UNITED NATIONS UNIVERSITY
UNU-WIDER

WIDER Working Paper 2018/182

# The dynamics of spatial and local inequalities in India

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December 2018

**Abstract:** Studies of the spatial dimensions of inequality in developing countries are mostly restricted to states, provinces, or districts, typically the smallest geographical units for which data are representative in national surveys. We introduce a procedure to calculate inequality between and within smaller spatial units in the context of India, taking advantage of census and satellite data available for a large number of characteristics at the level of the village and the urban sub-district (block). Using prediction models based on those characteristics and estimated at the district level, we impute average per capita consumption expenditure for villages and urban blocks in 2004 and 2011. These imputations allow us to calculate (spatial) inequality between villages and blocks and to derive (local) inequality within these spatial units. We find that the divergence observed for states and districts is not amplified at lower levels of disaggregation. Hence, the increase in inequality in urban India is mostly due to rising inequality within urban blocks. Neither rural inequality nor its local and spatial components have changed much at the national level, but there is substantial heterogeneity between states and across poor and rich districts. Finally, we find that urbanization, growth of employment, and 'good' jobs may be moving hand in hand with falling spatial inequalities but rising local inequalities. On the other hand, the expansion of literacy and access to banking and sanitation are linked to lower rises in inequality.

**Keywords:** decomposition, India, inequality, Theil
**JEL classification:** C53, D3, N35, O15

**Acknowledgements:** We wish to thank Hai-Anh Dang, Chris Elbers, Nicolas Gravel, Himanshu, Peter Lanjouw, Rinku Murgai, Gerton Rongen, and Roy Van Der Weide for comments. We also thank participants at the UNU-WIDER conference (Helsinki, 2018). This paper could not have been completed without the able research assistance of Ravendra Kumar and Rachit Kamdar. We would like to thank the World Bank for giving us access to their Spatial Database for South Asia.

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This study has been prepared within the UNU-WIDER project on 'Inequality in the Giants'.



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ISSN 1798–7237 ISBN 978-92-9256-624-1 https://doi.org/10.35188/UNU-WIDER/2018/624-1

Typescript prepared by Gary Smith.

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The Institute is funded through income from an endowment fund with additional contributions to its work programme from Finland, Sweden, and the United Kingdom as well as earmarked contributions for specific projects from a variety of donors.

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## 1 Introduction

Inequality is now universally acknowledged as a major economic phenomenon. It is not restricted to the developed world, with emerging economies recording high inequality.[1] India is certainly no exception, as its experience of impressive economic growth since the economic reforms in 1991 has been accompanied by a pattern of increasing inequality (Himanshu 2018). While different aspects around the trends in inequality have been explored in the Indian context, little is known about its evolution in spatial units smaller than districts and states. This evidence gap has largely been due to lack of representative income or consumption data for cities, blocks, and villages. In this paper, we overcome this measurement challenge using imputation techniques that draw upon census and satellite data for all urban sub-districts and villages of India. We chronicle the evolution of inequality in India over the period 2004–11, in the process providing estimates for inequalities that exist within and between such disaggregate spatial units.

Delving into the spatial distribution of inequality is pertinent, given the widely shared perception that gains from growth in India have been spatially uneven. For example, Sen and Drèze (2013) decry that a 'biased' growth process is making India 'look more and more like islands of California in a sea of Sub-Saharan Africa'. This markedly geographical description is not incidental, as it refers to the fundamental spatial heterogeneity that characterizes the Indian development experience. Indian cities have been singled out by their contrasting landscape of flourishing well-off residential areas and deprived slum dwellers. In line with these anecdotal observations, a strand of the academic literature has investigated the extent of segregation of Indian cities (Sidhwani 2015). It is therefore natural to wonder whether the national trend of increasing urban inequality is reproduced at smaller scales – within urban blocks. On the rural sector, existing research sends mixed signals on what kind of patterns can be expected. On the one hand, there is evidence that points towards widening differences between rural areas: Narayan and Murgai (2016) show that rural poverty is becoming increasingly concentrated in poor states, while Li and Rama (2015) document that small rural areas have worse 'location effects' than large rural areas, and find substantial spillovers from closeness to 'top locations'; all this suggests the existence of localized patterns of rural development, with some villages catching up and others lagging behind. On the other hand, detailed village studies have documented processes of increasing inequality within villages as new economic opportunities arise (Himanshu et al. 2013). It is thus a priori not obvious which of these phenomena will prevail when we aggregate up to the national level. These considerations underline the importance of tracking the evolution of inequality at the finest spatial level possible.

Our work adds to a rapidly burgeoning literature on inequality around the world. It connects most directly with the literature on the spatial dimensions of inequality in India. Based on consumption expenditure data from large consumption surveys (quinquennial surveys conducted by the National Sample Survey Organization, India, hereafter referred to as NSS), Chauhan et al. (2016) provide estimates of inequality (and poverty) *within* NSS regions for the period 1993–2011.[2] They document divergence of regional poverty rates, increases in inequality in most regions, as well as a positive association between inequality and prosperity: richer regions tend to be more unequal. Other studies have also attempted to shed light on the spatial dimensions of inequality through decompositions. The Recentered Influence Function (RIF) approach in Gradín (2018), based on

[1] The Gini coefficient for OECD countries increased from 0.29 in the 1980s to 0.31 in the late 2000s (OECD 2011). The Gini coefficients for large emerging countries were high as well; for example, in 2011 Brazil, Russia, and South Africa recorded Ginis of 0.531, 0.41, and 0.634 respectively (http://data.worldbank.org/indicator/SI.POV.GINI).

[2] A group of contiguous districts, roughly in the same agro-climatic zone, constitutes an NSS region.

income data from the Indian Human Development Survey of 2011, reveals that 'earnings inequality in India as well as its growing trend takes place mostly within states'. In one of the rare studies that try to go to sub-regional spatial units, Azam and Bhatt (2018) take the decomposition of inequality—both in terms of consumption as well as in terms of income—to the district level.[3] They find that expanding differences between states and districts play a major role in explaining growing income inequality in rural India between 1993 and 2011, while inequality in urban India is primarily explained by within-district and within-state developments.[4]

Our paper carries this work forward and focuses on smaller units: urban blocks (sub-districts) and villages. We fit a regression model of district-level real consumption expenditure per capita (sourced from the NSS) on a large host of district characteristics for which information is available as well for lower levels of aggregation, such as their geography, demography, structure of employment, and night-time luminosity.[5] We use consumption expenditure data from 2004 and 2011 to perform a temporal comparison. We select our prediction model on the basis of stepwise regression and out-of-sample forecast evaluations, and subsequently use it to impute per capita consumption expenditure for all villages and urban blocks in India.

After successfully validating the predictions of our model against NSS data at levels where such comparisons are feasible, we compute inequality measures for the country as well as for its states using imputed consumption at the village and urban block levels. Our procedure captures inter-village and inter-urban block differences and therefore underestimates total inequality by construction. Instead, it provides estimates of spatial inequalities between villages (for rural India) and urban blocks (for urban India). Moreover, this calculation of spatial inequality allows us to derive local inequality within villages and within urban blocks. The additive decomposability property of the Theil index allows us to recover these unique local inequality statistics by subtracting the inequalities between spatial units calculated in the first step from the total inequality numbers estimated using household data from the NSS. This procedure to derive inequality within villages and urban blocks combining a national survey and imputed data is a major contribution of this paper. Such methods can be useful to track inequality in other developing countries for which disaggregate statistics are hard to find, but the data underlying our prediction exercise are available.

Our results show that, overall, inequality increases between and within villages in rural India as a whole have been negligible, but rising inequality within and between urban blocks has been driving an increase in total urban inequality, though not with equal contribution. It should be noted that this lack of growth of inequality between villages contrasts with the vigorous increase in inequality between rural parts of districts, and reveals that villages within the same district are in general at

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[3] While the authors focus on income, thus providing estimates of income-based inequality, a rarity in the Indian context, they are plagued by the fact that the IHDS, their main dataset, is not designed to provide a consistent estimator of the district or state mean income. This is in contrast to studies using consumption expenditures from the NSS, which are designed to provide consistent estimators of districts means, albeit suffering from inefficiency due to small sample sizes for many districts.

[4] This growth of inequality is also consistent with the literature on regional divergence. A number of papers have looked at the evolution of regional aggregates of economic output, documenting divergence at the state (Ghosh 2012; Kumar and Subramanian 2011) and district levels (Bhattacharya and Sakthivel 2004) during the two decades following economic liberalization.

[5] Since the seminal contribution of Henderson et al. (2012), an emerging literature has employed night luminosity as a proxy for economic activity, in absence of other reliable disaggregated indicators—see Michalopoulos and Papaioannu (2013), Hodlar and Raschky (2014), or Alesina et al. (2016). Closely related to the present study are Lessman and Seidel (2017), who study regional inequality around the world, looking at regional GDP predictions based on night luminosity, and Myevange (2015) and Addison et al. (2017), who analyse trends of regional inequality in sub-Saharan Africa and their link to mining activities, respectively.

least not swiftly diverging. Also in urban areas, the divergence observed between districts is not reproduced within them—that is, at the block level.

However, this exercise also unveils vast heterogeneity in the evolution of inequality at the local level. Thus, the relative stillness in overall inequality hides a diverse landscape of changing inequalities. In particular, states show very different trends, with spatial and local inequalities often moving in different directions. By way of example, Kerala and Bihar show rising local inequality but falling spatial inequality. This is consistent with the idea that as these states bridge spatial gaps, at different levels of development, the inflow of income derived from work in urban areas—be it migrant remittances or commuting workers—raises village-level local inequalities in both. In many states (Bihar, Gujarat, Jharkhand) we find no discernible overall trend in inequality but opposing changes in local and spatial inequalities. This heterogeneity becomes even richer when we calculate separate within and between indices for rural and urban strata.

Having pointed out the heterogeneity of results at the state level, we move to the district level and explore how changes in inequality relate to baseline real consumption expenditure and its growth. We group districts in terms of per capita consumption expenditure (top and bottom 10 per cent, top and bottom quarter) and find that the inequality increase at the bottom decile is larger than at the top, driven by an even larger increase in local inequality (particularly pronounced for rural India) and attenuated by a decrease in between-inequality. Our results show that higher growth is strongly associated with increases in overall inequality, and low growth with reduction in such inequality, both within and between spatial units.

To better understand how changes in various socioeconomic indicators correlate with changes in inequality, we regress changes in total, within-, and between-inequalities at the district level on changes in covariates over time. Our results show that growing urbanization might contribute to the spatial diffusion of economic prosperity, but some are reaping its fruits earlier than others. Increased urbanization is correlated with a fall in spatial inequalities between villages. However, it has a positive correlation with the rise of overall inequality in rural areas, and both local as well as spatial inequalities in urban regions. In a similar spirit, employment, in particular regular employment, correlates with a fall in differences between spatial units (especially in the rural sector) but has come along with increased within-inequality. Underemployment mirrors (inversely) a similar result. What has unambiguously come along with lower rises in inequality is rising literacy: changes in literacy are correlated to slower growth in total inequality and, especially, within-inequality, both in rural areas and in the district as a whole. The expansion of access to banking services is robustly associated with slower growth in inequality. In rural areas and for the district as a whole, the associated decrease takes place through spatial inequality, while it is local inequalities that are most affected in urban areas. Similarly, access to sanitation (arguably, a strong proxy for pro-poor intervention) is associated with more sluggish growth in spatial inequalities.

Our paper is structured as follows: in Section 2 we describe the data used in this analysis. Section 3 reports inequality trends and decompositions from household consumption data from the NSS. In Section 4 we present the procedure used for imputation of per capita consumption. Section 5 presents the results on inequality that we obtain using the imputations. In Section 6 we explore heterogeneity at both the state and the district levels. In Section 6.1 we provide a detailed description of total, spatial, and local inequality for major states of India; in Section 6.2 we focus on how the evolution of inequality differs between the most and least prosperous and dynamic districts; and in Section 6.3 we analyse how changes in diverse characteristics are related to changes in district-level inequality. We conclude in Section 7.

## 2 Data

One of the main strategies of this paper is the prediction of indicators of economic prosperity for the villages and urban sub-districts of India, an exercise that requires variables at two levels of disaggregation. First, in order to build a prediction model, we need data on economic prosperity and its correlates at the lowest possible level of disaggregation, typically the district in the Indian case. We focus on per capita consumption expenditure as a welfare indicator, and use data from the consumption surveys of the NSS in 2004 and 2011 for our analysis.[6] We use data on household per capita consumption with a mixed recall period, using population weights to compute district means.[7] In order to obtain real per capita consumption, we apply deflators based on the Tendulkar poverty lines (which tether, as the base, prices to those of urban India in 2004) for spatial price adjustments and CPI-AL/IW (Consumer Price Index for Industrial workers and Consumer Price Index for Agricultural Labourers) for temporal adjustments.

Second, in order to carry out the imputation exercise, we source data on the predictors of consumption expenditure at the level of the village and the urban block from the World Bank's Spatial Database for South Asia. The database contains information from different sources, such as censuses (population, sex ratios, literacy, employment, percentage of population from scheduled castes and tribes) or satellites (weather and precipitation, forest cover, share of land under cultivation, night-time luminosity[8]). The data are provided at the various level of spatial disaggregation (all India, states, districts, blocks, and villages) for the years 2001 and 2011, harmonized to 2011 census boundaries. For the first four categories, data are available for the whole entity as well as the rural and urban part of it. These are based on an extensive map digitization exercise conducted by the World Bank.[9] We use data from 613 districts, 638,758 villages,[10] and 2,706 urban blocks in both years. For the sake of exposition, we refer to the data collected around 2001 (2011) as 2004 (2011) vintage data.[11]

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[6] In the NSS parlance, these are referred to as the 61st and 68th rounds. For the latter round, we use type 1 schedule data. We would have ideally wanted to use consumption data from 1999. However such data are riddled with recall error problems, making them unsuitable for our analysis.

[7] Sampling in the NSS is designed to provide consistent and unbiased estimators of strata-level indicators. Districts form the strata in the NSS. There are precision concerns with the estimated values due to low sample sizes in some districts. However, these are of less worry to us as we use these indicators as dependent variables in prediction models.

[8] The World Bank's Spatial Database reports DSMP-OLS Radiance Calibrated Night Light Data (RCNTL) from the National Oceanic and Atmospheric Administration's National Geophysical Data Center (NGDC) for the years 1999 and 2011.

[9] For further information on the database, as well as assumptions of the exercise and mapping over time, see Li et al. (2015).

[10] The total number of villages in India in 2011 was 640,867. The total number of districts in 2011 was 640. Our dataset is smaller due to missing data.

[11] We use lights from 1999 to predict consumption in 2004. This is necessitated by data limitations. The World Bank database provides lights at various levels of disaggregation for 1999 and not for 2004. However, as pointed out above, the 1999 data on consumption are heavily contaminated. In so far as the exercise is purely predictive, this is not of undue concern since the data at all levels of disaggregation are of the same vintage. Moreover, fitting based on 2011 where nights lights and per capital consumption correspond to the same year does not give very different results.

## 3 Consumption inequality: trends and decompositions

To begin with, let us look at inequality based on per capita real consumption from the NSS (Table 1). Inequality shows a slight rise at the all-India level with the Gini coefficient rising from 0.310 in 2004 to 0.323 in 2011.[12] This increase of inequality is, however, slightly larger when looking at the mean log deviation or the Theil index. The latter rises from 0.188 in 2004 to 0.210 in 2011. We will focus on the Theil index in our discussion. The reason for doing so is that we are mostly interested in the within and between decompositions, and the Theil index has desirable decomposability properties.

Table 1: All-India per capita consumption 2004–11

| | All India | | Rural | | Urban | |
|---|---|---|---|---|---|---|
| | 2004 | 2011 | 2004 | 2011 | 2004 | 2011 |
| Gini | 0.310 | 0.323 | 0.267 | 0.270 | 0.359 | 0.374 |
| MLD: GE(0) | 0.157 | 0.171 | 0.118 | 0.120 | 0.208 | 0.228 |
| Theil: GE(1) | 0.188 | 0.210 | 0.140 | 0.143 | 0.234 | 0.264 |

Source: authors' calculations based on data from the NSS.

Moving on to inequality for rural and urban India, trends from the NSS show that, while there has been very little change in rural inequality (the Theil index was 0.14 in 2004 as against 0.143 in 2011), there has been a rise in urban inequality, from 0.234 in 2004 to 0.264 in 2011. Thus, it would seem that the slight increase in overall inequality is driven by a rise in urban inequality.

How are these inequalities spread over space? We consider the two levels of disaggregation for which the NSS data are representative and can thus be used: states and districts. Table 2 reports the within–between decomposition of the Theil index for states and districts. For India as a whole, there is a rise in within-state inequality from 0.175 in 2004 to 0.189 in 2011. This is accompanied by a rise in inequality between states from 0.013 to 0.021. Once we disaggregate further and consider districts, we see that both within- and between-district inequalities have risen. These results are echoed when one looks only at rural India: between-state inequality rises (while within-state inequalities remains the same, the point estimate shows a very slight decline), where most of the rise in inequality when we consider districts takes place between them. While our numbers are different from those of Azam and Bhatt (2018), our results are consistent with their finding of rising between-district inequality in rural India being driven by between-state differences.[13] When we consider urban areas, we observe that the within-state and within-district components constitute a larger part of the inequality in both years, as compared to rural India. This is again consistent with the results of Azam and Bhatt (2018).[14] Table 2 shows that inequality has risen over time both within and between states as well as districts.

[12] While these indices are based on sample data, given the size of samples at all levels above the state, these are very precise.

[13] These results are also the same as those of Motiram and Vakulabharanam (2012), who look at within- and between-state decompositions.

[14] For our analysis, we use data on consumption expenditures based on a mixed reference period. These are different from Azam and Bhatt (2018). However, we get similar results to theirs when we use consumption expenditures based on a uniform reference period (30 days).

Table 2: Decomposition of inequality (Theil index)

| | 2004 | 2011 |
|---|---|---|
| **All India** | | |
| Within state | 0.175 | 0.189 |
| Between states | 0.013 | 0.021 |
| Within district | 0.149 | 0.157 |
| Between districts | 0.039 | 0.053 |
| **Theil (all India)** | **0.188** | **0.210** |
| **Rural** | | |
| Within state | 0.129 | 0.126 |
| Between states | 0.011 | 0.017 |
| Within district | 0.113 | 0.110 |
| Between districts | 0.027 | 0.034 |
| **Theil (rural India)** | **0.140** | **0.143** |
| **Urban** | | |
| Within state | 0.228 | 0.250 |
| Between states | 0.006 | 0.014 |
| Within district | 0.193 | 0.207 |
| Between districts | 0.041 | 0.057 |
| **Theil (urban India)** | **0.234** | **0.264** |

Note: numbers may not add because of rounding off.

Source: authors' calculations based on data from the NSS.

These trends have been noted in the literature, but they serve as an important background to evaluate our contribution. Our work begins here: we delve deeper, to a more granular level—the urban part of blocks and villages—to investigate what is happening to inequality in these spaces.

## 4 Imputing per capita consumption

As noted above, the NSS does not allow us to calculate descriptive statistics below the district level. Hence, we resort to imputation techniques.

### 4.1 Model selection and forecasting

Let *i* refer to a geographical unit such as a district (*d*), a village (*v*), or an urban block (*ub*), and let $Y_{it}$ be an indicator of economic prosperity of unit *i* at time *t*. We impute per capita real consumption expenditure in the following way:

We start by fitting a model at the district level. To do so, we consider several models where $Y_{it} = \log(mpce)_{dt}$. We consider eight different sets of candidate independent variables, detailed in Table 3. We select the best-performing model following these four steps:

1. We consider only 70 per cent of all districts for estimating the regression models (training sample) and leave 30 per cent of the districts for out-of-sample forecasting (forecast test sample).
2. For each set of candidate variables, we select the variables to be included in the model using stepwise regressions with forward selection on the training sample. We add a variable

from the list of candidate variables if the resulting *p*-value is less than 0.05 and remove a variable from the model if the resulting *p*-value is more than 0.055.

3. Once the stepwise regression procedure selects the final set of variables to be included in the model for each set of candidate variables under consideration, we predict per capita consumption in the forecast test sample. We calculate the adjusted $R^2$ and the mean square error (MSE) for each of the models.
4. In the final step, we choose the model with the highest adjusted $R^2$ and the lowest MSE.

Table 3: Variables considered for different models

| | Variables set | Additional variables |
|---|---|---|
| Model 1 | State-level dummy variables, population per sq. km, ambient population per sq. km, literacy rates (aged seven and above), male literacy rates, female literacy rate, sex ratio, mean decadal temperature for each month, standard deviation in decadal temperature for each month, deviation from decadal mean temperature for each month, elevation (metres), surface roughness (metres), percentage of Scheduled Castes in the population, percentage of Scheduled Tribes in the population, self-employed as a percentage of total workers, male self-employed as a percentage of total male workers, female self-employed as a percentage of total female workers, casual wage workers as a percentage of total workers, male casual wage workers as a percentage of total male workers, female casual wage workers as a percentage of total female workers, regular workers as a percentage of total workers, male regular workers as a percentage of total male workers, female regular workers as a percentage of total female workers, dummy for 2011. | Luminosity per sq. km. |
| Model 2 | As for model 1 | Log luminosity per sq. km. |
| Model 3 | As for model 1 | Luminosity per sq. km, luminosity per sq. km. × state dummies, percentage of regular workers as a percentage of total workers × state dummies, luminosity per sq. km × elevation, luminosity per sq. km × surface roughness |
| Model 4 | As for model 1 | Log of luminosity per sq. km, log of luminosity per sq. km. × state dummies, percentage of regular workers as a percentage of total workers × state dummies, log of luminosity per sq. km × elevation, log of luminosity per sq. km × surface roughness |
| Model 5 | As for model 1 | Luminosity per sq. km, percentage of land under forests, percentage of land under crops, percentage of Scheduled Castes in the population × percentage of land under crops, percentage of Scheduled Tribes in the population × percentage of land under crops |
| Model 6 | As for model 1 | Log of luminosity per sq. km, percentage of land under forests, percentage of land under crops, percentage of Scheduled Castes in the population × percentage of land under crops, percentage of Scheduled Tribes in the population × percentage of land under crops |
| Model 7 | As for model 1 | As in Model 5, luminosity per sq. km × percentage of land under forests, luminosity per sq. km × percentage of land under crops |
| Model 8 | As for model 1 | As in Model 5, log of luminosity per sq. km × percentage of land under forests, log of luminosity per sq. km × percentage of land under crops |

Source: authors' creation.

There are two other facts that are important to note. First, we pool the data for both 2001 and 2011 for imputation. Second, we estimate and evaluate the models separately for rural and urban districts.

Given these steps and the objective criterion, we find the best model such that

$$Y_{dt} = \alpha^l + \gamma^l Z_{dt}^l + \varepsilon^l{}_{dt} \quad (1)$$

where *l* indicates if it is the rural sample or the urban sample, $Z^l$ represents the covariates of the chosen model (which may differ for the urban and rural sample) and $\alpha^l$ and $\gamma^l$ denote the ordinary least squares (OLS) estimators.

As mentioned above, Table 3 provides all the variables that were included as candidates to be selected as explanatory variables by stepwise forward regression. In Table 4, we provide the statistics that allow us to evaluate the performance of the various models when forecasting out of sample: adjusted $R^2$ and MSE. Of the eight models considered, Model 6 provides the highest adjusted $R^2$ and lowest MSE for out-of-sample forecast in the case of rural districts. In the case of urban districts, the best prediction model is Model 4 (Table A1 provides the final regression results for the chosen models after stepwise regression has selected the most relevant variables).

Table 4: Out-of-sample model diagnostics

| Models | Adjusted $R^2$ | MSE |
|---|---|---|
| **Rural** | | |
| 1 | 0.564 | 0.036 |
| 2 | 0.573 | 0.034 |
| 3 | 0.59 | 0.031 |
| 4 | 0.6 | 0.031 |
| 5 | 0.56 | 0.033 |
| 6 | 0.61 | 0.03 |
| 7 | 0.56 | 0.033 |
| 8 | 0.59 | 0.03 |
| **Urban** | | |
| 1 | 0.483 | 0.05 |
| 2 | 0.488 | 0.049 |
| 3 | 0.48 | 0.049 |
| 4 | 0.489 | 0.049 |
| 5 | 0.41 | 0.054 |
| 6 | 0.43 | 0.052 |
| 7 | 0.41 | 0.053 |
| 8 | 0.44 | 0.05 |

Source: authors' calculations based on variables in Table 3 and consumption expenditure data from the NSS.

Given the chosen model, we move next to the data at the level of villages and urban blocks. With the parameters estimated in the previous step, we predict per capita consumption expenditures for villages and urban blocks. Hence, the predicted mpce for a unit *i* that belong to stratum *l* is given by:

$$Y_{it} = \alpha^l + \gamma^l Z_{it}^l \quad (2)$$

These predicted values are then used for subsequent analysis.[15]

### 4.2 Validation

Before we move on to inequality estimates, it is prudent to gauge how good are our imputations. Note, though, that at all levels (district, state, all India), the inequality index based on imputed values is not comparable to inequality estimates based on household data from the NSS. This is because, at best, the imputation captures variation *between* villages or urban blocks, but not *within* them. Hence, to validate our procedure we focus on indicators that can be obtained from the imputed data and compared to those from the household survey of the NSS.

We begin by examining mean urban and rural consumption expenditure (Table 5). The means are typically lower for imputed data, but not by much,[16] and changes over time are well estimated. For example, according to the NSS, the change in mpce between 2004 and 2011 is 170.4 rupees for rural India. Based on the imputed data, it is 179.4 rupees. The predictions for urban India are slightly worse, but still exhibit the same trend: whereas the increase in urban mpce is around 300 rupees according to NSS data, our imputations estimate it to be 278 rupees.

Table 5: Summary statistics comparing actual and imputed data

| | Rural India | | | Urban India | | |
|---|---|---|---|---|---|---|
| | 2004 | 2011 | Difference | 2004 | 2011 | Difference |
| **MPCE (NSS)** | | | | | | |
| Mean | 734.2 | 904.6 | 170.4 | 1,093.4 | 1,393.0 | 299.6 |
| Standard Dev | (487.0) | (629.5) | | (907.8) | (1,304.5) | |
| **Imputed MPCE** | | | | | | |
| Mean | 686.0 | 865.5 | 179.4 | 1,026.3 | 1,304.1 | 277.8 |
| Standard Dev | (184.7) | (240.6) | | (239.8) | (331.4) | |

Source: authors' calculations based on data from the NSS and the World Bank's Spatial Database for South Asia.

As pointed out above, our imputation assumes by construction that all individuals in each urban block and village have the same real per capita consumption expenditure. Hence the variation (standard error) of the mean is much larger in the NSS data as compared to imputed per capita consumption. This is not surprising; indeed, it points out the fact that there is considerable variation even within urban blocks and villages. We shall return to this point later.

Overall inequality is not comparable between the NSS and our imputation-based estimates, but the between components are. Hence, we present statistics on inequalities between states, districts, and rural/urban areas. We do so for the whole country (Table 6). It can be seen that we do a good job of capturing between-state inequalities. While we underestimate inequalities between districts,

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[15] While the complete statistical procedure would involve calculating forecasting errors, this necessarily involves adding residuals and bootstrapping the procedure many times. However, going from the residuals of equation (1) to equation (2) is not easy. This is because equation (1) involves the logarithm of a group mean which is *not* the mean of the logarithm of incomes for each unit in equation (2). Thus the connection between residuals of (1) and (2) are not readily apparent. While this is work in progress, to make up for the lack of error bands, we interpret a change in inequality indices as being robust if it is more than 20 per cent of baseline. We discuss this further in our results below.

[16] There is no automatic requirement that the means be the same. The OLS at the district level fits the average of the district level per capita consumption (for rural and urban India). Our forecasting exercises are run without weighting since weighting gives inferior forecasts: hence the model does not guarantee that the weighted mean of the imputed consumption of, say, all villages should necessarily fit the mean of rural India.

we still capture well their qualitative rise. We also match well inequality between sectors (urban/rural). Reassured by the success of these validations, we move on to the analysis of inequalities based on our imputations.

Table 6: Comparison between NSS and imputed MPCE

| | 2004 | | 2011 | |
|---|---|---|---|---|
| | NSS | Imputed | NSS | Imputed |
| **All India** | | | | |
| Between-state inequality | 0.013 | 0.014 | 0.021 | 0.022 |
| Between-district inequality | 0.039 | 0.030 | 0.053 | 0.039 |
| Between-sector (rural/urban) Inequality | 0.017 | 0.017 | 0.020 | 0.019 |

Source: authors' calculations based on data from the NSS and the World Bank's Spatial Database for South Asia.

## 5 Inequalities: villages and urban blocks

To begin, let us examine aggregate inequality and its trends when we use villages and urban blocks as the relevant units of disaggregation.[17] We find that the Gini coefficient is 0.18 for both years for rural and urban combined (Table 7). The Gini for rural India is 0.15 for both years, whereas for urban India it is 0.133 in 2004 and 0.145 in 2011.[18] These results are robust; whatever the inequality index, inequality in rural India has shown very little change (a slight rise according to point estimates), whereas inequality for urban India has shown a larger rise. These results do not perfectly echo the results in Table 1 (nor do they have to), which examines overall inequality. In fact, putting the two together, we can comment on what is happening to inequality in another dimension: within villages and urban blocks.

Table 7: Inequality based on Imputed MPCE

| | All India | | Rural | | Urban | |
|---|---|---|---|---|---|---|
| | 2004 | 2011 | 2004 | 2011 | 2004 | 2011 |
| Gini | 0.179 | 0.187 | 0.148 | 0.153 | 0.133 | 0.145 |
| MLD: GE(0) | 0.050 | 0.055 | 0.035 | 0.037 | 0.030 | 0.034 |
| Theil: GE(1) | 0.050 | 0.055 | 0.035 | 0.037 | 0.028 | 0.033 |

Source: authors' calculations based on data from the World Bank's Spatial Database for South Asia.

To approach this more formally, we use the decomposability property of the Theil index. Recall that the inequality estimate that we have from imputation is an underestimate of total inequality because it ignores the variation in consumption of households within an urban block/village or, in other words, it assumes that everyone in the village has the same per capita consumption expenditure. Hence, the Theil index constructed using, say, the imputed village per capita consumption data (appropriately weighted by its population), would provide us with between-village inequality in rural India. Given total inequality from household data in the NSS, one can

[17] Note that we frequency-weight each village and urban block by its population when we calculate inequality indices. This is because they are very heterogeneous in population.

[18] Between-inequality in rural and urban India are, strictly speaking, not comparable since there are far more villages than urban blocks.

now derive intra-village inequality using the decomposability property of the Theil index. For rural India, for example, within-village inequality is given by

$$\textit{within inequality}_v = \textit{total rural inequality (NSS)} - \textit{between inequality}_v$$

We can conduct a similar exercise for urban India, with urban blocks as the relevant group. Moreover, total inequality can be calculated precisely for each state with NSS data, and we can similarly estimate between-village inequalities at the state level using our imputation. Thus, we can compute as well inequality within villages in each state of India. The same is true for urban blocks.

Given this insight, we present the total inequality of India (rural and urban separately), and its decomposition into within and between spatial units (Table 8). For rural India, 75 per cent of the inequality comes from within-village inequality and this proportion stays more or less the same over time. This lack of movement is expected since we have shown above that both total rural inequality and rural inequality using imputations (that is, the between part) have remained more or less unchanged. For urban India, the within component accounts for 88 per cent of inequality. However, what is more significant is that within-inequality has been going up over time (as has the between component).

Table 8: Inequality decomposition

| | 2004 | 2011 |
|---|---|---|
| **All India (NSS)** | **0.188** | **0.210** |
| Imputation-based inequality (between spatial units) | 0.050 | 0.055 |
| Residual: within spatial unit | 0.138 | 0.155 |
| **Rural India (NSS)** | **0.140** | **0.143** |
| Rural inequality based on village-level imputation (between) | 0.035 | 0.037 |
| Residual: within village | 0.105 | 0.106 |
| **Urban India (NSS)** | **0.234** | **0.264** |
| Urban inequality based on urban blocks (Between) | 0.028 | 0.033 |
| Residual: within urban block | 0.206 | 0.231 |

Source: authors' calculations based on data from the NSS and the World Bank's Spatial Database for South Asia.

Applying the decomposability property of the Theil index one more time, we can also split national inequality between villages into two components: (1) inequality between states or districts; and (2) inequality between villages within states or districts. Simple calculation for the country as a whole shows that 28 per cent of spatial inequality in 2004 can be attributed to differences between states, and 60 per cent to districts (Table 9). Another pattern worth noting is that the upward trend we find for inequality between states and districts (see Table 2 for NSS estimates or Table 9 for estimates based on our imputation) seems less pronounced for inequality between villages or urban blocks. In fact, the point estimates suggest that there might even have been convergence of spatial units within districts (states), since between-district (state) inequality increases more than between-village/-block inequality in the period 2004–11. Since the estimated increases in within-state and within-district inequality are quite small, they should be interpreted with caution due to the uncertainty associated with our imputation method. However, even with reservations on the sign of overall changes, it seems safe to conclude that the marked divergence observed for districts and states will not be reproduced and accentuated by smaller units within them.

Table 9: Inequality decomposition

| | 2004 | 2011 |
|---|---|---|
| **All India** | | |
| Between states (imputed) | 0.014 | 0.022 |
| Between village/block within states | 0.036 | 0.032 |
| Between districts (imputed) | 0.030 | 0.039 |
| Between village/block within districts | 0.020 | 0.016 |
| **Rural India** | | |
| Between states (imputed) | 0.015 | 0.019 |
| Between villages within states | 0.020 | 0.018 |
| Between districts (imputed) | 0.021 | 0.025 |
| Between villages within districts | 0.014 | 0.012 |
| **Urban India** | | |
| Between states (imputed) | 0.005 | 0.011 |
| Between blocks within states | 0.023 | 0.022 |
| Between districts (imputed) | 0.021 | 0.027 |
| Between blocks within districts | 0.007 | 0.006 |

Source: authors' calculations based on data from the NSS and the World Bank's Spatial Database for South Asia.

These analyses inform us about what is happening within villages and urban blocks across India and provide us with an impression of rather small movements on the inequality frontier, especially in rural India. Is this a consequence of generalized stability, or is this national average hiding an amalgam of very different development in different parts of the country? To be able to answer this question, we move next to state-level analysis and delve into how inequality is evolving in villages and urban blocks within each state.

## 6 Heterogeneity analysis

### 6.1 State inequalities: which states showed changes?

The literature on inequality in India shows that state-level differences often drive inequality. For example, as pointed out above, Azam and Bhatt (2018) find that between-district inequality can be explained by state-level differences. In this section, we calculate inequality for each state (all India, rural, and urban separately) and discuss the contributions of the spatial and local components. Given the lack of standard errors, we restrict the discussion to major states of India for which NSS-based estimates are precise. The states we consider are Punjab, Haryana, Uttar Pradesh (UP), Uttaranchal, Bihar, Rajasthan, Assam, West Bengal, Maharashtra, Madhya Pradesh, Tamil Nadu, Andhra Pradesh, Karnataka, Odisha, Kerala, Gujarat, Chhattisgarh, and Jharkhand.[19] Moreover, we describe only changes larger than 20 per cent of the baseline inequality in magnitude, since we expect these changes to be robust.

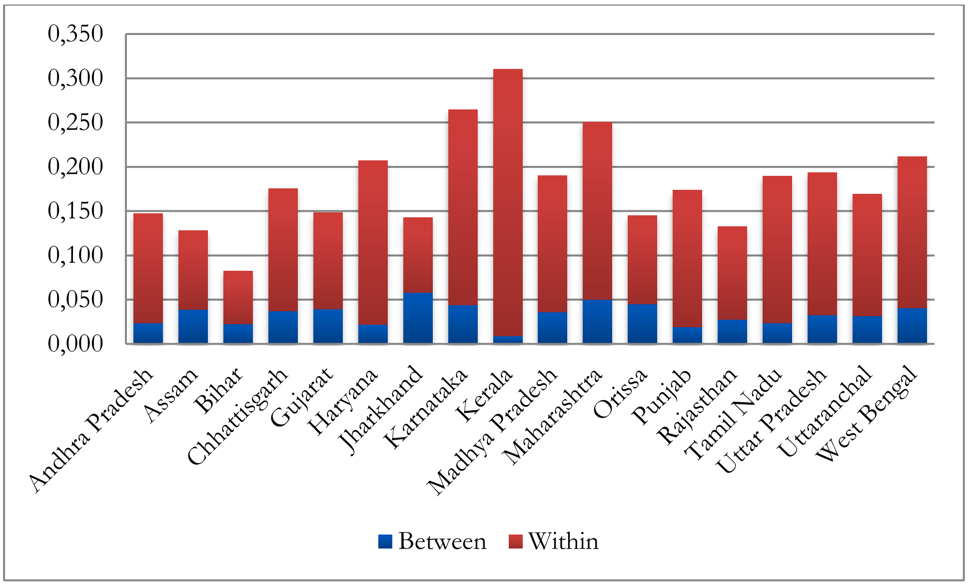
Let us first describe the 2011 snapshot of the states before moving on to the changes. Kerala has the highest inequality among all states (Figures 1–3), consistent with other studies on state-level inequality.[20] Virtually all the inequality in Kerala is found within and not between spatial units. While within-inequality accounts for the largest share of inequality in all states and strata, as usual

[19] Our tables report results for other states as well, but they should be interpreted with care.

[20] Sreeraj and Vakularbharanam (2015) find a similar result.

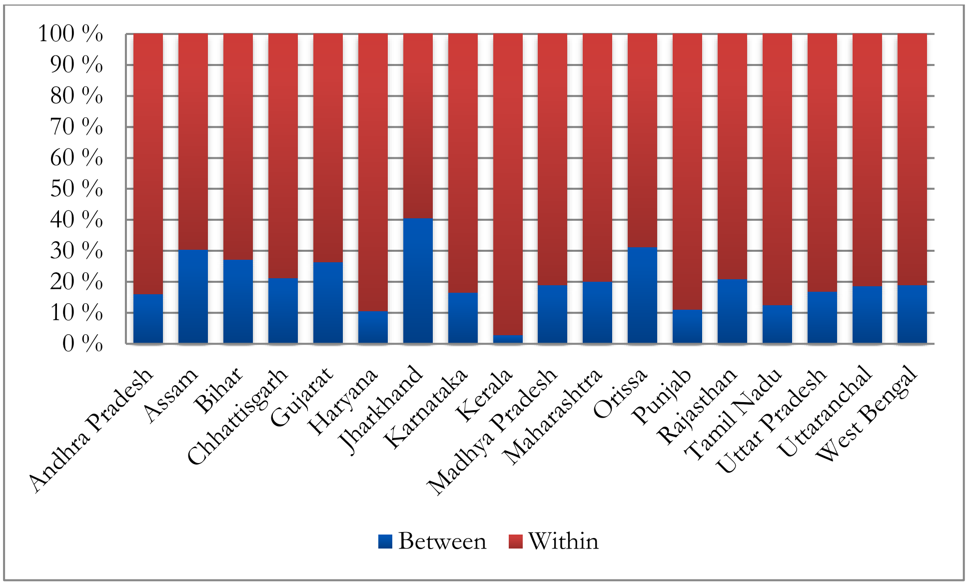
with these decompositions, there is substantial variation in the relative importance of the between component: from below 15 per cent in states such as Haryana, Karnataka, Kerala, Punjab, or Tamil Nadu, to above 30 per cent in Assam, Jharkhand, or Odisha. Kerala, Maharashtra, and Karnataka make up the three states with highest inequality. The top three states in rural inequality are Kerala, Tamil Nadu, and Karnataka, with the majority of the inequality driven by within-inequality. Assam, Jharkhand, and Odisha are the three states with the highest between-village inequality, closely followed by Bihar. The top three states in urban inequality are UP, Karnataka, and Chhattisgarh, with Bihar, Andhra Pradesh, and Gujarat having the highest inequality between urban blocks. While we report these descriptives, it is important to again point out that the states differ in terms of urban blocks as well as villages. The decompositions reflect some of the difference in the number of such groups across states.

Figure 1a: State inequality (Theil): rural + urban (2011)



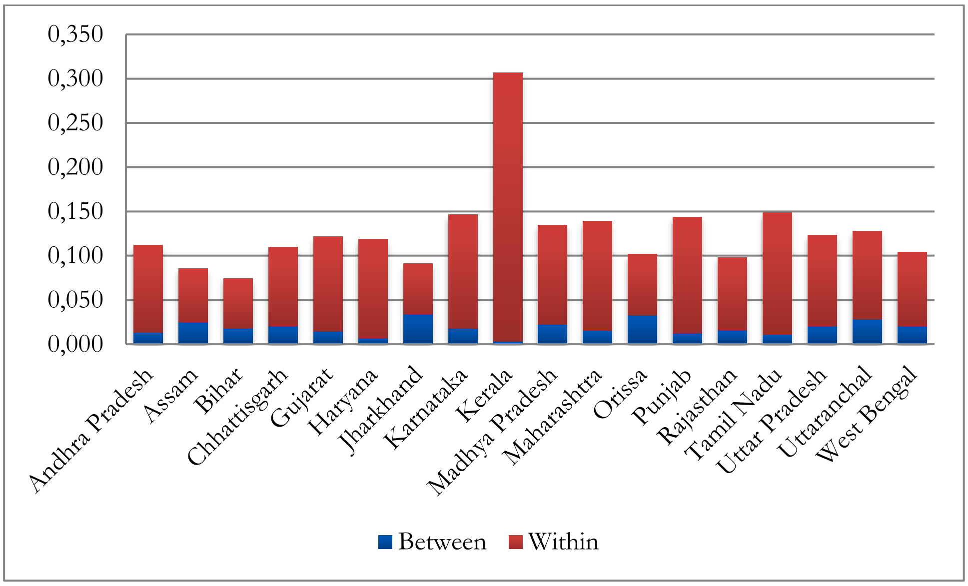

Source: authors' calculations based on data from the NSS and the World Bank's Spatial Database for South Asia.

Figure 1b: State inequality (Theil), decomposition: rural + urban (2011)



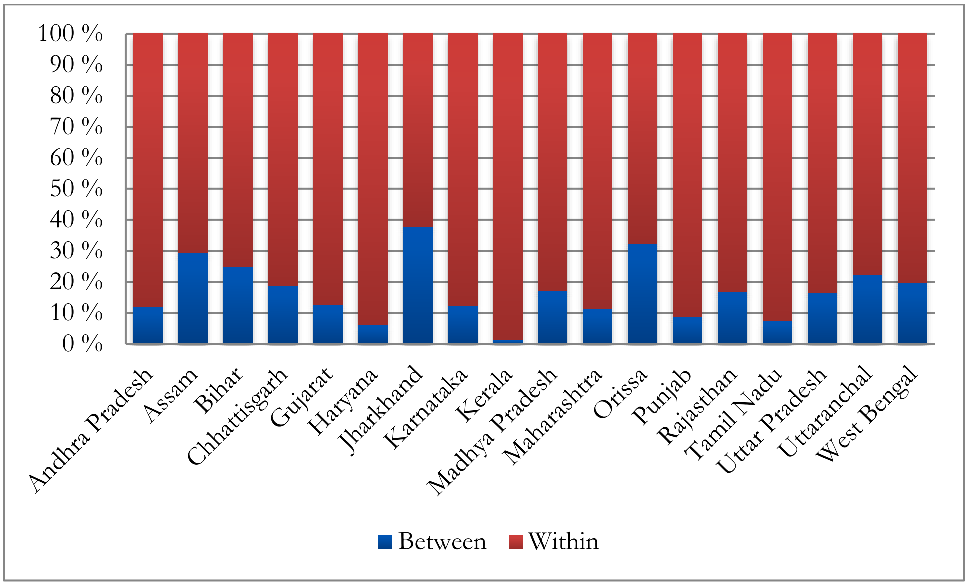

Source: authors' calculations based on data from the NSS and the World Bank's Spatial Database for South Asia.

Figure 2a: State inequality (Theil): rural (2011)



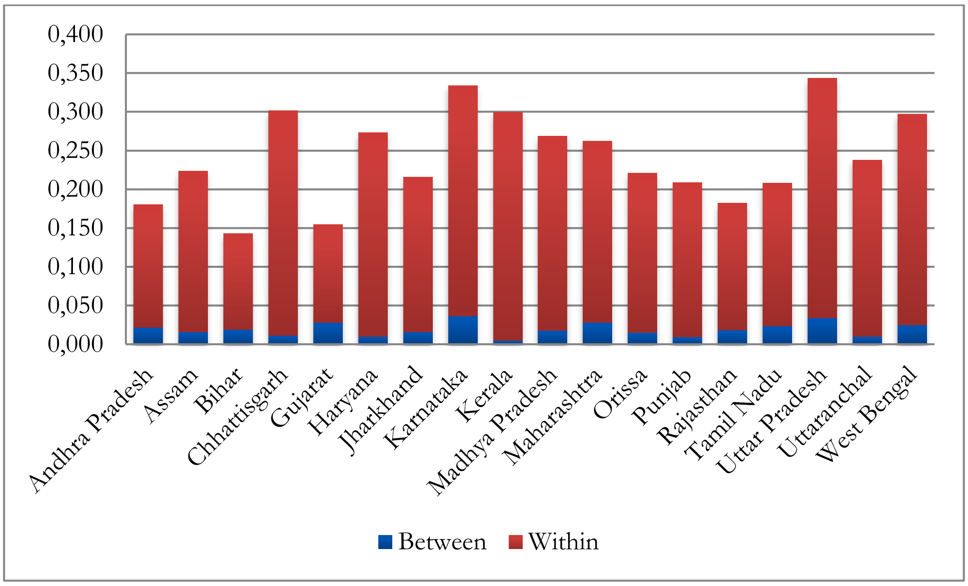

Source: authors' calculations based on data from the NSS and the World Bank's Spatial Database for South Asia.

Figure 2b: State inequality (Theil), decomposition: rural (2011)



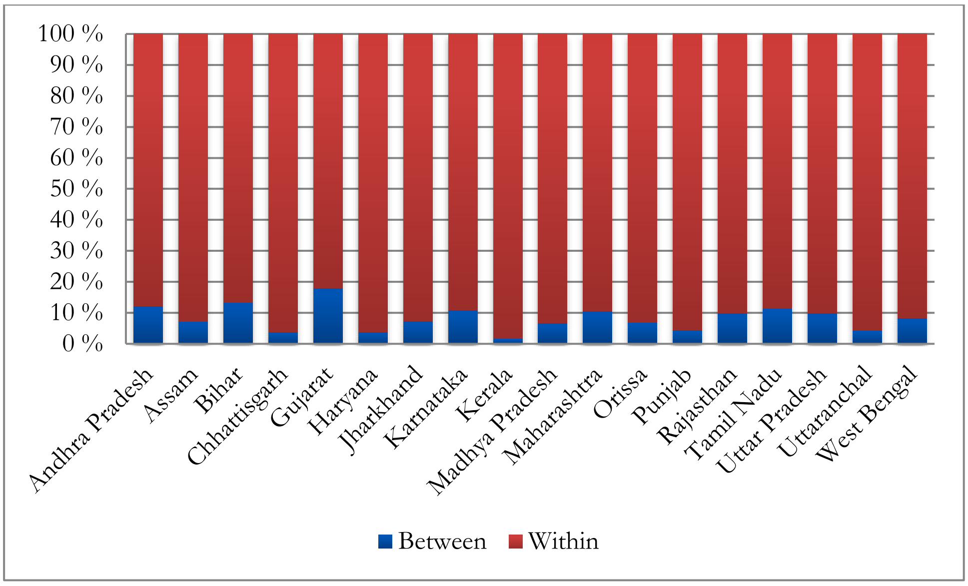

Source: authors' calculations based on data from the NSS and the World Bank's Spatial Database for South Asia.

Figure 3a: State inequality (Theil): urban (2011)




Source: authors' calculations based on data from the NSS and the World Bank's Spatial Database for South Asia.

Figure 3b: State inequality (Theil), decomposition: urban (2011)




Source: authors' calculations based on data from the NSS and the World Bank's Spatial Database for South Asia.

Moving to changes over time (2004–11), if we combine rural and urban India (Table 10), we find that inequality (based on the NSS) has risen in the states of Assam, Karnataka, Kerala, UP, and Uttaranchal. It does not show an appreciable decline in any state. Spatial inequality between village/urban blocks has, however, risen in Gujarat, Haryana, and Karnataka, while it has fallen in Bihar, Jharkhand, Kerala, Odisha, Punjab, Rajasthan, and Uttaranchal, among the major states. Moving to the residual, the within-inequality component, the major states that show a rise in total inequality also show a rise in this component. In addition, Bihar and Jharkhand show a rise and Gujarat shows a fall in local inequality, but they show no large movements in total inequality. The cases of Bihar, Gujarat, Jharkhand, Kerala, and Uttaranchal are interesting as they show opposite movements in the two components of inequality.

Table 10: State-wise: rural + urban

| State name | NSS 2004 | Imputed 2004 | Within 2004 | NSS 2011 | Imputed 2011 | Within 2011 |
|---|---|---|---|---|---|---|
| Jammu & Kashmir | 0.096 | 0.058 | 0.038 | 0.143 | 0.037 | 0.106 |
| Himachal Pradesh | 0.173 | 0.030 | 0.143 | 0.169 | 0.025 | 0.144 |
| Punjab | 0.179 | 0.024 | 0.155 | 0.174 | 0.019 | 0.155 |
| Chandigarh | 0.225 | 0.006 | 0.218 | 0.268 | 0.002 | 0.265 |
| Uttaranchal | 0.139 | 0.046 | 0.093 | 0.169 | 0.032 | 0.138 |
| Haryana | 0.223 | 0.018 | 0.205 | 0.207 | 0.022 | 0.185 |
| Delhi | 0.191 | 0.009 | 0.183 | 0.260 | 0.002 | 0.257 |
| Rajasthan | 0.125 | 0.036 | 0.089 | 0.133 | 0.028 | 0.105 |
| UP | 0.158 | 0.034 | 0.124 | 0.194 | 0.033 | 0.161 |
| Bihar | 0.082 | 0.036 | 0.045 | 0.082 | 0.022 | 0.060 |
| Sikkim | 0.129 | 0.040 | 0.089 | 0.097 | 0.041 | 0.056 |
| Arunachal Pradesh | 0.118 | 0.037 | 0.081 | 0.202 | 0.038 | 0.164 |
| Nagaland | 0.089 | 0.037 | 0.052 | 0.074 | 0.027 | 0.047 |
| Manipur | 0.046 | 0.030 | 0.016 | 0.076 | 0.021 | 0.054 |
| Mizoram | 0.076 | 0.035 | 0.041 | 0.129 | 0.042 | 0.087 |
| Tripura | 0.116 | 0.026 | 0.090 | 0.104 | 0.022 | 0.082 |
| Meghalaya | 0.068 | 0.056 | 0.012 | 0.085 | 0.050 | 0.036 |
| Assam | 0.086 | 0.047 | 0.039 | 0.128 | 0.039 | 0.089 |
| West Bengal | 0.190 | 0.044 | 0.146 | 0.212 | 0.040 | 0.171 |
| Jharkhand | 0.144 | 0.075 | 0.069 | 0.143 | 0.058 | 0.085 |
| Orissa | 0.155 | 0.067 | 0.088 | 0.145 | 0.045 | 0.100 |
| Chhattisgarh | 0.193 | 0.040 | 0.153 | 0.175 | 0.037 | 0.138 |
| Madhya Pradesh | 0.173 | 0.042 | 0.131 | 0.190 | 0.036 | 0.154 |
| Gujarat | 0.167 | 0.028 | 0.139 | 0.148 | 0.039 | 0.109 |
| Daman & Diu | 0.153 | 0.037 | 0.116 | 0.068 | 0.007 | 0.061 |
| Dadra and Nagar Haveli | 0.225 | 0.063 | 0.161 | 0.219 | 0.066 | 0.153 |
| Maharashtra | 0.225 | 0.050 | 0.174 | 0.251 | 0.050 | 0.200 |
| Andhra Pradesh | 0.183 | 0.022 | 0.161 | 0.147 | 0.024 | 0.123 |
| Karnataka | 0.194 | 0.034 | 0.159 | 0.264 | 0.044 | 0.221 |
| Goa | 0.182 | 0.011 | 0.171 | 0.165 | 0.005 | 0.160 |
| Lakshadweep | 0.122 | 0.004 | 0.118 | 0.140 | 0.003 | 0.137 |
| Kerala | 0.258 | 0.012 | 0.246 | 0.310 | 0.009 | 0.301 |
| Tamil Nadu | 0.216 | 0.024 | 0.192 | 0.190 | 0.024 | 0.166 |
| Pondicherry | 0.202 | 0.004 | 0.198 | 0.133 | 0.008 | 0.124 |
| Andaman & Nicobar Islands | 0.240 | 0.027 | 0.213 | 0.203 | 0.028 | 0.174 |

Source: authors' calculations based on data from the NSS and the World Bank's Spatial Database for South Asia.

Recall that rural India shows very little dynamism in total inequality. At the state level, though, there are changes in overall inequality (based on the NSS) in some states: Assam and Kerala (Table 11) show a rise, whereas there are decreases in Chhattisgarh, Haryana, and Odisha. States that show a decrease in between-village inequality are Andhra Pradesh, Assam, Kerala, Rajasthan, and Uttaranchal, whereas inequality between villages has increased in Karnataka. The states that register a change in total inequality go through similar changes in within-inequality; however, the states of Bihar and Jharkhand show an increase and West Bengal a fall in local inequality without any discernible change in overall inequality.

Table 11: State-wise: rural

| State name | NSS 2004 | Imputed 2004 | Within 2004 | NSS 2011 | Imputed 2011 | Within 2011 |
|---|---|---|---|---|---|---|
| Jammu & Kashmir | 0.084 | 0.041 | 0.043 | 0.126 | 0.034 | 0.092 |
| Himachal Pradesh | 0.169 | 0.023 | 0.147 | 0.150 | 0.022 | 0.129 |
| Punjab | 0.150 | 0.012 | 0.138 | 0.144 | 0.012 | 0.131 |
| Chandigarh | 0.117 | 0.003 | 0.114 | 0.123 | 0.003 | 0.120 |
| Uttaranchal | 0.109 | 0.037 | 0.073 | 0.128 | 0.029 | 0.099 |
| Haryana | 0.228 | 0.008 | 0.219 | 0.119 | 0.007 | 0.111 |
| Delhi | 0.157 | 0.004 | 0.153 | 0.119 | 0.004 | 0.116 |
| Rajasthan | 0.090 | 0.021 | 0.069 | 0.098 | 0.016 | 0.082 |
| UP | 0.121 | 0.020 | 0.102 | 0.124 | 0.021 | 0.103 |
| Bihar | 0.063 | 0.018 | 0.045 | 0.074 | 0.019 | 0.056 |
| Sikkim | 0.118 | 0.027 | 0.091 | 0.069 | 0.018 | 0.051 |
| Arunachal Pradesh | 0.121 | 0.037 | 0.084 | 0.197 | 0.034 | 0.163 |
| Nagaland | 0.081 | 0.037 | 0.044 | 0.064 | 0.033 | 0.031 |
| Manipur | 0.044 | 0.029 | 0.015 | 0.070 | 0.025 | 0.045 |
| Mizoram | 0.061 | 0.023 | 0.038 | 0.107 | 0.013 | 0.094 |
| Tripura | 0.081 | 0.023 | 0.058 | 0.081 | 0.014 | 0.067 |
| Meghalaya | 0.040 | 0.042 | –0.002 | 0.054 | 0.027 | 0.027 |
| Assam | 0.062 | 0.034 | 0.028 | 0.085 | 0.025 | 0.060 |
| West Bengal | 0.128 | 0.021 | 0.107 | 0.104 | 0.020 | 0.084 |
| Jharkhand | 0.077 | 0.036 | 0.041 | 0.091 | 0.034 | 0.057 |
| Orissa | 0.128 | 0.039 | 0.089 | 0.102 | 0.033 | 0.069 |
| Chhattisgarh | 0.143 | 0.024 | 0.119 | 0.110 | 0.021 | 0.089 |
| Madhya Pradesh | 0.117 | 0.019 | 0.098 | 0.135 | 0.023 | 0.112 |
| Gujarat | 0.131 | 0.018 | 0.113 | 0.122 | 0.015 | 0.107 |
| Daman & Diu | 0.142 | 0.043 | 0.100 | 0.041 | 0.022 | 0.019 |
| Dadra and Nagar Haveli | 0.198 | 0.053 | 0.145 | 0.183 | 0.035 | 0.147 |
| Maharashtra | 0.153 | 0.019 | 0.134 | 0.139 | 0.016 | 0.123 |
| Andhra Pradesh | 0.133 | 0.017 | 0.116 | 0.112 | 0.013 | 0.099 |
| Karnataka | 0.131 | 0.015 | 0.116 | 0.146 | 0.018 | 0.128 |
| Goa | 0.149 | 0.007 | 0.142 | 0.146 | 0.006 | 0.139 |
| Lakshadweep | 0.128 | 0.002 | 0.127 | 0.110 | 0.002 | 0.107 |
| Kerala | 0.239 | 0.007 | 0.231 | 0.307 | 0.004 | 0.303 |
| Tamil Nadu | 0.152 | 0.013 | 0.139 | 0.149 | 0.011 | 0.137 |
| Pondicherry | 0.212 | 0.006 | 0.206 | 0.120 | 0.006 | 0.115 |
| Andaman & Nicobar Islands | 0.213 | 0.026 | 0.187 | 0.154 | 0.020 | 0.134 |

Source: authors' calculations based on data from the NSS and the World Bank's Spatial Database for South Asia.

Moving to urban India, we find there is a visible increase in total inequality in Assam, Haryana, Karnataka, UP, and Uttaranchal (Table 12). Inequality between urban blocks has fallen for Assam, Bihar, and Odisha, with no state showing a robust increase. On the other hand, Andhra Pradesh displays a decline in total inequality. Spatial inequality between blocks has fallen in Assam, Bihar, Kerala, Odisha, Punjab, Rajasthan, and Uttaranchal, while it has risen in Tamil Nadu. Local inequalities show similar changes to total inequalities (where any such changes exist), although local inequality increases in Chhattisgarh and Uttaranchal do not come along with any movement of total inequality. We summarize all these results for major states in Table 13.[21]

[21] The changes when we do not impose any thresholds to show movement are summarized in Table A2.

Table 12: State-wise: urban

| State Name | NSS 2004 | Imputed 2004 | Within 2004 | NSS 2011 | Imputed 2011 | Within 2011 |
|---|---|---|---|---|---|---|
| Jammu & Kashmir | 0.114 | 0.078 | 0.036 | 0.160 | 0.021 | 0.139 |
| Himachal Pradesh | 0.141 | 0.011 | 0.130 | 0.215 | 0.003 | 0.212 |
| Punjab | 0.215 | 0.015 | 0.200 | 0.209 | 0.009 | 0.199 |
| Chandigarh | 0.214 | 0.000 | 0.214 | 0.277 | 0.000 | 0.277 |
| Uttaranchal | 0.178 | 0.015 | 0.163 | 0.238 | 0.010 | 0.228 |
| Haryana | 0.208 | 0.012 | 0.196 | 0.273 | 0.010 | 0.263 |
| Delhi | 0.191 | 0.008 | 0.183 | 0.269 | 0.002 | 0.267 |
| Rajasthan | 0.187 | 0.025 | 0.163 | 0.182 | 0.018 | 0.164 |
| UP | 0.242 | 0.033 | 0.209 | 0.344 | 0.034 | 0.310 |
| Bihar | 0.177 | 0.036 | 0.141 | 0.143 | 0.019 | 0.124 |
| Sikkim | 0.106 | 0.008 | 0.098 | 0.068 | 0.001 | 0.068 |
| Arunachal Pradesh | 0.094 | 0.027 | 0.067 | 0.182 | 0.018 | 0.164 |
| Nagaland | 0.093 | 0.034 | 0.059 | 0.085 | 0.009 | 0.076 |
| Manipur | 0.046 | 0.023 | 0.023 | 0.072 | 0.006 | 0.066 |
| Mizoram | 0.086 | 0.017 | 0.069 | 0.103 | 0.013 | 0.090 |
| Tripura | 0.177 | 0.008 | 0.169 | 0.141 | 0.006 | 0.135 |
| Meghalaya | 0.119 | 0.004 | 0.115 | 0.088 | 0.006 | 0.082 |
| Assam | 0.161 | 0.021 | 0.140 | 0.223 | 0.016 | 0.207 |
| West Bengal | 0.250 | 0.017 | 0.233 | 0.297 | 0.025 | 0.272 |
| Jharkhand | 0.195 | 0.014 | 0.181 | 0.216 | 0.016 | 0.200 |
| Orissa | 0.200 | 0.026 | 0.174 | 0.221 | 0.015 | 0.206 |
| Chhattisgarh | 0.252 | 0.010 | 0.241 | 0.301 | 0.012 | 0.290 |
| Madhya Pradesh | 0.245 | 0.022 | 0.224 | 0.268 | 0.018 | 0.250 |
| Gujarat | 0.179 | 0.031 | 0.148 | 0.154 | 0.028 | 0.126 |
| Daman & Diu | 0.134 | 0.000 | 0.133 | 0.107 | 0.001 | 0.106 |
| Dadra and Nagar Haveli | 0.166 | 0.000 | 0.166 | 0.164 | 0.000 | 0.164 |
| Maharashtra | 0.242 | 0.026 | 0.216 | 0.263 | 0.028 | 0.235 |
| Andhra Pradesh | 0.250 | 0.022 | 0.229 | 0.180 | 0.022 | 0.158 |
| Karnataka | 0.242 | 0.036 | 0.206 | 0.334 | 0.037 | 0.297 |
| Goa | 0.239 | 0.002 | 0.237 | 0.184 | 0.002 | 0.182 |
| Lakshadweep | 0.115 | 0.003 | 0.112 | 0.169 | 0.002 | 0.167 |
| Kerala | 0.299 | 0.013 | 0.286 | 0.299 | 0.005 | 0.294 |
| Tamil Nadu | 0.238 | 0.019 | 0.219 | 0.208 | 0.024 | 0.184 |
| Pondicherry | 0.191 | 0.003 | 0.188 | 0.135 | 0.009 | 0.126 |
| Andaman & Nicobar Islands | 0.255 | 0.004 | 0.251 | 0.221 | 0.002 | 0.219 |

Source: authors' calculations based on data from the NSS and the World Bank's Spatial Database for South Asia.

Table 13: State changes in inequality

| | Rural + urban | | | Rural | | | Urban | | |
|---|---|---|---|---|---|---|---|---|---|
| States | T | B | W | T | B | W | T | B | W |
| Andhra Pradesh | | | – | | – | | – | | – |
| Assam | + | | + | + | – | + | + | – | + |
| Bihar | | – | + | | | + | | – | |
| Chhattisgarh | | | | – | | – | | | + |
| Gujarat | | + | – | | | | | | |
| Haryana | | + | | – | | – | + | | + |
| Jharkhand | | – | + | | | + | | | |
| Karnataka | + | + | + | | + | | + | | + |
| Kerala | + | – | + | + | – | + | | – | |
| Madhya Pradesh | | | | | | | | | |
| Maharashtra | | | | | | | | | |
| Orissa | | – | | – | | – | | – | |
| Punjab | | – | | | | | | – | |
| Rajasthan | | – | | | – | | | – | |
| Tamil Nadu | | | | | | | | + | |
| UP | + | | + | | | | + | | + |
| Uttaranchal | + | – | + | | – | + | + | – | + |
| West Bengal | | | | | | – | | + | |

Note: T: total, B: between, W: within

Source: authors' calculations based on data from the NSS and the World Bank's Spatial Database for South Asia.

To summarize some broad trends: spatial inequality is falling in Kerala, but rising local inequality, especially in rural areas, is leading to higher overall inequality. Bihar shows declining spatial inequality, with a similar trend between urban settlements. However, there is a rise in local inequality in this state, especially marked in villages. It is interesting to note a broad common trend of rising within-inequality in these economies dependent on remittances, with falling inequality between settlements. Rajasthan shows greater spatial equality between all settlements and so does Uttaranchal, though in the case of the latter state, rising local inequality is translated into more overall inequality. Karnataka is another interesting state with rising spatial inequality across its rural areas and rising local inequalities in its urban areas, while in Gujarat we find overall rising spatial inequality and falling local inequality. The absence of any trends in either its urban or rural components suggests a widening gap between rural and urban areas.

While an analysis of each individual state is outside the scope of the paper, we would like to emphasize the interesting differences that such decompositions yield, with often opposing forces at play at very local spatial levels. To understand some of the forces at play, we move next to understanding how changes have occurred at the level immediately below the state: the district.

### 6.2 Inequality changes and prosperity

In this section, we adopt a different perspective to look at the heterogeneity underlying the evolution of inequality in India. We analyse separately the patterns for the richest and poorest districts in terms of real per capita consumption expenditure at baseline (Table 14), and also for those districts where consumption is growing fastest and slowest (Table 15). In each of the cases, we look at the top and bottom 10 per cent and 25 per cent performers and repeat the analysis conducted for the full country in the previous sections.

Table 14: Top and bottom districts: log real consumption expenditure per capita

| | NSS 04 | Between 2004 | Within 2004 | Change total | Change between | Change within |
|---|---|---|---|---|---|---|
| **All India** | | | | | | |
| Top 10 per cent | 0.242 | 0.025 | 0.217 | 0.033 | 0.003 | 0.030 |
| Top 25 per cent | 0.219 | 0.036 | 0.183 | 0.022 | 0.000 | 0.022 |
| Bottom 25 per cent | 0.100 | 0.034 | 0.066 | 0.021 | –0.006 | 0.027 |
| Bottom 10 per cent | 0.095 | 0.034 | 0.062 | 0.038 | –0.006 | 0.044 |
| **Rural** | | | | | | |
| Top 10 per cent | 0.225 | 0.030 | 0.195 | 0.031 | 0.003 | 0.028 |
| Top 25 per cent | 0.176 | 0.029 | 0.147 | 0.008 | 0.000 | 0.008 |
| Bottom 25 per cent | 0.083 | 0.026 | 0.056 | 0.024 | –0.003 | 0.026 |
| Bottom 10 per cent | 0.080 | 0.027 | 0.053 | 0.042 | –0.003 | 0.045 |
| **Urban** | | | | | | |
| Top 10 per cent | 0.238 | 0.010 | 0.228 | 0.028 | 0.003 | 0.025 |
| Top 25 per cent | 0.231 | 0.017 | 0.214 | 0.023 | 0.002 | 0.020 |
| Bottom 25 per cent | 0.175 | 0.024 | 0.152 | 0.008 | –0.006 | 0.014 |
| Bottom 10 per cent | 0.188 | 0.022 | 0.166 | 0.021 | –0.006 | 0.027 |

Source: authors' calculations based on data from the NSS and the World Bank's Spatial Database for South Asia.

Table 15: Top and bottom districts: growth in real consumption expenditure per capita

| | NSS 04 | Between 2004 | Within 2004 | Change total | Change between | Change within |
|---|---|---|---|---|---|---|
| **All India** | | | | | | |
| Top 10 per cent | 0.156 | 0.038 | 0.118 | 0.096 | 0.008 | 0.088 |
| Top 25 per cent | 0.189 | 0.046 | 0.143 | 0.054 | 0.006 | 0.048 |
| Bottom 25 per cent | 0.199 | 0.052 | 0.148 | –0.033 | –0.006 | –0.026 |
| Bottom 10 per cent | 0.196 | 0.050 | 0.146 | –0.054 | –0.007 | –0.046 |
| **Rural** | | | | | | |
| Top 10 per cent | 0.129 | 0.032 | 0.097 | 0.041 | 0.007 | 0.034 |
| Top 25 per cent | 0.143 | 0.036 | 0.107 | 0.030 | 0.002 | 0.028 |
| Bottom 25 per cent | 0.147 | 0.031 | 0.115 | –0.045 | –0.001 | –0.044 |
| Bottom 10 per cent | 0.125 | 0.028 | 0.096 | –0.023 | 0.002 | –0.025 |
| **Urban** | | | | | | |
| Top 10 per cent | 0.181 | 0.018 | 0.164 | 0.118 | 0.005 | 0.113 |
| Top 25 per cent | 0.226 | 0.024 | 0.201 | 0.060 | 0.004 | 0.055 |
| Bottom 25 per cent | 0.254 | 0.031 | 0.223 | –0.007 | –0.004 | –0.003 |
| Bottom 10 per cent | 0.270 | 0.032 | 0.238 | –0.075 | –0.007 | –0.067 |

Source: authors' calculations based on data from the NSS and the World Bank's Spatial Database for South Asia.

If we look at top and bottom places in terms of living standards in 2004, we see that local inequality is initially much larger for richer districts, as one may expect, but spatial inequality between places is at least as important at the bottom as it is at the top. Turning to the evolution over time, we can observe similar patterns for total inequality at the top and at the bottom: increases of approximately 0.2 when we focus on the extreme quartiles and around 0.35 for the top and bottom 10 per cent. The latter are much larger than those registered at the national level, and in particular the increase at the bottom is very large in relative terms: 40 per cent of the initial level. Interestingly, this development in the poorest places masks an enormous increase in within-inequality (0.44, two-thirds of baseline inequality), attenuated by a decrease in between-inequality. By contrast, between-inequality is increasing for rich districts. To interpret this result correctly, it is important to bear in mind that between-inequality numbers combine developments between habitations within a district with convergence or divergence between districts. In fact, the differences between rich and poor districts to this respect are mainly driven by substantially faster divergence between rich districts).[22]

All in all, the picture for rural India is rather similar, although here the rise of local inequality at the bottom is even more pronounced in relative terms, as it has more than doubled between 2004 and 2011. All in all, there is not much action for the top 25 per cent, while inequality increases for the rural top 10 per cent are mostly due to within-inequalities. Differences between top and bottom locations in terms of changes in inequalities between villages are less stark than overall or for urban areas.

Baseline values and changes in inequality within urban blocks are much more similar across top and bottom locations. They are also smaller than the rises in rural inequality described above. Again, we find remarkable declines in between-inequality in poorer places, which, at baseline, was more important there. In this case, this reflects decreasing gaps between blocks at the bottom.

We shall examine now differences according to consumption growth. Higher growth is associated in all India to increases in inequality, and low growth to compression, both within and between spatial units. Here, the latter reflect opposing developments between districts as well as between villages/blocks within districts at the top and bottom On the other hand, in rural India, no decreases in between-inequality are observed in districts with the lowest growth. The jump between the top 10 per cent and the top 25 per cent is larger than that between the top 25 per cent and the bottom 25 per cent. In urban India, the unequalizing effects of growth are observed very clearly, as within-inequality increases by 0.11 (more than 60 per cent!) in the top 10 per cent districts.

The contrasting patterns revealed by these results further underline the importance of heterogeneity analysis. However, prosperity and economic growth are unlikely to be the only factors behind the evolution of inequality. To better understand what are the forces in play, we explore further the partial correlates of the evolution of inequality in Indian districts in the next section.

### 6.3 District-level inequality and its covariates: a dynamic view

To delve into the co-evolution of inequality and its determinants, we regress inequality and its constituents on changes in the correlates examined above. Again, we conduct this exercise for the full district (Table 16), as well as rural and urban areas separately (Tables 17 and 18 respectively).

[22] Results of this district decomposition are not reported here, but are available upon request.

Table 16: Covariates of changes in district inequality (rural + urban)

| Dependent variable: growth rate of inequality | Total ineq. | Between | Within |
|---|---|---|---|
| Inequality 2004 | –4.430*** | –7.083*** | –6.064*** |
| | (0.324) | (1.174) | (0.420) |
| Per capita consumption expenditure 2004, growth | 0.592*** | 0.0605 | 0.677*** |
| | (0.0939) | (0.0726) | (0.122) |
| Urban (percentage of population), change | 0.537 | 0.764*** | 0.824* |
| | (0.371) | (0.283) | (0.477) |
| Scheduled Caste population (percentage), change | 0.000114 | 0.00172 | 0.00920 |
| | (0.00962) | (0.00742) | (0.0125) |
| Scheduled Tribe population (percentage), change | –0.00318 | 0.00453 | –0.0175* |
| | (0.00717) | (0.00567) | (0.0100) |
| Literacy rate, 7+ years, total (percentage), change | –0.0113** | –2.88e–05 | –0.0185*** |
| | (0.00483) | (0.00363) | (0.00629) |
| Proportion of population employed (percentage), change | 0.00528 | –0.0150*** | 0.0134** |
| | (0.00517) | (0.00402) | (0.00676) |
| Regular wage earners (percentage of total employed), change | 0.0122*** | –0.00517* | 0.0138*** |
| | (0.00398) | (0.00305) | (0.00509) |
| Yield per acre, growth | –0.0148 | 0.0187 | –0.0208 |
| | (0.0322) | (0.0248) | (0.0411) |
| Proportion of households with access to banking service, change | –0.00233 | –0.00479*** | –0.00131 |
| | (0.00204) | (0.00161) | (0.00267) |
| Proportion of households with improved sanitation, change | –0.000877 | –6.86e–05 | –0.00107 |
| | (0.00186) | (0.00142) | (0.00240) |
| Proportion of male labour force underemployed, change | –0.00164 | 0.0152*** | –0.00233 |
| | (0.00524) | (0.00425) | (0.00685) |
| Constant | 0.564*** | –0.0336 | 0.729*** |
| | (0.0938) | (0.0676) | (0.116) |
| Observations | 479 | 472 | 465 |
| R-squared | 0.370 | 0.149 | 0.384 |

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Source: authors' calculations based on data from the NSS and the World Bank's Spatial Database for South Asia.

Table 17: Covariates of changes in district inequality (rural)

| Dependent variable: growth rate of inequality | Total | Between | Within |
|---|---|---|---|
| Inequality 2004 | –5.828*** | –7.126*** | –7.459*** |
| | (0.359) | (1.651) | (0.523) |
| Real rural per capita consumption Expenditure 2004, growth | 0.668*** | –0.00642 | 0.719*** |
| | (0.0942) | (0.0647) | (0.138) |
| Urban (percentage of population), change | 0.657* | –1.273*** | 0.813 |
| | (0.392) | (0.264) | (0.574) |
| Rural Scheduled Caste population (percentage), change | 0.000199 | –0.00274 | –0.00314 |
| | (0.00892) | (0.00608) | (0.0130) |
| Rural Scheduled Tribe population (percentage), change | –0.00575 | –0.00322 | –0.00280 |
| | (0.00685) | (0.00482) | (0.0104) |
| Rural literacy rate, 7+ years, change. | –0.00871* | 0.00110 | –0.0203*** |
| | (0.00467) | (0.00323) | (0.00701) |
| Rural proportion of population employed (percentage), change | –0.00303 | –0.00574* | 0.000724 |
| | (0.00490) | (0.00337) | (0.00720) |
| Rural regular wage earners, (percentage of total employed), change | 0.0182*** | 0.000788 | 0.0243*** |
| | (0.00415) | (0.00283) | (0.00613) |
| Yield per acre, growth | 0.0311 | –0.0154 | 0.0141 |
| | (0.0344) | (0.0236) | (0.0502) |
| Rural proportion of households with access to banking service, change | –0.000872 | –0.00508*** | 0.00353 |
| | (0.00187) | (0.00130) | (0.00280) |
| Rural proportion of households with improved sanitation, change | 0.000322 | –0.00307** | –0.000467 |
| | (0.00177) | (0.00120) | (0.00262) |
| Rural proportion of male labour force underemployed, change | –0.000707 | 0.0126*** | –0.0227*** |
| | (0.00489) | (0.00351) | (0.00717) |
| Constant | 0.489*** | 0.103* | 0.640*** |
| | (0.0916) | (0.0604) | (0.132) |
| Observations | 479 | 472 | 466 |
| R-squared | 0.442 | 0.156 | 0.376 |

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Source: authors' calculations based on data from the NSS and the World Bank's Spatial Database for South Asia.

Table 18: Covariates of changes in district inequality (urban)

| Dependent variable: growth rate of inequality | Total | Between | Within |
|---|---|---|---|
| Urban inequality 2004 | –3.860*** | –18.89*** | –4.034*** |
| | (0.313) | (4.624) | (0.334) |
| Real per capita urban consumption expenditure 2004, growth | 0.489*** | –0.189 | 0.598*** |
| | (0.0770) | (0.187) | (0.0836) |
| Urban (percentage of population), change | 0.719* | –0.605 | 0.841* |
| | (0.428) | (1.050) | (0.458) |
| Urban Scheduled Caste population (percentage), change | –0.0161 | –0.141*** | –0.00801 |
| | (0.0138) | (0.0344) | (0.0148) |
| Urban Scheduled Tribe population (percentage), change | –0.0167 | –0.0236 | –0.00599 |
| | (0.0110) | (0.0339) | (0.0156) |
| Urban literacy rate, 7+ years, change. | 0.00561 | –0.0315 | 0.00428 |
| | (0.0105) | (0.0278) | (0.0120) |
| Urban proportion of population employed (percentage), change | 0.0166* | 0.0236 | 0.0212** |
| | (0.00858) | (0.0222) | (0.00974) |
| Urban regular wage earners (percentage of total employed), change | 0.00215 | –0.0179 | 0.00297 |
| | (0.00535) | (0.0138) | (0.00592) |
| Yield per acre, growth | 0.0108 | 0.119 | 0.0312 |
| | (0.0380) | (0.0926) | (0.0397) |
| Urban proportion of households with access to banking service, change | –0.00598* | –0.000318 | –0.00826** |
| | (0.00305) | (0.00791) | (0.00341) |
| Urban proportion of households with improved sanitation, change | –0.00162 | –0.0166** | –0.00112 |
| | (0.00252) | (0.00655) | (0.00282) |
| Urban proportion of male labour force underemployed, change | –0.00515 | –0.0126 | 0.00114 |
| | (0.0213) | (0.0545) | (0.0234) |
| Constant | 0.581*** | 0.345 | 0.572*** |
| | (0.104) | (0.238) | (0.114) |
| Observations | 470 | 445 | 443 |
| R-squared | 0.365 | 0.106 | 0.397 |

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Source: authors' calculations based on data from the NSS and the World Bank's Spatial Database for South Asia.

The first conclusion is the confirmation of the unequalizing effect of economic growth that was already detected when comparing top and bottom districts above. After controlling for other factors, growth in consumption expenditures is significantly linked to increasing total and especially within-inequalities, both in urban and rural areas separately as in the country as a whole. Again, growth does not seem to be particularly pro-poor.

Urbanization is another relevant, and complex, correlate of inequality growth. If we focus on all India, we detect a mild positive relation with total inequality and a much stronger link with spatial inequality. The latter result is not reproduced for urban or rural areas separately, and thus probably just reflects a rising rural–urban gap as more people live in cities and towns, which might be due both to agglomeration economies driving urban areas apart from their rural hinterlands, as well as to increased rural–urban migration in districts where moving to the city becomes more economically attractive. In fact, a growing share of urban population in the district is very strongly linked to a reduction of inequalities between villages. This resounds with the finding on the important role of secondary town growth for reducing rural poverty in the most deprived areas (Gibson et al. 2017). Alternatively, it could also be consistent with a Lewis–Kuznets process in which the villages with most excess labour (and which are poorer) send more immigrants to urban areas, alleviating population pressures and increasing productivity. On the other hand, faster urbanization is associated with more total inequality in rural areas, and with an increase of overall and within-block urban inequality. All in all, it seems that growing urbanization might contribute to the spatial diffusion of economic prosperity, but some are reaping its fruits earlier than others.

A growing share of the employed working for a regular wage is significantly associated with increasing total and within-inequality in rural areas, and also for the district as a whole. On the other hand, inequalities between spatial units grow slower for the full district where regular wage employment grows at a faster pace, but not for its rural or urban constituents separately. Again, we can think that such opportunities are gradually reaching rural areas, reducing the rural–urban gap and hence overall between-inequality but increasing inequality within villages. Similarly, when looking at the full district, growth in the proportion of employed people in the population goes along with less spatial and more local inequality, and the latter pattern is reproduced in rural areas. Finally, an increase in underemployment works in the opposite direction, as it arrives with growing gaps between villages (and also between spatial units in the district as a whole) but a slower increase in inequalities within villages. It seems intuitive that when employment opportunities are less stable, their relation with changes in inequalities is more muted.

Turning to factors with an unambiguously equalizing role, changes in literacy are correlated to slower growth in total inequality and, especially, within-inequality, both in rural areas and in the district as a whole. The expansion of access to banking services is robustly linked to slower growth in inequality. Interestingly, in rural areas and for the district as a whole, the associated decrease takes place through between-inequality, while in urban areas within- and total inequalities are the magnitudes related to banking. This is consistent with financial inclusion of the poor progressing at the extensive margin (i.e. reaching poorer, more remote areas) in the rural sector, and at the intensive margin in urban centres. On the other hand, access to sanitation is associated with more sluggish growth in inequality between places both in urban and rural areas. This pattern supports the interpretation of sanitation as a proxy for pro-poor public investment outlined above, and can possibly be rationalized for urban areas as a second step in the Lewis–Kuznets process, as individuals in the most deprived blocks gradually get integrated in the urban economy and improve their living standards. Of course, given the correlational nature of this exercise, we are not able to discern whether these factors are mitigating inequality, or instead if it is the case that the relatively improved situation of the poor in those districts is allowing them to improve their access to education, financial services, and sanitation.[23]

Even though it is far from straightforward to put all the pieces back together to explain the evolution of each particular case, looking back at the state-level results in Section 6.1 we can find certain cases that can be easily related to the patterns uncovered in the previous two subsections. For instance, the results for the poorest districts in Section 6.2 resound in the substantial increase in local rural and overall inequality estimated for Bihar, the poorest of the major states in 2004. With large growth in urbanization, high growth, and a robust expansion of the regular wage employment sector, Kerala seemed an ideal candidate for the increase in local inequality and decrease in spatial inequality it registered. Finally, Karnataka, one of the fastest-growing states, has seen inequality rise in several dimensions.

## 7 Conclusion

The topic of inequality has garnered attention all over the world. A large focus has been placed on top incomes and the attempts to quantify inequality driven by the gap between the very rich and the rest. While this is an essential and laudable exercise, not enough emphasis has been placed in the literature on the evolution of inequalities within and between smaller habitations such as cities, blocks, or villages. Decomposing inequality into its spatial and local components is relevant because each of them can have very different economic interpretations and political consequences. However, the main challenge to doing so is paucity of representative data (income, assets, consumption) at these disaggregate levels.

In this paper, motivated by the literature on regional inequality, we propose a method to estimate consumption inequality with the help of imputation techniques based on night-time luminosity and a host of demographic and economic variables, typically available in census data. Observed consumption levels for districts from the NSS and a host of covariates available both at the block and village levels allow us to fit a model with the help of stepwise regression techniques. We then use the model to impute real per capita consumption expenditure for villages as well as for urban blocks. These imputed per capita consumption expenditures are enough to calculate inequality between villages and between urban blocks. Given the group decomposition properties of the Theil index, we can finally compute inequalities within villages and within urban blocks for India and its states.

We find that both local and spatial inequalities have risen over time in Indian urban areas. Rural inequalities, both within and between villages, are more static. The latter result contrasts with the stylized fact of growing differences between districts, suggesting that convergence between villages within districts might have taken place between 2004 and 2011. Moreover, we find large heterogeneity when taking the analysis to the state and district levels. We can find examples both for rise and fall of within- and between-inequalities, which often do not go in the same direction for most states. A separate look at the most and least affluent districts reveals that widening local inequalities have been rising particularly in deprived rural areas, a development that might raise concerns about the fate of the poorest of the poor. On the other hand, economic growth is seen

[23] We also find that an increase of the Scheduled Caste population share in urban areas is associated with declining inequality between urban blocks. On the other hand, a growing share of Scheduled Tribes goes along with more timid growth in within-inequality for the full district. An explanation of these results would need us to look more deeply into settlement and migration patterns, which is outside the scope of this paper.

to come along with widening inequalities. A correlation exercise between changes in district-level covariates and inequality growth show that structural factors like urbanization and regular job growth are associated with opposite developments in spatial and local inequalities. They may lower the first while simultaneously increasing the second. These opposing forces may often lead to a false impression that there is no dynamism in inequalities in India. To refer back to the metaphor of Sen and Drèze (2013), it would be a serious mistake to imagine the country as a calm sea.

Our preliminary forays into imputation-based estimates of local inequality suggest that this is a promising avenue for future research. The paper uses data that are commonly available: night-time luminosity and census variables, and suggests that such analyses can be conducted for other countries as well.

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## Appendix

Table A1: Prediction model

| Variables | (1) Log real mpce (rural) | Variables | (2) Log real mpce (urban) |
|---|---|---|---|
| Log lights per sq. km | 0.0360*** | Log lights per sq. km | 0.157*** |
| | (0.00559) | | (0.0114) |
| Female literacy rate | 0.00495*** | Female literacy rate | 0.00928*** |
| | (0.000504) | | (0.00102) |
| Percentage of regular male workers | 0.00302*** | Percentage of self-employed among male workers | –0.00613*** |
| | (0.000493) | | (0.00226) |
| Sex ratio (males/females) | –0.00701*** | Proportion of Scheduled Tribes | 0.00179*** |
| | (0.00107) | | (0.000489) |
| Percentage of casual workers | –0.00141*** | Mean of decadal precipitation in February | 0.00185** |
| | (0.000520) | | (0.000807) |
| Percentage of self-employed among female workers | –0.00283*** | Mean of decadal temperature in May | –0.0202*** |
| | (0.000849) | | (0.00250) |
| Mean of decadal temperature in March | –0.00762*** | Standard deviation of temperature in January (last decade) | –0.234*** |
| | (0.00175) | | (0.0471) |
| Mean of decadal temperature in November | 0.000933*** | Standard deviation of temperature in April (last decade) | –0.141*** |
| | (0.000118) | | (0.0218) |
| Standard deviation of temperature in January (last decade) | –0.253*** | Standard deviation of temperature in February (last decade) | 0.274*** |
| | (0.0438) | | (0.0543) |
| Standard deviation of temperature in February (last decade) | 0.263*** | Standard deviation of temperature in August (last decade) | 0.539*** |
| | (0.0415) | | (0.0808) |
| Standard deviation of temperature in June (last decade) | –0.0909*** | Deviation of temperature in July (from decadal average) | –0.143*** |
| | (0.0222) | | (0.0425) |
| Standard deviation of temperature in August (last decade) | –0.147** | Deviation of precipitation in November (from decadal average) | –0.00327*** |
| | (0.0593) | | (0.000658) |
| Standard deviation of temperature in October (last decade) | 0.154*** | Standard deviation of precipitation in August (last decade) | 0.00108*** |
| | (0.0541) | | (0.000265) |
| Standard deviation of precipitation in October (last decade) | –0.000885*** | Deviation of precipitation in October (from decadal average) | –0.00104** |

| | | | |
|---|---|---|---|
| | (0.000283) | | (0.000486) |
| Standard deviation of precipitation in October (from decadal average) | –0.00247*** | Standard deviation of precipitation in October (last decade) | –0.328*** |
| | (0.000374) | | (0.0535) |
| Dummy state (4) | –0.504*** | Deviation of temperature in August (from decadal average) | 0.130*** |
| | (0.122) | | (0.0343) |
| Dummy state (9) | 0.0603*** | Standard deviation of precipitation in in March (last decade) | –0.00323*** |
| | (0.0189) | | (0.000485) |
| Dummy state (11) | –0.284*** | Density (pop./area) | –3.66e–06 |
| | (0.0685) | | (2.38e–06) |
| Dummy state (13) | 0.262*** | Log lights per sq. km × dummy state (32) | 0.0522*** |
| | (0.0430) | | (0.0177) |
| Dummy state (14) | –0.315*** | Log lights per sq. km × dummy state (7) | –0.0527*** |
| | (0.0433) | | (0.0115) |
| Dummy state (16) | –0.199*** | Log lights per sq. km × dummy state (35) | 0.235*** |
| | (0.0602) | | (0.0474) |
| Dummy state (18) | –0.275*** | Percentage of regular workers × dummy state (14) | –0.00397*** |
| | (0.0273) | | (0.00108) |
| Dummy state (22) | 0.0877*** | Percentage of regular workers × dummy state (24) | 0.0134** |
| | (0.0326) | | (0.00616) |
| Dummy state (23) | 0.0364* | Dummy state (24) | –1.305** |
| | (0.0215) | | (0.548) |
| Dummy state (26) | –0.317*** | Dummy state (28) | 0.162*** |
| | (0.118) | | (0.0374) |
| Dummy state (28) | 0.262*** | Constant | 6.126*** |
| | (0.0302) | | (0.119) |
| Dummy state (30) | 0.245*** | | |
| | (0.0852) | | |
| Dummy state (35) | 0.326*** | | |
| | (0.0884) | | |
| Dummy 2011 | 0.137*** | | |
| | (0.0127) | | |
| Constant | 7.120*** | | |
| | (0.129) | | |
| | | | |
| Observations | 1,169 | Observations | 1,164 |
| R-squared | 0.682 | R-squared | 0.553 |

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: authors' calculations based on data from the NSS and the World Bank's Spatial Database for South Asia.

Table A2: Changes based on point estimates

| | Rural + urban | | | Rural | | | Urban | | |
|---|---|---|---|---|---|---|---|---|---|
| States | Ineq. | B | W | Ineq | B | W | Ineq. | B | W |
| Andhra Pradesh | – | + | – | – | – | – | – | + | – |
| Assam | + | – | + | + | – | + | + | – | + |
| Bihar | + | – | + | + | + | + | – | – | – |
| Chhattisgarh | – | – | – | – | – | – | + | + | + |
| Gujarat | – | + | – | – | – | – | – | – | – |
| Haryana | – | + | – | – | – | – | + | – | + |
| Jharkhand | – | – | + | + | – | + | + | + | + |
| Karnataka | + | + | + | + | + | + | + | + | + |
| Kerala | + | – | + | + | – | + | + | – | + |
| Madhya Pradesh | + | – | + | + | + | + | + | – | + |
| Maharashtra | + | – | + | – | – | – | + | + | + |
| Orissa | – | – | + | – | – | – | + | – | + |
| Punjab | – | – | – | – | + | – | – | – | – |
| Rajasthan | + | – | + | + | – | + | – | – | + |
| Tamil Nadu | – | – | – | – | – | – | – | + | – |
| UP | + | – | + | + | + | + | + | + | + |
| Uttaranchal | + | – | + | + | – | + | + | – | + |
| West Bengal | + | – | + | – | – | – | + | + | + |

Source: authors' calculations based on data from the NSS and the World Bank's Spatial Database for South Asia.