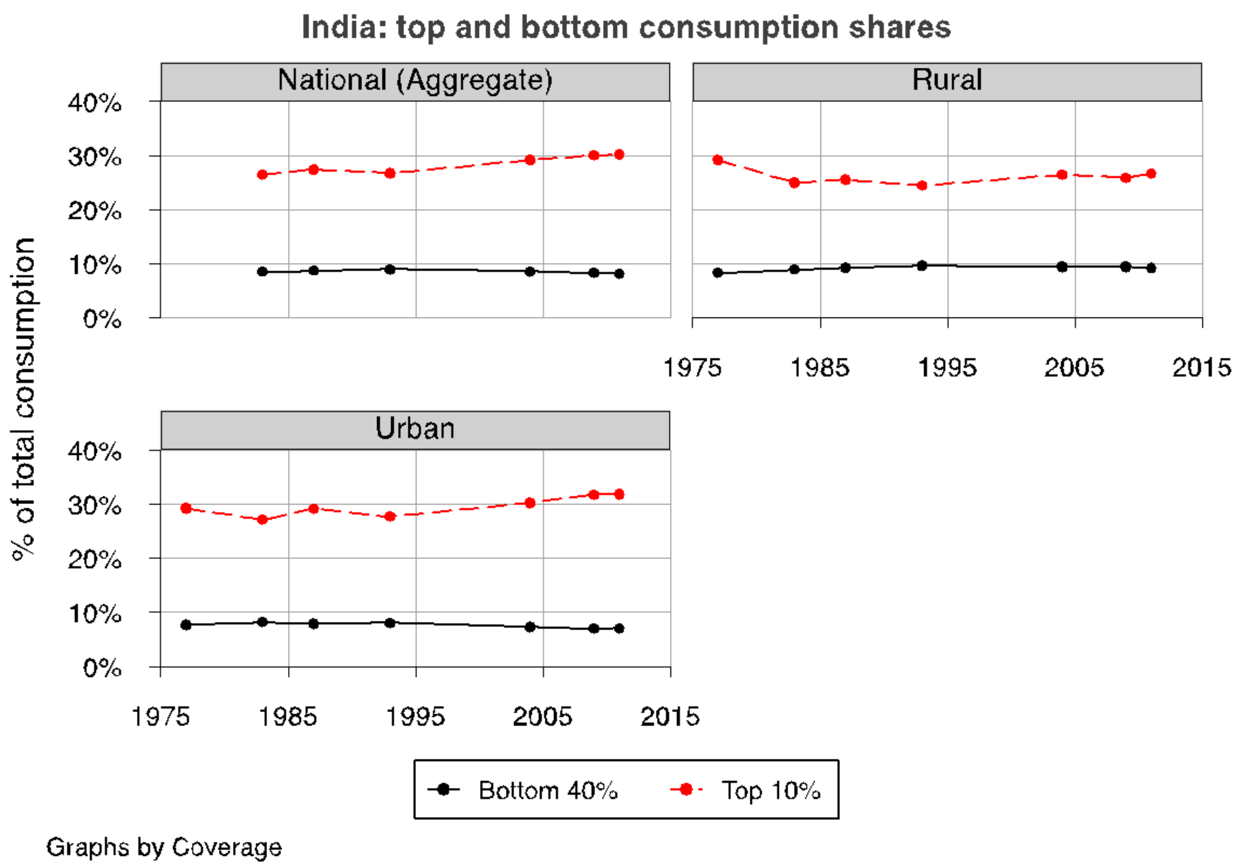
NAS and NSSO (Subramanian & Jayaraj, 2015).[14] Within the estimates as they currently exist, the Indian Gini appears distinct because its urban component drives the trend in the national aggregate, with the latter rising from around 32% to 40% between 1990 and 2011. China and Indonesia's Ginis are dominated by trends in rural inequality. For example, Chinese inequality declines after 2010, mirroring its rural Gini.

Figure 1: Gini indices in India, China and Indonesia



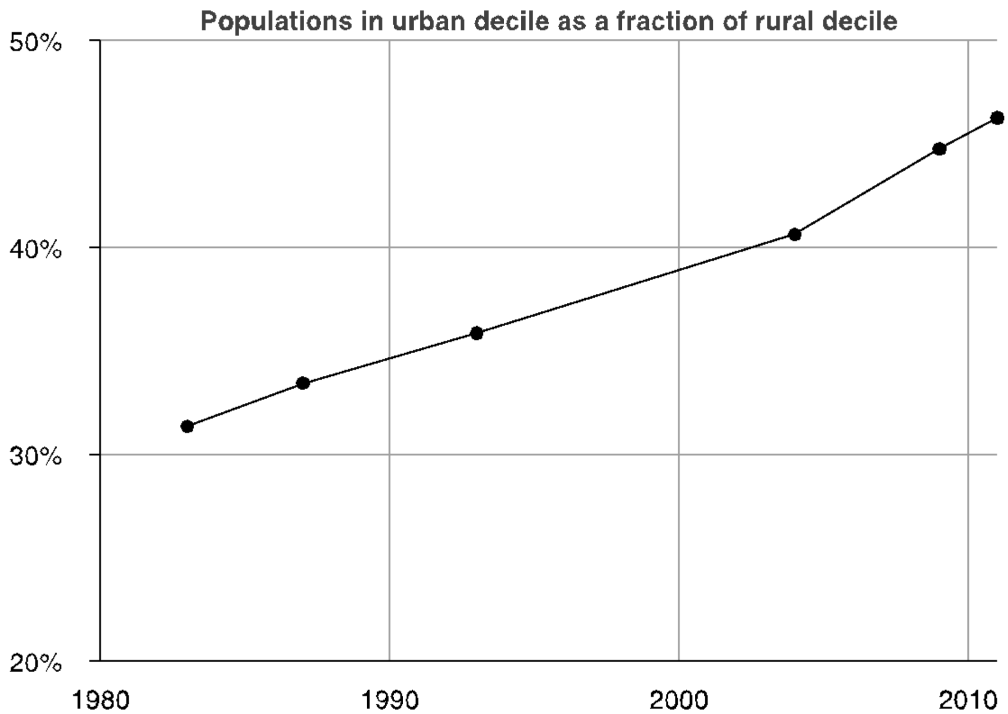
[14] Another important part of this puzzle (diverging survey and NAS consumption) is that national accounts impute owner-occupied rents and these adjustments flatten the actual standard of living (Sundaram & Tendulkar 2003; Deaton & Kozel, 2005).

Figure 2: Top 10% vs Bottom 40% shares in consumption



For India, the two ends of the consumption distribution are congruent with aggregate trends in the Gini. In Figure 2, we plot the evolution of consumption shares for the Top 10% against the Bottom 40% for India. The Top 10% (Bottom 40%) increased (decreased) their share at both the national and urban level, though in rural India there was no real divergence. Another demographic trend is that India's urban population has increased very visibly throughout the period in question (Figure 3). In 1983, the urban population was around 30% of the rural population in size but steadily increased to nearly 50% by 2011. Thus, even holding the level of urban inequality constant, it is plausible that a rising share of the urban population will produce larger aggregate Ginis in India.

Figure 3: Urban versus rural population in India

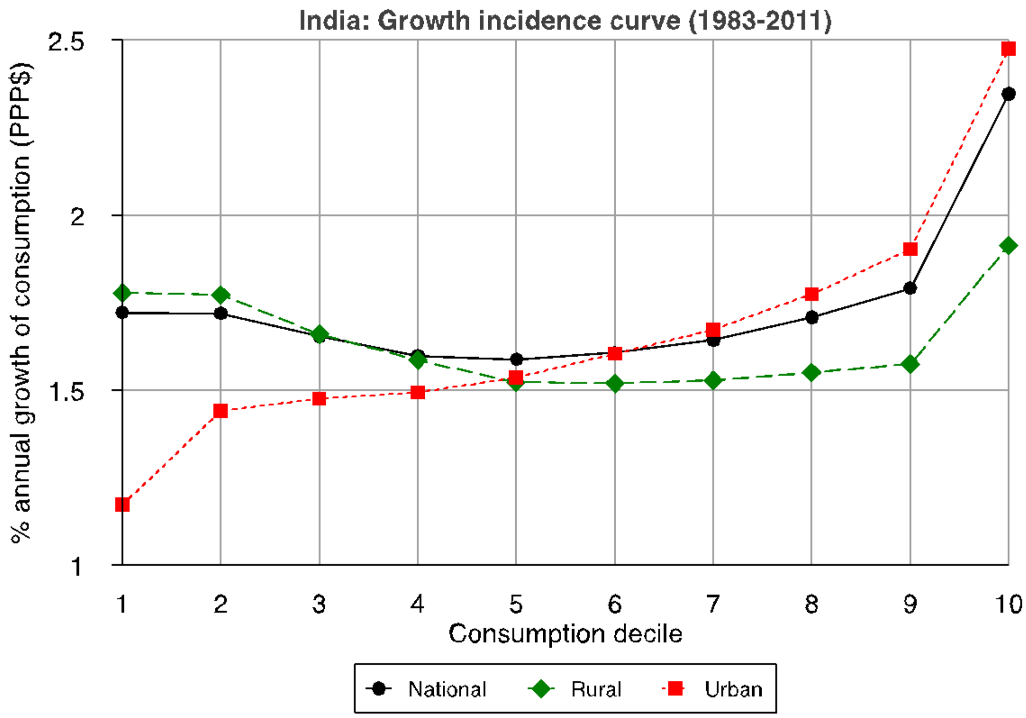


While the Gini measures rise or fall of overall inequality, it does not give information on where (across the distribution) consumption growth is concentrated or lagging. This can potentially hide divergence in consumption growth over time - for instance, concentrated growth across most deciles versus exclusive growth in the top 2-3 deciles. To get more granularity on changes within the distribution itself, we employ Growth Incidence Curves (GIC) for the 1983-2011 period. For every decile of the population and subpopulation (rural, urban) we compute annual consumption growth rates in 2011 PPP dollars and plot them in Figure 4.[15] If growth is equally shared by all quantiles

[15] Note that the GIC is not longitudinal in that we are not accounting for movement of individuals between deciles over time. Approaches towards computing the GIC vary depending on whether growth rates are calculated at the percentile level or as averages for the decile group. We have used the latter approach, as in Lakner & Milanovic (2016).

of the population, then the GIC should be flat; an upward sloping GIC indicates higher growth amongst relatively richer groups.

Figure 4: Growth Incidence Curve 1983-2011



Our estimates effectively show two trends. The first is the well-documented decline of rural poverty in India since the 1980s (Deaton & Dreze, 2002) – the lowest rural deciles on average saw some of the highest growth rates. Secondly, the middle class at the aggregate level appears relatively flat, with the top decile capturing the highest growth. Given that India's population was living predominantly in rural India in the initial period (1983), the GIC corroborates declining rural poverty and a prosperous elite in urban India. As we will address later, these growth rates may not be uniform over time across each decile; and this in turn has implications for how divergence in consumption growth reshuffles class and living standards between rural and urban groups.

4. Variation in living standards in India as of 2011-12

We organize our microdata into percentiles by location, with C_{ij} denoting the (log of) mean consumption of percentile i in location j. Clearly both location and one's position in the distribution matter for the determination of living standards in India. We thus pose our main question: *what proportion of a person's consumption can be explained on the basis of location alone?* The argument can be stated in the form of a simple regression equation following the model of Milanovic (2015), except that here the role of a country is replaced by a within-country location:

$$\mathbf{C}_{ij} = b_0 + b_1\, \mathbf{SGDPpc}_j + b_2\, \mathbf{Gini}_j + \mathbf{u}_{ij} \qquad \text{.................(1)}$$

Thought we refer to C_{ij} as the (log of) *individual* i's consumption whilst residing in state j, as noted above individual consumption is the mean consumption of a person in a given percentile. The covariates are the log of SGDP per capita as a measure of industrialization (hence employment, incomes etc.) and inequality (Gini) in that location.[16] Our specification considers the so-called "individual viewpoint" in that our regression is not weighted by the size of the population in different states and urban/rural locations. This formulation also has the advantage, as Milanovic notes, that the covariates are independent of the individual's level of effort, specific circumstances and luck (u_{ij}) because they are macro level factors; thus, an individual is too atomistic to change them. [17] The fit of this equation can indicate the extent to which an individual's living standards are accounted for by factors largely beyond their control.

It is important to note that while Milanovic uses this equation at the global level, the fact that we focus on the Indian situation matters for fit. This is because in India it is well

[16] In future work, we intend to see if other state-wide measures (such as physical and social infrastructure) play a role over and above state GDP per capita. We also plan to includes measures of informality as the Gini index may not fully reflect the informal economy.

[17] In this case, we could also write $u_{ij} = k_{ij} + e_{ij}$ where k is the individual's own effort and human capital while e is a shock that could be termed as luck.

documented that caste plays a salient role: an individual is born into it and as long as outcomes are strongly linked to caste (Zacharias & Vakulabharanam, 2011), it adds an explanation as to why individual effort may or may not matter. These social groupings have negligible impact in Milanovic's study because at the international level caste fades away and country level mean incomes matter more; India's caste system is important for Indian inequality, but not necessarily that influential on global inequality.[18] Thus, from the start we cannot expect to achieve the same level of fit for an India-specific case. However, these locational dynamics are clearly important given the role of urban inequality in the national story. Additionally, while caste applies primarily to the 80% Hindu majority of India, the entire population can be said to have had location 'assigned' to them.

Eq. (1) is estimated in two different forms to disentangle the importance of interstate heterogeneity from rural-urban differences. Our first model is at the State level (j = State) and we have complete information for 32 States thus giving us nearly 3200 total observations.

Table 1: State-level regression results

Model 1	Estimates of equation (1)	Location dummies
Independent variables	**Dependent variable: Log of consumption**	**Dependent variable: Log of consumption**
Log of state GDP per capita	0.55^{***}	
State Gini (0-100)	-0.001	
Constant	3.85^{**}	10.51^{***}
State dummy	No	Yes
R^2	**0.18**	**0.25**
N	**3189**	**3189**

Notes: Std. errors clustered at State level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[18] It may be argued, however, that gender and racial biases affect opportunities at the global level, just as factors like caste and religion might in India at the country level.

Our results (Table 1) for the State level regression show that 18% of the variation in living standards can be determined on the basis of SGDP and the Gini of state consumption. The log of State GDP per capita has a positive coefficient with log consumption so that state elasticity of consumption (55%) is positive – being from a richer state increases an individual's living standards. However, inequality appears to have no influence at all because the coefficient on the state Gini is statistically insignificant. In a second variant of this model, we replace all the covariates and use only State dummies in a simple Least Square Dummy Variable (LSDV) model. According to this model, the fit goes up to around 25%. The coefficients on these dummy variable - which serve as location penalties or premiums relative to the omitted state - alone *explain a quarter of the variation* in consumption. At this aggregated level, the picture is quite simple – Indians in richer states enjoy higher living standards irrespective of the level of inequality in that location.

Table 2: State and rural/urban level regression results

Model 2	Estimates of equation (1)	Location dummies
Independent variables	**Dependent variable: Log of consumption**	**Dependent variable: Log of consumption**
Log of state GDP per capita	0.40^{***}	
State-Sector Gini (0-100)	0.02^{***}	
Constant	4.79^{***}	10.3^{***}
State-Sector dummy	No	Yes
R^2	**0.18**	**0.31**
N	**6114**	**6114**

Notes: Std. errors clustered at State-Sector level; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The next set of results uses a definition of location using a combination of both states and the rural or urban subregion within that state. In this second model, we divide individual data (per state) into rural and urban percentile level distributions. Each percentile of consumption is now C_{ijk} where k takes on the values 1 (rural), 2 (urban) for a total of

200 percentiles per state (100 urban, 100 rural) and 6400 (200 percentiles for each of 32 states) total observations. SGDP still enters at the State level but the variable $Gini_j$ is now $Gini_{jk}$ thus representing inequality in the rural or urban part (k) of the State j.

When we re-estimate the model using this specification (Table 2), we find that state elasticity of consumption goes down somewhat (40% compared to 55%). And interestingly, now the coefficient for Gini acquires strong statistical significance - and has a positive sign. For a unit increase in the subregion Gini, there is a 2.5% associated increase in consumption. What do these estimates imply? Suppose we consider three individuals A, B, C where A and B reside in a state with higher per capita GDP than C. Relative to B, A lives in a more unequal subregion of their state. Then, while A and B can be expected to have higher expected consumption than C, individual A's consumption will also be higher than that for B due to the positive coefficient on $Gini_{jk}$.

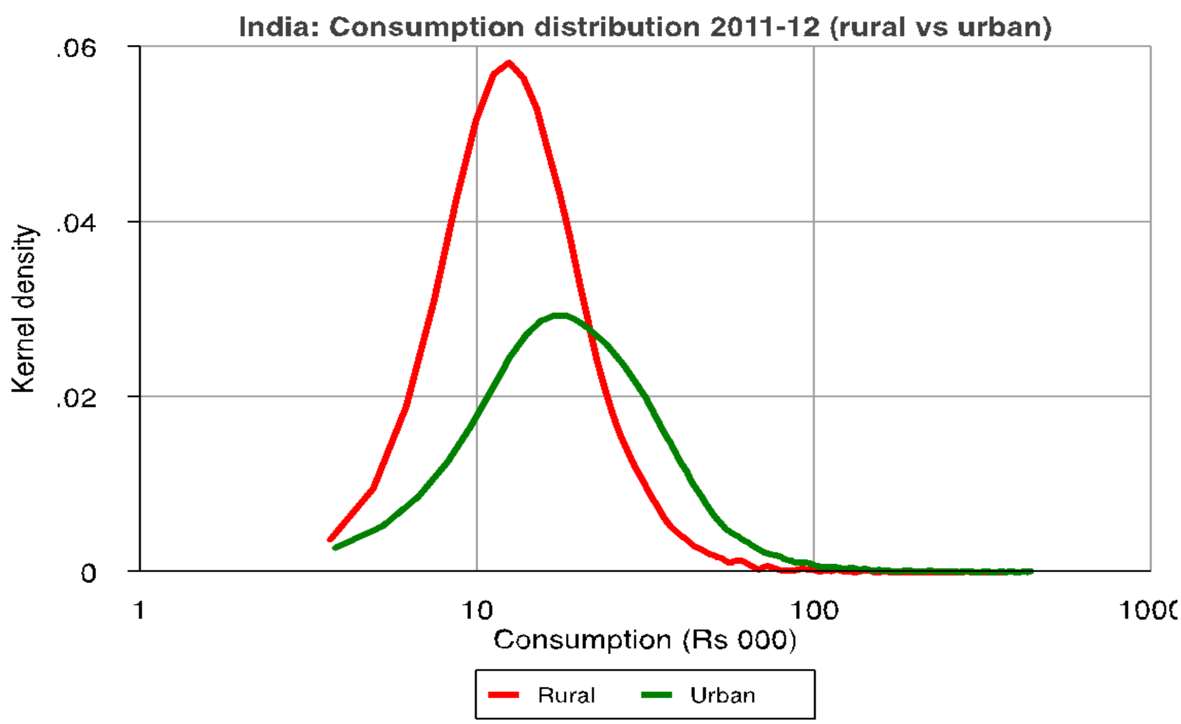
Compared to the state level regression in Table 1, taking only state-sector dummies as covariates in a LSDV model (i.e. each state has a rural and urban dummy) increases the fit to 31% (see the second regression estimates reported in Table 2). Thus, nearly one-third of the variation in consumption can be explained exclusively on the basis of our definition of location. The estimates of location premiums suggest that relative to the omitted state-sector (rural Andaman & Nicobar), one mostly enjoys premiums moving to the urban areas of Top 5 states and penalties in almost all rural subregions.[19]

What accounts for the positive relationship between inequality and consumption? This aspect can be better understood by looking at kernel density plots for the rural and urban distributions separately (Figure 5). Compared to the rural distribution, urban India has both a higher modal consumption level and shows wider divergence from the mode relative to rural India – the latter is more equal. Most people in rural India will end up at a lower level of consumption relative to urban India. Much of the upper tail of the consumption distribution is accounted for by urban India. So the urban rich (who pull the

[19] These estimates are not reported here but are available separately as an appendix table on request.

tail to the right, creating more inequality) will also account for the highest consumption levels in India. From this perspective, individuals placed in rural India will find themselves closer to most other people's consumption levels whilst simultaneously lowering their expected living standards. Our result differs from that found by Milanovic (2015). For global data, Milanovic found an inverse relationship between opportunity and inequality because poorer countries tend to be more unequal than richer welfare states. At the global level, it makes sense to migrate from a poor, unequal country to (say) rich Sweden. But from a within-country perspective, opportunity is higher for individuals moving from stagnant rural states to unequal but dynamic urban states.

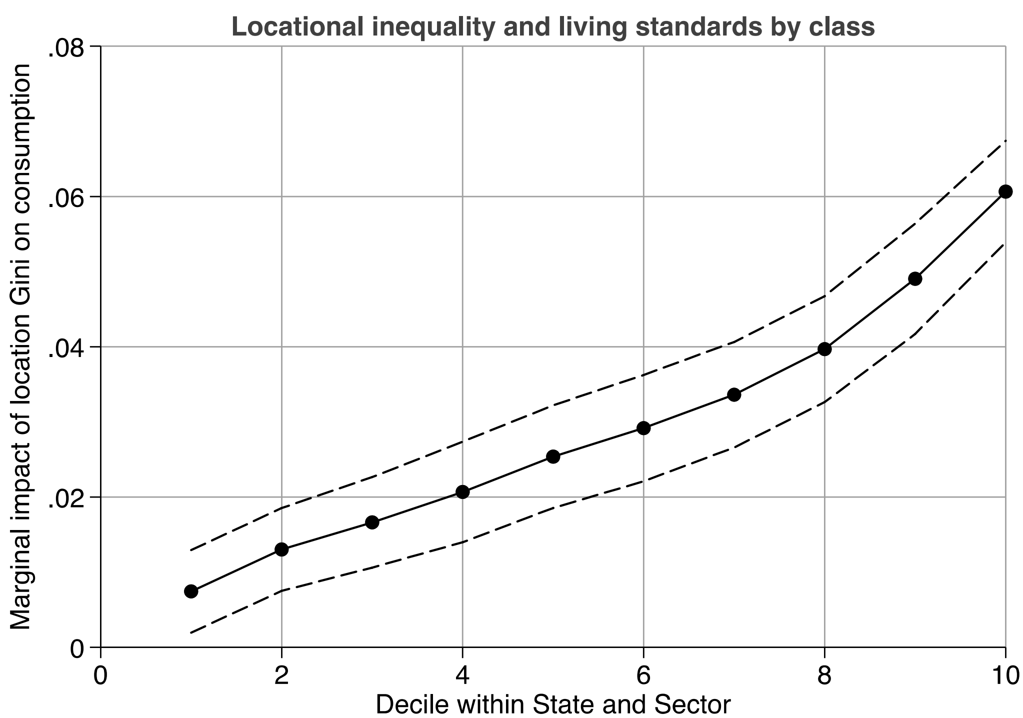
Figure 5: Kernel Density of consumption distribution (2011-12)



Note: The horizontal axis is on a logarithmic scale.

Are the marginal effects of inequality on consumption consistent across class? Our regressions so far only capture the 'mean' effect of location on consumption. But in more granular terms, the rich are the ones who gain most from inequality in their location since they constitute the upper tail. To shed further light on class and location, we ran separate regressions for each decile under the same format as the specification used in Table 2. Thus, we are now comparing people across different states whilst holding their class constant – the poor in one state against the poor in another state, the rich in one state against the rich in another state, and so on. Detailed results are provided in the appendix. Interestingly, the elasticity between SGDP per capita and consumption is relatively flat across class (around 33-36%). In contrast, the relationship between consumption and Gini is (as expected) increasing as a function of class (Figure 6). The poor gain very little (between 0.7-2% for the lowest 4 deciles) but the effect is still significant. These decile level regressions also explain a larger portion of the variance (R-squared between 35-78%) in within-class consumption. The fit is strongest for the middle to upper-middle classes, but regardless, remains higher for each class than our previous population level regressions. The implication is that while class position is important in relative terms, location is more important in absolute terms.

Figure 6: Decile level relationship between consumption and Gini



One potential explanation of the gap in consumption levels between rural and urban India lies in differential costs of living.[20] For instance, higher spending on urban housing could imply that while consumption appears higher, in a real sense this balances out because rural Indians pay less in rents. We investigated this relationship on the basis of adjustments for cost of living and its evolution over time.

Figure 7: Mean consumption at each rural, urban and national decile 1983-2011

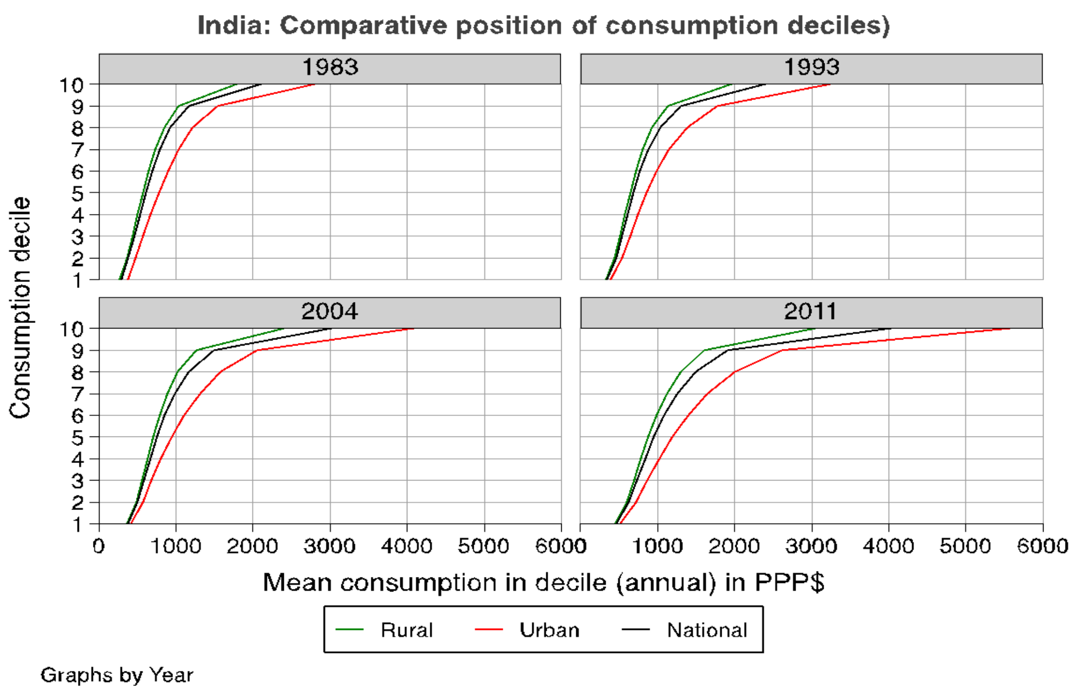
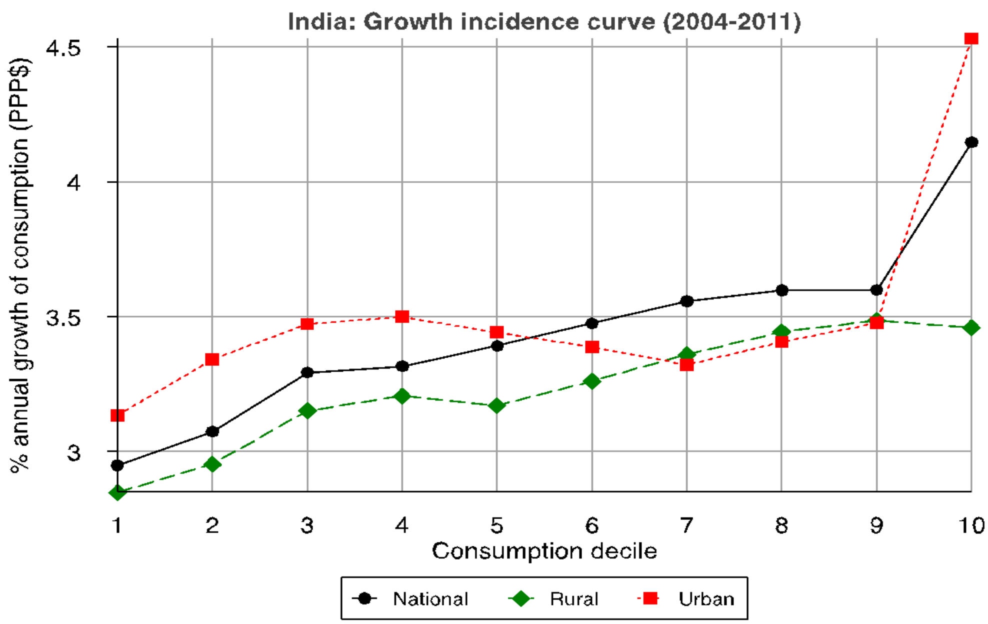


Figure 7 shows mean consumption by decile for the national, rural and urban distributions in 2011 PPP dollars with PovCalNet's adjustment for cost of living. Notably, the mean consumption in any urban decile is higher than its equivalent rural class and this gap persists (even increases) over time. In fact, even with cost of living adjusted for location (rural or urban), consumption levels for an urban decile tend to be closer to a higher rural decile. For example, in 2011, the mean consumption level associated with the 6th rural decile is equivalent to the mean for the 4th urban decile. One point to note is that the top (10th) urban decile has pulled away much more drastically

[20] We are grateful to reviewers at NITI Aayog and the Indian Ministry of Finance (Department of Economic Affairs) for stressing these various measurement issues, which we intend to continue to investigate in future work.

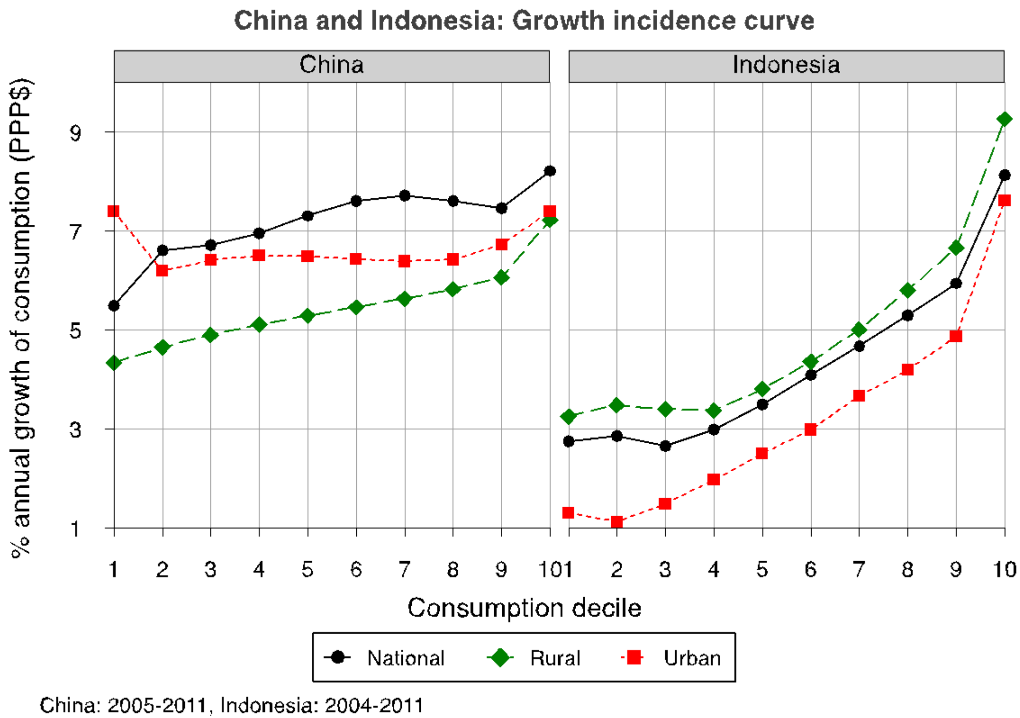
around 2011, thus also pulling with it the national distribution further away from the rural distribution. This may have likely strengthened the positive relationship between consumption and inequality at the national level, consistent with our regression results. Regardless, the adjusted data confirm that our results remain robust to differential cost of living.

Figure 8: Growth incidence curve for India: 2004-2011



The higher growth of incomes of most urban classes above those of rural India appears slightly in opposition to the long-term trend in India's GIC (1983-2011). As we had previously shown, the incidence of growth primarily lifted consumption in rural India's lower/lower-middle classes – what fundamentally appears as a decline in poverty due to India's impressive economic growth. Here, it is important to highlight the staggered timing of growth, per group, which in our view made a difference to the lower end of the urban distribution. We computed the GIC for the fast growth phase (2004 onwards) in Figure 8. For this period, the GIC is upward sloping at the national level – the top decile experienced nearly one additional percent of consumption growth relative to the lowest decile. But more strikingly, the urban distribution is non-linear with the highest growth rates accruing to the lowest four deciles and the top decile (the biggest gainer). The differences between the national and subnational groups is quite apparent – the lowest urban deciles experienced more consumption growth than most of rural India.

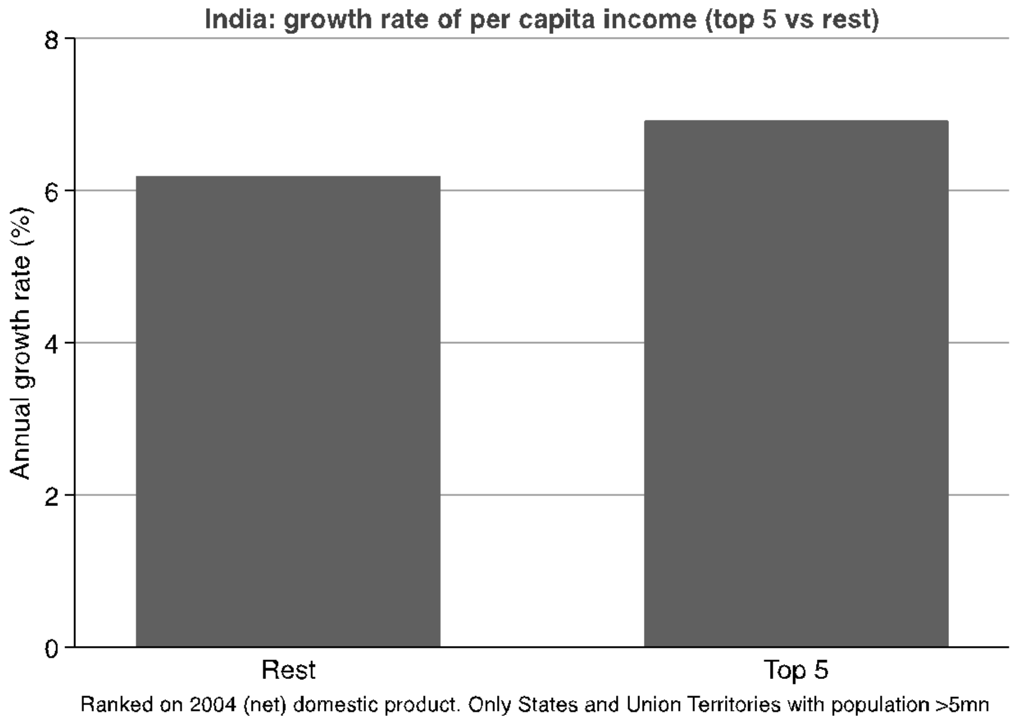
Figure 9: Growth incidence curve for China and Indonesia 2005-2011



Our urban premium is reinforced by the fact that the GIC incorporates the effects of the MGNREGA rural jobs program, but this effects of this policy still do not overcome (in relative terms) the improvement of the lower classes in urban India.[21] Since these series adjust for rural and urban cost of living, the effect is driven explicitly by a marked improvement in living standards for the urban poor (as opposed to price differentials). These data imply that in terms of consumption levels it was better to be poor in urban India than to remain in the middle class of rural India. This GIC puts India's distributional changes somewhere between Indonesia (higher rural growth) and China (unambiguously higher urban growth) for the same period (Figure 9).

[21] One potential reason may be that the rural jobs program raised wages in rural India, thereby increasing the 'drawing' wage (as in a Lewis type dual-sector process) necessary to attract labor to urban India.

Figure 10: Inter-state growth rates of GDP per capita



Our regressions have consistently shown that states with higher per capita income tend to improve an individual's consumption. The reason this effect is important is that even comparing two individuals in urban India, one has to account for the state as an important determinant of their relative living standards. To an extent, our finding is congruent with growing inter-state inequalities over the 1990s as highlighted by Deaton & Dreze (2002). A remaining question is whether there was shuffling of growth across states in more recent periods, or whether this trend represent a continuation of trends from the 1990s/early 2000s. In our view, the latter seems to be more accurate. Taking the Top 5 states, ranked in 2004, vs the rest shows almost a 1% growth differential on a per annum basis (Figure 5). Thus, those states which were already rich, on a per capita basis, continued to expand their lead so that the inter-state SGDP gap widened during India's fast growth phase in the first decade of the 21st Century. This divergence is consistent with initial investment levels in infrastructure and schooling (Bandyopadhyay, 2011; Bhalla, 2011) which may have continued to give higher returns to lead states in the form of better SGDP per capita growth.

5. Conclusion

Our results show that the growing rural-urban gap and divergence in growth across states exacerbates the otherwise slow rise of consumption inequality in India. These gaps have created significant location premiums which explain between 25-31% of the variation in living standards. While class is an important determinant of consumption, the rural vs. urban location also plays a significant role. This is one potential explanation of the persistence of migration from rural to urban India despite the latter contributing to growing inequality. The best way to illustrate the relevance of our findings is to recall the example with which we started this paper. Consider Bihar, mostly rural, and at 10% of SGDP per capita compared to Delhi. Assume one-to-one proportionality between consumption and income. Then, if an individual placed at an income level of $1/10^{th}$ of the mean income in Bihar is shifted to Delhi but has to accept $1/20^{th}$ of the mean income level there, this individual still sees a five-fold increase in their actual income. The downgrade in relative class position is accompanied by an upgrade in absolute gains.[22] To conclude, note that we have not included socioeconomic factors like caste, gender or religion that may be specific to each individual. These are likely to further explain differences in consumption levels for the Indian population, but we leave this topic to future research.

In ongoing work, we are extending the results to cover the decade since the 2011/12 NSSO survey, which will equip us better to draw out the policy implications of our findings. We note that issues of rural-urban migration are being extensively discussed in Indian policy circles and several policies are attempting both to foster better prospects in the rural sector (e.g. provision of urban amenities to rural areas) and to improve conditions for poor urban migrants.

[22] We are grateful to Sanjay Reddy for highlighting this point.

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APPENDIX

Tabulated results of regression by deciles

Decile of rural or urban India	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Log of consumption									
Log of state GDP per capita	.37***	.40***	.39***	.39***	.38***	.39***	.40***	.38***	.37***	.36***
State-Sector Gini (0-100)	.007**	.013***	.016***	.02***	.025***	.029***	.033***	.039***	.049***	.060***
Constant	4.7***	4.54***	4.6***	4.6***	4.75***	4.6***	4.5***	4.7***	4.79***	5.06***
R^2	.349	.557	.552	.57	.61	.64	.67	.71	.74	.58
N	10707	9216	8781	9053	9286	9369	10010	10863	11615	12251

Std errors clustered at State-Sector level

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$