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The Persistence of Inequality across Indian States

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The persistence of inequality across Indian states

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Abstract

The persistence of regional inequalities in developing countries is well recognised to be of great concern. In this paper I track stochastic convergence in relative incomes for Indian states between 1960-2011 with the intent to identify high persistence and mean reversal. Traditional unit root tests suggest that shocks to relative incomes across the Indian states are permanent thus contradicting the stochastic convergence hypothesis. Interval estimates of the largest autoregressive root for the relative incomes of 15 Indian states are very wide. However, confidence interval estimates of the half life of the relative income shocks, that are robust to high persistence and small samples, reveal that in most cases they die out within 10 years, suggesting mean reversion for a large number of states. Finally, I estimate a fractionally integrated model and obtain mixed evidence of mean reversion in the data, with six out of the fifteen states experiencing mean reversion. In sum, while the evidence obtained does not support the stochastic convergence hypothesis, our findings reveal that the relative incomes have a relatively short half life and that some states' relative incomes are mean-reverting. This result is encouraging and in contrast to earlier studies which indicate long term divergence and polarisation (Bandyopadhyay 2011).

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Keywords: Inequality, Stochastic Convergence, Half Life, Fractional Integration, India.

1 Introduction

There is increasing evidence of persistent regional inequality and slow convergence in GDPs across sub-national regions within countries, particularly for poor countries.[1] The discussion on cross-country and regional inequality and convergence has mostly thown light on patterns of the evolution of GDPs, such as divergence, polarisation and stratification. The theoretical literature has sought to explain these patterns using models of multiple equilibria and history dependence.[2]

There is however comparatively less empirical evidence and treatment on the nature and characteristics of the persistence of inequality in GDPs at the sub-national level (see Gennaioli et al. (2014 and 2013) for a review of countries where sub-national convergence is examined).[3] Documenting and understanding the nature of persistence of regional inequality at the sub-regional level is important as the causes are often vastly different for developing countries compared with developed countries.[4] The social and economic fallout of the persistence of regional inequalities are also more harsh in developing countries compared with developed countries. Evidence from African countries (Østby et al. 2009, Østby 2008) suggests that backward regions are more likely to have social unrest and conflict, often even fuelled by regional favouritism (Hodler and Raschky 2014). There is a large literature that regional inequalities, especially in countries where ethnic, racial and religious groups are regionally concentrated have a strong relationship with political and violent conflict (Cederman et al. 2011, Stewart 2008).

In this paper I use the Indian states example to examine the dynamics of the persistence of regional inequality between 1960-2011. The Indian example is an excellent case study due to its distinct extremes[5] and also for the fact that the distance between the richest and poorest states

[1] On an average, Barro's "iron law" of the 2% rate of convergence has been found to be supported by studies on regional convergence in rich countries, but for poor countries the rate of convergence is much slower.

[2] The literature addressing regional and cross country convergence is large, see Durlauf et al (2009) for the full survey of the literature. On the one hand empirical contributions using a wide range of methods have sought to understand differences in growth performances using the neoclassical and endogenous growth models. On the other, new theoretical approaches have sought to understand what are the barriers to convergence in growth across countries and regions via the role of history and institutions.

[3] Outside the macroeconometric treatment of persistent regional income inequalities there exists a large and robust literature on persistent individual income inequalities. See Piketty (2000), Mookherjee and Ray (2003), Durlauf (1996), Galor and Zeira (1993) for a review and discussion of the literature where inequality persists across dynasties.

[4] Dufrénot et al. (2009) examines convergence across developing countries using non-stationary long-memory and wavelet models and finds no evidence of convergence. Their analysis suggests that the dynamics of convergence across and within developing countries is likely to be significantly different from that within and across developed countries.

[5] Some of the richest states such as Maharashtra, have GDPs comparable to countries such as Portugal and Venezuela (at over US$ 233 billion). Yet others, such as Bihar and Odisha are at par with countries such as Ethiopia and Ghana at around US$ 47 billion, and some of the poorest, Jammu and Kashmir, at par with South Sudan at US$11 billion (World Bank 2014 values). The inequality is not just discernible in its GDP differences. Female literacy in the poorest states of Bihar and Odisha is at a low of 52 per cent (Indian census, 2011), lower than that of the Democratic Republic of Congo and Liberia (each at 57 per cent), while states of Kerala are at 92 per cent, comparable to any industrialised

has increased substantially over the post-independence period. Recent studies have shown that the trends are that of divergence (Bajpai and Sachs (1990) and Nagaraj et al (1996)), but also that there is evidence of polarisation and convergence clubs, with a club of rich states and a club of poor states moving apart (Bandyopadhyay (2004, 2011), Trivedi (2002)). There is also very little evidence of mobility across the two clubs in recent years (Bandyopadhyay (2011). In this paper I track the trends in persistence of inequality across Indian states with particular interest in assessing stochastic convergence and high persistence. For example, are these tendencies of increasing inequalities deeply persistent? Or are these divergent tendencies weak? Tracking the persistence of inequality trends will inform policy makers on how to abate these diverging and polarising tendencies.

I extend the discussion in at least two different aspects. First I extend the study to start to cover years 1960 to 2011. Second, in obtaining a longer time series it is now possible for us to investigate for trends for stochastic convergence using new techniques allowing us to test for high persistence, and using a fractionally integrated model to test for intermediate states between stationarity and non-stationarity.

While much of the empirical literature testing for stochastic convergence uses standard unit root approach to tests, there are well known problems with these tests. Unit roots are known to suffer from low power, and in addition incomes are prone to a low speed of convergence. Further, with small samples (as is the case for Indian states), these problems could lead to an incorrect acceptance of a null of non-convergence.

To address this problem I model the DGP of state income as a fractionally integrated process, where one can assume non-integer values for the parameter of integration. This allows one to observe intermediate scenarios - where the income process is non-converging but mean reverting, and this also handles the problem of low speed of convergence.

Our empirical analysis reveals two sets of findings. First, I find no evidence of any stochastic convergence. Unit root tests reveals evidence of high persistence. This adds on to the already existing set of findings discussed earlier of divergence, polarisation and club convergence. Second, to better understand the trends of persistence, I estimate the half-life of the persistence of a shock to the relative incomes of the states. I observe the half life of a shock to be between 0 and 10 years for most states. This is a very interesting and new finding for the Indian case - it means that a shock to the income dissipates within 10 years for most states, implying mean reversion.[6] Third, a fractionally integrated model of the relative incomes also uncovers similar findings - I observe mean reversion in relative incomes in six states, and for the rest, I observe non-stationary outcomes. This is an optimistic result, given that the literature on Indian spatial inequality has consistently documented evidence of divergence and polarisation.

The paper is organised as follows. Section 2 presents some basic trends of state level GDPs.

country in the world.

[6] Mello (2011) documents a half life for the US states to be of a similar range (0 to 10 years), with the median half life being smaller than the Indian states.

Section 3 presents the unit root tests and Section 3.1 estimates the confidence intervals of the estimated autoregressive coefficient. Section 3.2 presents interval estimates of an alternate measure of persistence - the half life of the relative income shocks using a new method proposed by Rossi (2005) and Section 4 presents the estimates of the fractional integrated model and estimations. Section 5 discusses the findings and its relevance in the international context. Section 6 concludes.

2 Some descriptive statistics

Our dataset consist of the relative per capita income for 15 Indian states from 1960 to 2011. Relative income is measured as the natural logarithm of the ratio of per capita state GDP to the per capita national GDP. I use 15 Indian states instead of the 16 largest states - this is due to the fact that I extend the dataset to 1960 and lose the state of Haryana, which was created in 1965. The states are listed in the Appendix and constitute over 80% of India's total population.

In this section I take a cursory look at the winners and losers across the Indian states over the period 1960 to 2011. Some back-of -the-envelope calculations suggest that there is no indication of the richest and the poorest states equalising. Figure 1 illustrates this fact.

I present the rankings of the relative (to the national average) per capita incomes (relative incomes for short hereafter) of the Indian states for each of the six decades (1960s to 2011) in Table 1. The winners and the losers are clear. The rich "club" of states have been persistent since the 1960s - consisting of Maharashtra, Punjab, Gujarat, and the poor club has included Bihar, Odisha and Madhya Pradesh.[7] There are also a number of states which have remained in the middle - namely, Andhra Pradesh, Karnataka are steady middle income states, and after the 1960s, West Bengal.

In addition, there has been some mobility. The most noticable movement has been that of the Southern states, Tamil Nadu and Kerala, which in the 1960s and 70s were mostly (low) middle income group states, but by the 1990s and 2000s had clearly become top income states. West Bengal has however seen a gradual drop in its ranking in the income distribution - starting off in the rich group of states in the 1960s, and gradually dropping in ranking as we move into the 2000s.

Persistence at the bottom end of the income distribution is evident for the poorest six states - Bihar, Uttar Pradesh, Assam, Madhya Pradesh, Odisha and Rajasthan. Barring one or two years, these six states have held the lowest positions all throughout six decades.

Our basic rankings reveal a picture of persistence at the top and the bottom, with some middle income states' mobility. Figure 2 presents the trends of their relative incomes from 1960 to 2011. In addition to the rich remaining rich and the poor remaining poor, it is also clear that the rich and the poor are moving apart, with little intradistributional mobility.

[7] The state of Haryana, which is also traditionally part of the rich club is currently not in the analysis as it was created in 1965. To maximise the number of years available in our analysis we have dropped Haryana. See Bandyopadhyay (2004, 2011) for detailed estimates on the rich and poor convergence clubs, which also includes Haryana in the analysis.

In Figure 3 I plot the standard deviation of the relative incomes from the 1960s to 2011. It confirms our findings from Figure 2, that the rich and the poor states have been consistently moving apart, and thereby conclude no evidence of sigma convergence. This result confirms earlier findings of Bandyopadhyay (2004, 2011), Trivedi (2002) of persistent diverging tendencies.

In the following section, I will take this finding further to test for persistence in the relative income process, using unit root and KPSS tests.

3 Looking for persistence I: Unit root tests

The previous section highlights the trends in spatial inequality across Indian states. Traditional tests for stochastic convergence constistute unit root tests. These tests will allow us to identify the presence of persistence in the state GDP data. There are, however, well known problems associated with these tests, such as low power, and therefore we will discuss a number of tests that take this problem into account. We will turn to these issues shortly. The framework used in these sections are modelled on the basis of that used in Mello (2007) and Mello and Guimarães-Filho (2007).

We start our analysis by undertaking some standard unit root tests to observe any tendencies of persistence. Let us set up the relative income model. Following Carlino and Mills (1993), I assume that each state is moving towards a time invariant equilibrium level of income, given by the following DGP:

$$y_{it} = y_i^q + e_{it}, i = 1, .., 15 \text{ and } t = 1960, .., 2011 \tag{1}$$

where, y_{it} is the natural logarithm of relative GDP per capita in state i in time t, y_i^q is the state i's time invariant equilibrium GDP per capita (natural logarithm of) and e_{it} is a random term accounting for deviations from the time invariant equilibrium level. To take into account that each state can converge to their respective different equilibriums, we have $y_i^q \neq 0$.

I model e_{it} with a linear time trend and a stationary stochastic term, given as follows:

$$e_{it} = \varepsilon_{i0} + \beta t + \varepsilon_{it} \tag{2}$$

where ε_0 is the deviation from the equilibrium level of relative income, and beta is the rate of convergence. In other words, if $\varepsilon_0 > 0$, that is the state is above its initial equilibrium, it will grow slower than the entire country, implying $\beta < 0$. Likewise if we have $\varepsilon_0 < 0$, then for convergence, one requires $\beta < 0$. This rate of convergence is allowed to vary across the different states.

Combining equations 1 and 2, and suppressing the i subscript, one can present:

$$y_t = \lambda + \beta t + \varepsilon_t \tag{3}$$

where, $\lambda = \varepsilon_0 + y^q$. The standard definition of stochastic convergence is based on the above equation: stochastic convergence is obtained when deviations from the trend growth, ε_t, is temporary (Carlino and Mills, 1993).

Following Carlino and Mills (1993) ε_t is a zero-mean stationary stochastic process with finite and summable autocovariances, modelled as:

$$a(L)\varepsilon_t = u_t \tag{4}$$

$$(1 - \rho L)b(L) = a(L) \tag{5}$$

where, u_t is white noise, $b(L)$ is a finite order polynomial lag with $p - 1$ distinct and stable roots, and ρ is a large (close to 1) and stable root. High persistence of the y_{it} series is accounted for by ρ being large. Shocks to the income will be permanent when $\mid \rho \mid= 1$, and temporary when $\mid \rho \mid< 1$.

Combining equations 3 and 4 we obtain the Dickey-Fuller regression form as presented in Stock (1991):

$$y_t = \mu_0 + \mu_1 t + \alpha(1)y_{t-1} + \sum \alpha^*_{j-1}\Delta y_{t-j} + u_t \tag{6}$$

where the constants are given by $\mu_0 = -c\frac{b(1)w}{T} - c\frac{b^*(1)\beta}{T} + \rho b(1)\beta, \mu_1 = \frac{c}{T}wb(1), \alpha(L) = L^{-1}[1 - a(L)], \alpha(1) = 1 + \frac{c}{T}b(1), \alpha^*_j = -\sum_{i=j+1}^{k}\alpha_j$,

$b^*_j = -\sum_{i=j+1}^{k} b^*_j, \rho = 1 + c/T$,and $k = p - 1$.[8]

I present our results with an ADF, DF-GLS and KPSS tests for the Indian states in Table 2. In the first column, I tabulate the results for the t statistic of the ADF test, where the lag length is determined by the BIC criterion. For column 1 we have the t statistic of the ADF test, where the lag length is determined by the BIC criterion. Here we observe that there are three states rejecting the nonstationary null at the 1% level, two states rejecting the null at the 5% level and three states at the 10% level. The following column presents results using the DF-GLS tests, with the lag length chosen by the BIC criterion and the MAIC criterion in the following column 3 - here we find that for all cases, the null of nonstationarity is rejected. The final column reports the results for the KPSS tests. For the KPSS test the null hypothesis is of stationarity. I find that for all states the null of stationarity is rejected - suggesting non-stationarity. I therefore obtain quite widely differing results. Barring the states of Gujarat, Madhya Pradesh, Bihar and Rajasthan, I obtain consistent evidence of non-stationarity, In other words, a shock to the relative incomes appears to be permanent, and therefore there does not appear to be any evidence of stochastic convergence across Indian states over the period of study.

As mentioned earlier, there are however several concerns with standard unit-root and KPSS tests, especially given that our sample size is quite small. Such small samples sizes may over-estimate or

[8] Carlino and Mills (1993) model the ε_t term to be an AR(2) process, i.e. they assume p=2.

under-estimate the effect of the shock on the relative incomes, and thus the low power of these tests and the high persistence of the relative income processes may be responsible for the acceptances of a non-stationary null, and rejections of the stationary null (for the KPSS tests).

3.1 Looking for persistence II: confidence intervals of the autoregressive coefficient

To provide a more reliable assessment of the persistence of the relative income process, I estimate confidence intervals of the largest autoregressive parameter ρ as estimated in equation 6 to account for sampling uncertainty. I follow Mello (2007) and use two types of bootstrapping procedures to estimate the confidence intervals; those proposed by Stock (1991) and Hansen (1999). Stock's (1991) approach to generating confidence intervals for ρ involves inverting the t statistic generated by the ADF test. Since asymptotic distributions of the t statistic is non-normal and nontrivially dependent on the noncentrality constant c, the following expression is proposed by Stock (1991) for the confidence interval:

$$(\rho_{low}, \rho_{upper}) = (1 + c_{low}/T, 1 + c_{upper}/T). \tag{7}$$

In the case of conventional asymptotic methods being insufficient, bootstrap methods are used to estimate confidence intervals. However, Hansen (1991) reports that traditional bootstrap methods such as the percentile-t methods applied to the autoregressive model has incorrect first order coverage. To correct for it, a grid-bootstrap method is proposed where the confidence interval is estimated using a grid of values (as opposed to a single OLS estimate of ρ in the percentile-t bootstrap), which has accurate first order asymptotic coverage.[9]

Table 4 displays confidence interval estimates for the largest autoregressive root, ρ. Interval estimates of ρ based on Stock's (1991) methodology suggest that the unit root is outside the interval in thirteen cases, namely, for the states Andhra Pradesh, Assam, Bihar, Gujarat, J & K, Karnataka, Kerala, Maharashtra, Odisha, Punjab, Rajasthan, Tamil Nadu, West Bengal. The average lower bound of the interval estimate is 0.08, and the average upper bound is 1. The median lower bound and the median upper bound are, respectively, 0.00 and 1.08.

Interval estimates based on Hansen's (1999) methodology suggest the unit root is outside the interval in all 15 cases. The average lower bound of the interval estimate is 0.00, and the average upper bound is 1.02. The median lower bound and the median upper bound are, respectively, 0.00 and 0.24.

Both methods generate interval estimates that are very wide, and are persistent and not stable. Our interval estimates in Table 4 therefore suggest that with sample variability taken into account we

[9] See Hansen (1991) for details. In particular, the grid-bootstrap corrects for the Type I error globally in the parameter space.

have substantial evidence that the state relative income processes are non-stationary, which suggests the lack of any stochastic convergence. I am however unable to shed any light on any intermediate states, such as mean reversion, which I will now approach in the following two sections.

3.2 Looking for persistence III - Half life

In this section I estimate an additional metric of persistence, that of the half life, in order to measure the extent of mean reversion of the relative income shocks. This will be particularly useful for us to be able to assess whether the diverging tendencies observed in the Indian case are likely to be reversed in the medium run or the long run. The Indian evidence (as in Bandyopadhyay 2004 and 2011) suggests strong polarising tendencies,. Evidence from US states suggests that the half life is around 5 years, suggesting strong mean reverting tendencies.

The half life is defined as the time h taken so that the expected value of y_{t+h} reverts to half of the initial post-shock value.

$$E(y_{t+h}) = \frac{1}{2}y_t \tag{8}$$

For the $AR(1)$ process, $y_{t+h} = \alpha y_{t-1} + u_t$ the half life is known to be:

$$h = \ln(1/2)/\ln(\alpha) \tag{9}$$

For our purposes, however, we will need to estimate the half life directly from the impulse response function, as we mostly deal with AR (p) processes, for which the half life is estimated via resolving $\delta y_{t+h}/\ \delta u_t = 1/2$. In particular, I adopt a method proposed by Rossi (2005) (also used by Mello (2007)) to take into account high persistence in the relative incomes for small samples for computing the confidence intervals.

Following Rossi (2005) and Mello (2007) I estimate two metrics of half-life: the exact half life and approximate half life. Rossi (2005) estimates the exact half life as follows:

$$h = \ln[1/2.b(1)]/\ln(\rho) \tag{10}$$

where ρ is the largest autoregressive parameter in equation 4 and $b(1)$ is the correction factor defined in equation 6.

The approximate half life proposed by Rossi (2005) is given by

$$h_\alpha = \ln(1/2)/\ln\alpha(1) \tag{11}$$

Exact and approximate half lives are the same when $p = 1$, such that $b(1) = 1$.

Following Rossi (2005) I compute the confidence intervals using the following steps. I use Stock (1991) to estimate the condfidence intervals for ρ, $(\rho_{low}, \rho_{upper})$. Using the expression $\rho = 1 + \frac{c}{T}$, we use $c = T(\rho - 1)$ to derive confidence intervals for c, (c_{low}, c_{upper}). I now use these confidence intervals to estimate the confidence intervals of the exact and approximate half life, h and h_α respectively, using

$$T\left[\frac{\ln[1/2.\hat{b}(1)]}{c_{upper}}, \frac{\ln[1/2.\hat{b}(1)]}{c_{low}}\right], T\left[\frac{\ln[1/2]}{c_{upper}\hat{b}(1)}, \frac{\ln[1/2]}{c_{low}\hat{b}(1)}\right] \tag{12}$$

It is also important for us to present classical estimates of the confidence intervals. This is because the Rossi (2005) estimators are designed to take into account a large autoregressive parameter (close to 1). For cases where the autoregressive parameter is not so close to one, the classical estimators of the confidence interval are a better estimator than the Rossi (2005) estimators. For the approximate half life, $h_\alpha = \ln(1/2)/\ln\alpha(1)$, I can use the delta method to obtain a 95% confidence interval given by $\hat{h}_\alpha \pm 1.96\hat{\sigma}_{\alpha(1)}(\ln(1/2)/\ln\hat{\alpha}(1)[\ln(\hat{\alpha}(1)]^{-2}$, where $\hat{\sigma}_{\alpha(1)}$ is an estimate of the standard error of $\hat{\alpha}(1)$. I provide estimates of classical estimates of the confidence intervals in the following table in addition to the Rossi (2005) estimates.[10]

In Column 1 I present the estimates of the CI of the half life using classical methods. Here I observe that the majority of half life intervals ranges from 0-30 years, with a mean of the lower bound being close to 0 and upper bound (barring the extreme case of Gujarat) is 24.3, the median lower bound is 0 and upper bound is 19.57. Given that a half life of 8 years corresponds to an autoregressive coefficient taking the value 0.92 (Rossi 2005), the results here conform with our Table 3 results of persistence and non-stationarity.

Column 2 present results of the upper bound of the confidence interval for the exact half life, when $p = 1$. For this case, the exact and approximate expressions for the half life are identical.[11] The interval estimates of the upper bound of the half life has a mean upper bound of 9.1 (including Gujarat) and a median of 5.9 years. These suggest that the shocks to the relative incomes die out over a period of 7-10 years on an average.

In the following column I present the estimates with an $AR(2)$ process (i.e., with $p = 2$) for $a(L)$. The upper bound estimates of the confidence interval have a mean of 7.1 and median of 5.6 years. For an $AR(3)$ structure, estimates for which are in Column 4, the mean of the upper bound of the confidence interval is also quite similar to that for the $AR(2)$ process (I also find that the upper bound estimates are in general similar to those with a $AR(3)$ structure, results presented in Column 4).

In addition, in Column 5 I present estimates of the upper bound of the confidence interval for the approximate half-life, for $p = 2$. It is not surprising that the estimates are similar to those of the exact half life, as we have a short lag structure for our estimates.

One should keep in mind that the Rossi (2005) estimation procedure for confidence intervals is particularly tailored to account for the largest autoregressive root being close to one. Thus, for the states where it isn't close to one the classical estimates of the CI are more accurate. The theoretical

[10] This approach is also adopted in Mello (2011)

[11] This is due to $b(1) = 1$.

DGP of the relative incomes includes a time trend, thus our estimates in Table 4 also account for that.

Our findings here provide evidence of mean reversion for most of the states. This is a new finding, especially in contrast to our estimates in previous tables, which only allow us to test for stochastic convergence, or not. That I obtain an average half life within 10 years for most states is highly suggestive that while I do not obtain stochastic convergence, there is evidence of mean reversion in relative incomes. In the following section, I will test for specific models that will allow us to test for intermediate states, such as that of mean reversion.

4 Are there any states reverting to the mean?

The next step from having estimated the half life is to formally test for whether there are Indian states reverting to the mean. There are many ways of estimating these new definitions of stochastic convergence. The one I employ is popularly known as fractional stochastic convergence, following Michelacci and Zaffaroni (2000), Mello (2007) and Mello and Guimarães-Filho (2007). This approach estimates convergence of a stationarised time series. The Fractional stochastic convergence address the problem of low speed of convergence by modelling the income per capita as an Autoregressive Fractionally Integrated Moving Average (ARFIMA) process. In light of our earlier sections' analysis, Michelacci and Zaffaroni (2000) argue that testing for stochastic convergence using the standard unit root tests leaves us with two extreme scenarios to test for. One of the null, of non-stationarity, the $I(1)$ process where the effect of a shock to the income stream is permanent, and the alternative is of stationarity, $I(0)$. However, as we know, convergence or the lack of it, can be observed in intermediate states, and of those where the process is not converging but just mean reverting. Such intermediate states are best treated under a fractionally integrated DGP of the relative income process, where the parameter of integration assumes non-integer values, and thereby making it possible to test for intermediate states, and account for the low speed of convergence that may characterise the DGP. Fractionally integrated (FI) processes contain unit roots as a particular case but by allowing for a fractional order of integration are able to represent a richer class of behaviours.[12]

To fix ideas, let us define an $ARFIMA(0, d, 0)$ process. Assume a stochastic process for relative income, y_t, given by $(1 - L)^d y_t = u_t$, where u_t is a zero-mean, constant-variance, and se-

[12] There is abundant evidence that supports the empirical relevance of FI models in macroeconomics and finance, justified from both a theoretical and an applied perspective (see Henry and Zaffaroni (2002), Durlauf et al. (2009) for a list of references on this subject). The time series literature also notes that conventional procedures for detecting and dating structural changes tend to find spurious breaks, usually in the middle of the sample, when in fact there is only fractional integration in the data (see Nunes et al. (1995), Krämer and Sibbertsen (2002) and Hsu (2001)). There also is increasing amounts of empirical evidence suggesting that GDP data is well fitted by a fractionally integrated process. Michellacci and Zaffaroni (2000) show that convergence across OECD countries is best described by a fractionally integrated process.

rially uncorrelated error term, and d is the parameter of integration, which can assume non integer values. When $d > -1$, the term $(1-L)^d$ can be expressed as a binomial expansion $(1-L)^d = 1 - dL + d(d-1)L^2/2! - d(d-1)(d-2)L^3/3! + ...$ Invertibility holds when $-1/2 < d < 1/2$. Assuming invertibility, the moving average expression is obtained as $y_t = \sum_{j=0}^{\infty} \psi_j u_{t-j}$, where $\psi_j = \Gamma(j+d)/\Gamma(d)\Gamma(j+1)$, and $\Gamma(.)$ is the gamma function, given by $\Gamma(\alpha) = \int_0^{\infty} t^{\alpha-1} e^{-t} dt$.

If parameter d lies in the interval $(-0.5, 0.5)$ then the above process is deemed stationary; for values $(0.5, 1)$, the process is nonstationary, but mean-reverting. Mean reversion requires the cumulative impulse response function $c_N = \sum_{j=0}^{N} \psi_j$, $N = 0, 1, 2, ..$,to convergence zero at ∞.[13]

Likewise, it can be shown that if $d < 1$, then $c_\infty = 0$, in other words, then the process is mean-reverting.When $d > 1$, then $c_\infty = \infty$ and when $d = 1$, c_∞ is constant and finite, and the process is not mean-reverting. In short, we are to look for a range of estimates $(-0.5, 0.5)$.

In Table 5 I present our results of our estimates of the fractional integration parameter based on methods of Geweke and Porter-Hudak (1983) and the Robinson (1995) multivariate semi-parametric method, as is undertaken in Mello (2007). In total, I find that the estimates of d lie in the stationary or mean-reverting region for 6 cases, out of 15 states (Andhra Pradesh, Assam, Gujarat, Karnataka, Madhya Pradesh and Rajasthan[14]). I also find that none of the estimates lie in the range for the stationary region. Our findings therefore suggest some mean-reversion in relative incomes, for six states, though with no signs of convergence.

Pulling together all of our findings from Sections 3, 3.1, 3.2, and 4:

- Unit root and KPSS tests suggest no evidence of stochastic convergence, but that of high persistence.
- Specially developed metrics of half life (Rossi 2005) suggest evidence of mean reversion for most states.
- Finally, modelling the relative incomes as a fractionally integrated process reveals that six out of the fifteen states provide evidence of mean reversion.

In short, metrics designed specifically to deal with intermediate stages, such as that of mean reversion, reveal that while we have no evidence of stochastic convergence, the relative incomes have a relatively short half life, and that some states' relative incomes are mean-reverting.

This finding sheds new light on the convergence story for the Indian case. Previous studies Bandyopadhyay (2004, 2011) have uncovered evidence of the lack of convergence, and that of polarisation and stratification. Analysing the time series trends of the Indian states' relative incomes has allowed

[13] This means that the effect of a unit shock on the level of the series after N periods converges to zero at infinity, i.e.$\lim_{N \to \infty} c_N = 0$.

[14] Out of these six, Bihar, Madhya Pradesh, Gujarat and Rajasthan are also found to be stationary with unit root tests in Section 3.

us to observe the long run trends of the spatial inequality. That we observe a relatively short half life for most states and mean reversion for some states is an optimistic finding. However, I also do not observe mean reversion for the rest of the states. It is therefore not possible for us to deduce a highly optimistic scenario of potential convergence in the future. However, the states that obtain mean reversion could provide researchers and policy makers some direction for future economic policies and institutions that enable successful mean reversion.

5 Discussion: what explains the observed persistence and mean reversion?

What explains the observed persistence and mean reversion for the Indian states? It is in fact not unusual as a developing country to observe such dynamics of both high persistence and mean reversion. The Mexican experience (Carrion-i-Silvestre and German-Soto (2006)) documents no evidence of stochastic convergence using traditional methods. The Brazilian experience is similar to the Indian case (Mello and Guimarães-Filho (2007)) where some mean reversion is observed, using an identical testing framework to that used in this paper. The Chinese experience (Su and Chang (2013), Pedroni and Yao (2006)) reveals sub-national divergence with some localised convergence in the east and western states. Other developing country examples document divergence, some though without any direct testing for mean reversion (Kharisma and Saleh (2013) for Indonesia, Rahman and Hossain (2009) for Bangladesh). In most cases, the reasons for the lack of convergence are also widely varied or not fully tested for. Gennaioli et al. (2014) document that sub-national regional convergence is slower in developing countries and test for the role of low mobility of capital and labour as a reason for slow convergence. They conjecture it is possible that the slow observed convergence and persistence of spatial inequality may be tied to regulation, technologies or externalities - that some regions are not able to implement growth enhancing policies as easily or quickly as others. There are no international studies which investigate causes for the lack of mean reversion, possibly due to the relatively recent introduction of this technique, and also the uniqueness of each country's political economy and history. There is also the additional problem due to this technique's use in growth and convergence being relatively new, hence the lack of the development of appropriate econometric tools which would allow us to test for causality using the same testing framework.

There are some obvious potential reasons that explain the Indian experience of the lack of mean reversal. The democratic federal system whereby each Indian state elects its own government could well be responsible for both persistence and mean reversion. The states have conservative to centrist governments with socialist economic policies on one hand, to communist governments on the other. Each government can devise their own economic plans, thereby either extending or breaking with the previous government's economic policies. While most fiscal (and all monetary) policy is centrally administered, substantial changes in state-level industrial policy which could lead to an increase in state level GDP or a drop in state level GDP due to a new government less able to generate growth. Both mean reversion and persistence could be due to growth enhancing or growth stifling state government policies.

The other side of the story is about poor states which typically have poor governance. Poor governance and corruption leads to the ineffective use of resources and planning for growth and development thus contributing to the high persistence story in poor states.

A closer examination of the states that have mean-reverting properties - Andhra Pradesh, Assam, Gujarat, Karnataka, Madhya Pradesh and Rajasthan - may reveal some suggestive explanations. Of these Gujarat, Karnataka, Andhra Pradesh are economic powerhouses with stable governments. It is therefore not surprising that their GDPs have mean-reverting properties, in that they are able to weather the effect of shocks to their GDPs. The other three states, Assam, Madhya Pradesh and Rajasthan are long term poor states at the bottom of the income rankings. What explains their mean-reverting properties is not immediately clear and requires further investigation.

The growth literature (Pritchett and Summers (2014), Easterly et al. (1993)) however suggests that mean reversion or drop-off in growth is more the norm than the exception. It is difficult to sustain high levels of growth in the medium to long term. Pritchett and Summers (2014) use the example of fast growers such as China, that its recent rapid growth can be expected to slow down due to high levels of state control and corruption along with high measures of authoritarian rule. The continuation of the growth experience requires a constant renewal of good policy along with good luck, and that the goal post for what constitutes growth enhancing policies constantly shifts. Thus the mean reversion observed for the six Indian states, both poor and rich, may simply come down to good policy at the right time and the same economic policies may not work in the future.

The findings in this paper therefore are at odds with the international experience. There is more evidence of persistence than mean-reversion. Our findings are therefore reminiscent of Rostow's stages of growth (Rostow 1960) - that each Indian state is at different levels of development, and that persistence or mean-reversion in the state's GDP is indicative of where it stands in this process of development. In other words, each state has its own growth path and trajectory, and there may not be a specific set of policy tools that will assist in convergence or mean-reversion in state GDPs.

6 Conclusion

In this paper I have documented trends in persistence in spatial inequality and stochastic convergence across Indian states for 1960 to 2011. Using new methods proposed by the current literature, I find no evidence of stochastic convergence. While standard unit root tests do not suggest any stochastic convergence, the literature suggests that the low power problem of unit root tests, in addition to the high persistence in small samples, may be responsible for this finding. To resolve this problem I estimate confidence intervals of the largest autoregressive coefficient, instead of just unit root tests to account for sampling uncertainty. I also estimate the half life of shocks to the relative income as an alternative measure of persistence.

I find that interval estimates of the largest autoregressive root are very wide, and that the alternatives are persistent. These findings are suggestive of no stochastic convergence and that shocks to the relative incomes are highly persistent. The findings are consistent with earlier studies that suggest diverging tendencies, with convergence clubs (Bandyopadhyay 2011).

However, using a new procedure to estimate the interval estimates of the half life of the relative income shocks, that is robust to high persistence and small samples, reveals a new story. I find that for the majority of the states the half life of the relative income shocks is between 0 to 10 years. This is a highly optimistic finding. Inspite of many of the states being extremely poor, for the majority of them the effect of a shock wears off within 10 years. Modelling the relative incomes as a fractionally integrated process lends greater insight into this finding. I obtain evidence of mean reversion for six of the fifteen states studied. These findings suggest that while there is some mean reversion for some of the states, for the majority I do not find any evidence of mean reversion.

There are several implications of our findings in this paper. The finding that the long run trends of relative income are divergent, but are mean reverting for some is a moderately optimistic finding compared to earlier studies (such as Bandyopadhyay 2004, 2011) which suggest divergence and polarisation. However the finding of high persistence for most others suggests that the polarising tendencies uncovered in the literature are due to continue, that the rich and poor states will continue to move apart.

That these trends persist inspite of the efforts of both the Federal and state level governments' efforts to equalise economic growth in the respective states, is suggestive that traditional tools for economic growth and development as pursued by developing countries, and by the Indian state, may not be able to contain the strong diverging tendencies observed. The Indian case will likely require a new set of aggresive development strategies specifically designed to bring in the gap between the richest and the poorest states. The continuing diverging trends present a serious problem for the steep social and class divide that characterises India and may even fuel separatist and secessionist forces that already exist.

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A Appendix

States that are included in the analysis:

Andhra Pradesh
Assam
Bihar
Gujarat
Jammu and Kashmir
Karnataka

Kerala
Madhya Pradesh
Maharashtra
Odisha
Punjab
Rajasthan
Tamil Nadu
Uttar Pradesh
West Bengal

Table 1: Ranking of 15 Indian states by relative GDP per capita, across decades

State	1960	State	1970	State	1980	State	1990	State	2000	State	2010
Maharashtra	1.36	Punjab	1.71	Punjab	1.68	Punjab	1.77	Punjab	1.74	Maharashtra	1.61
West Bengal	1.30	Gujarat	1.32	Maharashtra	1.53	Maharashtra	1.59	Maharashtra	1.42	Gujarat	1.45
Punjab	1.22	Maharashtra	1.25	Gujarat	1.22	Gujarat	1.26	Tamil Nadu	1.31	Tamil Nadu	1.41
Gujarat	1.21	West Bengal	1.15	J & K	1.12	Tamil Nadu	1.06	Kerala	1.25	Kerala	1.38
Tamil Nadu	1.11	Rajasthan	1.04	West Bengal	1.11	West Bengal	1.00	Gujarat	1.15	Punjab	1.35
Assam	1.05	Karnataka	1.02	Karnataka	0.95	Karnataka	0.98	Karnataka	1.14	Andhra Pr.	1.22
Karnataka	0.99	Kerala	0.95	Kerala	0.95	Andhra Pr.	0.97	Andhra Pr.	1.07	Karnataka	1.18
Rajasthan	0.95	Andhra Pr.	0.93	Tamil Nadu	0.94	Assam	0.91	West Bengal	1.03	West Bengal	0.94
Andhra Pr.	0.92	Tamil Nadu	0.93	Andhra Pr.	0.87	Kerala	0.90	J & K	0.89	Rajasthan	0.82
J & K	0.90	J & K	0.88	Madhya Pr.	0.85	Rajasthan	0.89	Rajasthan	0.81	Odisha	0.78
Kerala	0.86	Assam	0.85	Odisha	0.83	Madhya Pr.	0.86	Assam	0.80	J & K	0.73
Uttar Pradesh	0.84	Uttar Pradesh	0.78	Assam	0.81	J & K	0.81	Madhya Pr.	0.74	Madhya Pr.	0.62
Madhya Pr.	0.84	Madhya Pr.	0.77	Uttar Pradesh	0.80	Uttar Pradesh	0.77	Odisha	0.65	Assam	0.59
Odisha	0.72	Odisha	0.76	Rajasthan	0.77	Odisha	0.66	Uttar Pradesh	0.61	Uttar Pradesh	0.51
Bihar	0.72	Bihar	0.64	Bihar	0.58	Bihar	0.57	Bihar	0.40	Bihar	0.40

Table 2: Unit Root and KPSS Tests

State	ADF with BIC	DF-GLS with BIC	DF-GLS with MAIC	KPSS
Andhra Pr.	-0.3376	-6.0434***	-6.0859***	0.9104***
Assam	-1.1799	-6.2144***	-6.1317***	0.6138***
Bihar	-1.1392	-6.969***	-7.0083***	0.2838***
Gujarat	-3.7148***	-4.7957***	-4.2526***	0.0678
J & K	-1.6325	-5.5086***	-5.4928***	0.4928***
Karnataka	-1.4538	-6.1878***	-6.2159***	0.9674***
Kerala	0.7063	-6.0981***	-6.1971***	1.0453***
Madhya Pr.	-2.8925*	-5.9881***	-5.651***	0.3413***
Maharashtra	-1.3484	-5.5888***	-5.3659***	0.2556***
Odisha	-3.4576**	-5.7654***	-5.7044***	0.2692***
Punjab	-1.8774	-4.8114***	-4.8767***	0.6852***
Rajasthan	-3.5334**	-5.8648***	-5.5684***	0.2621***
Tamil Nadu	0.5708	-6.0387***	-6.1359***	0.9585***
Uttar Pr.	-0.6972	-6.8767***	7.0172***	0.4789***
West Bengal	-1.7673	-6.276***	-6.1848***	0.4241***

Notes: *** Significant at the 1% level, ** significant at the 5% level, * significant at the 1% level

Table 3: Confidence Intervals for the Largest Autoregressive Root

State	*Stock (1991)*	*Hansen (1999)*
Andhra Pr.	(-0.46, 1.19)	(-0.63, 0.24)
Assam	(-0.88, 1.11)	(-0.26, 0.57)
Bihar	(-0.78, 1.12)	(-0.09, 1.33)
Gujarat	(-1.36, 0.65)	(-0.24, 0.62)
J & K	(-1.17, 1.06)	(-1.24, 0.12)
Karnataka	(-1.20, 1.05)	(-1.27, 0.12)
Kerala	(0.00, 1.23)	(-0.02, 6.63)
Madhya Pr.	(1.05, 1.08)	(-1.97, 0.06)
Maharashtra	(-1.49, 0.96)	(-0.53, 0.28)
Odisha	(-3.88, 0.20)	(-2.51, -0.23)
Punjab	(-0.73, 1.13)	(-1.22, 0.12)
Rajasthan	(-2.25, 0.76)	(-2.37, 0.06)
Tamil Nadu	(-0.11, 1.23)	(-0.03, 4.52)
Uttar Pradesh	(0.20, 1.37)	(-0.10, 0.49)
West Bengal	(-1.95, 0.86)	(-2.51, 0.06)

Table 4: Confidence Intervals for the Half-life

State	*Classical CI for the half-life*		*Upper bound on the exact half-life, p=1*	*Upper bound on the exact half-life, p=2*	*Upper bound on the exact half-life, p=3*	*Upper bound on the approximate half-life, p=2*
Andhra Pr.	(-1.236,	22.0325)	6.0739	5.5619	4.7387	5.7203
Assam	(-6.901,	42.9364)	9.8838	9.3441	9.9315	9.5331
Bihar	(-3.601,	29.6975)	7.4294	5.9517	7.1837	7.0772
Gujarat	(-49.669	132.738)	17.5987	16.4395	15.6115	17.2498
J & K	(-1.941	25.1196)	6.7829	6.4171	7.1675	6.4301
Karnataka	(1.942	9.9802)	4.0727	3.6945	3.3455	3.7153
Kerala	(-1.0259	20.8574)	5.8287	5.5972	4.4608	5.4748
Madhya Pr.	(-2.7297	25.9292)	6.4843	4.9079	2.7619	6.1312
Maharashtra	(1.1713	15.1698)	4.9453	5.2028	1 5.22	4.5901
Odisha	(0.5646	15.6264)	5.0284	4.3957	2.1291	4.6732
Punjab	(1.9015	17.2159)	6.0158	5.8594	5.7543	5.6622
Rajasthan	(0.0485	17.0425)	5.1322	4.5981	4.0613	4.7772
Tamil Nadu	(-0.1444	19.5761)	5.9326	5.6663	5.3379	5.5789
Uttar Pr.	(-4.8985	35.5104)	8.4206	5.5072	1.2845	8.0691
West Bengal	(1.5335	16.7406)	5.8277	4.8322	5.9132	5.4738

Table 5: Fractionalizing Differencing Parameters for the Logged Relative GDP process

State	**Andhra Pr.**	**Assam**	**Bihar**	**Gujarat**	**J & K**
d-GPH	0.80	0.51	1.66	0.54	1.05
	(0.43)	(0.68)	(0.26)	(0.26)	(0.25)
d-Robinson	0.74	0.57	0.78	0.31	0.68
	(0.18)	(0.18)	(0.10)	(0.09)	(0.12)

State	**Karnataka**	**Kerala**	**Madhya Pr.**	**Maharashtra**	**Odisha**
d-GPH	0.83	1.21	0.77	1.28	1.01
	(0.57)	(0.13)	(0.36)	(0.43)	(0.17)
d-Robinson	0.41	0.67	0.38	0.84	0.42
	(0.12)	(0.10)	(0.10)	(0.12)	(0.10)

State	**Punjab**	**Rajasthan**	**Tamil Nadu**	**Uttar Pradesh**	**West Bengal**
d-GPH	1.02	0.84	1.23	1.27	1.03
	(0.35)	(0.28)	(0.25)	(0.16)	(0.30)
d-Robinson	0.76	0.43	0.74	0.77	0.73
	(0.11)	(0.10)	(0.11)	(0.08)	(0.10)

Notes: The power parameter for the estimates above is 0.5. Figures in parentheses are robust standard errors.

Figure 1a: India, relative GDP per capita quintiles in 1960

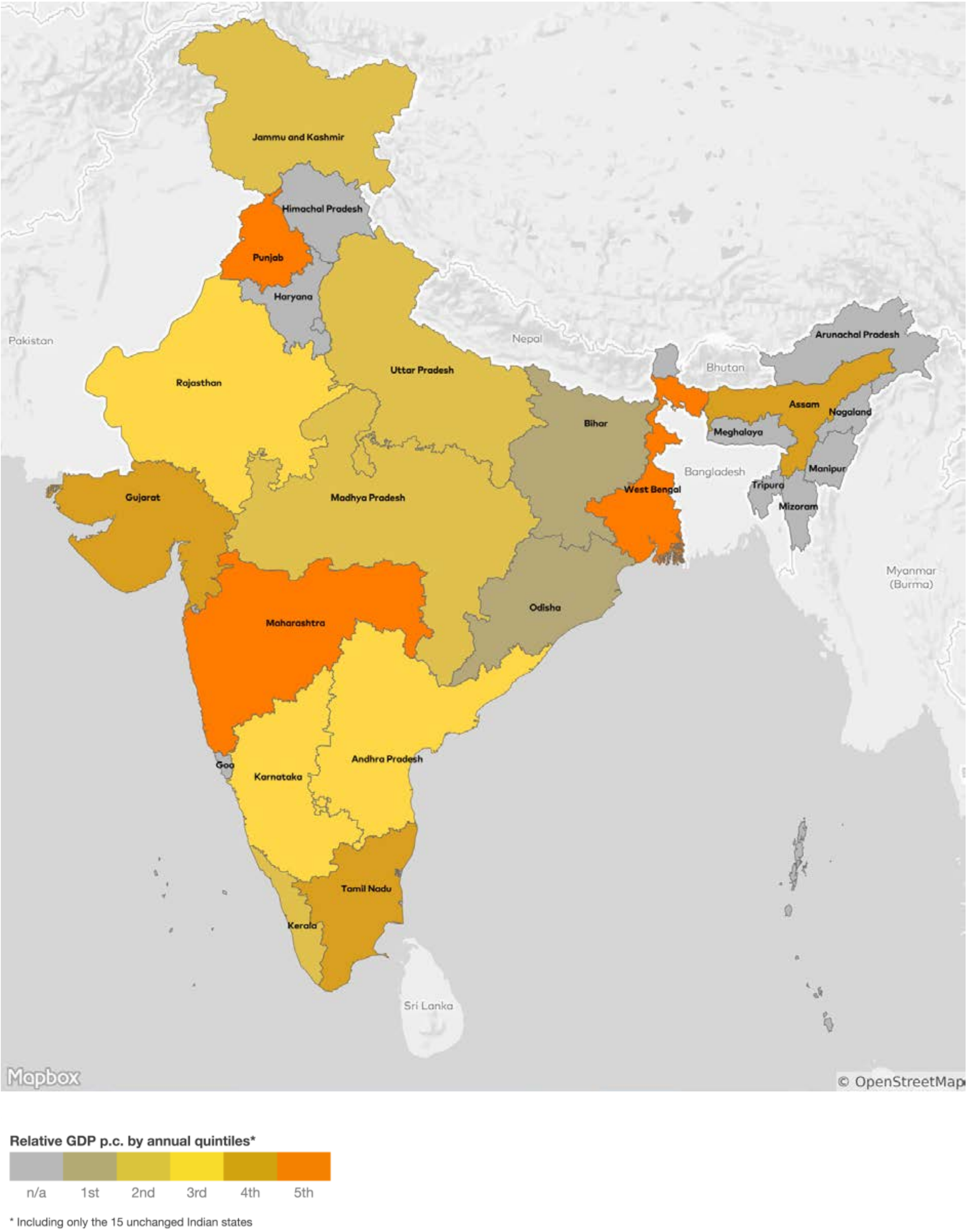

Figure 1b: India, relative GDP per capita quintiles in 2010

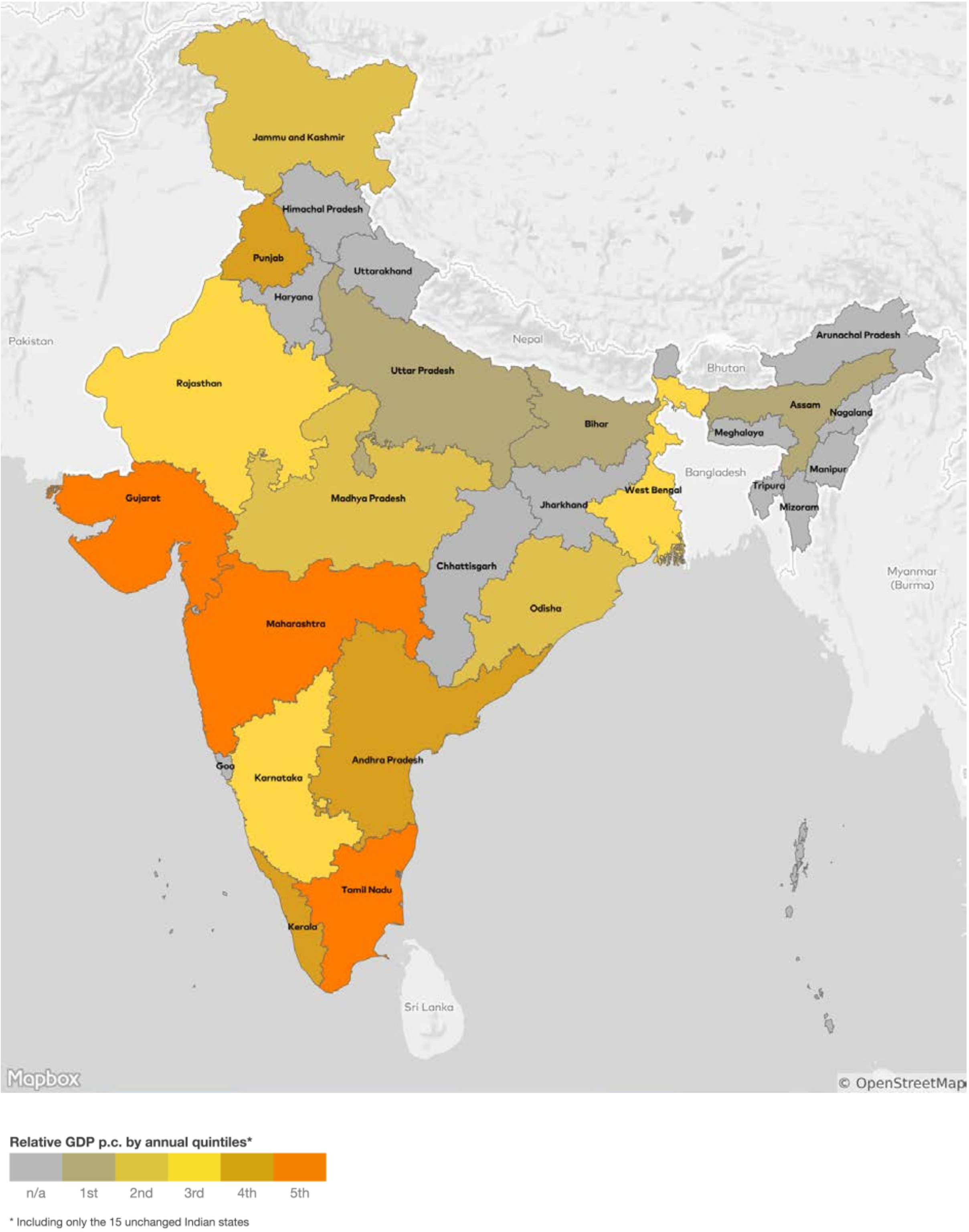

Figure 1c: India, relative GDP per capita quintiles by decade, 1960 to 2010

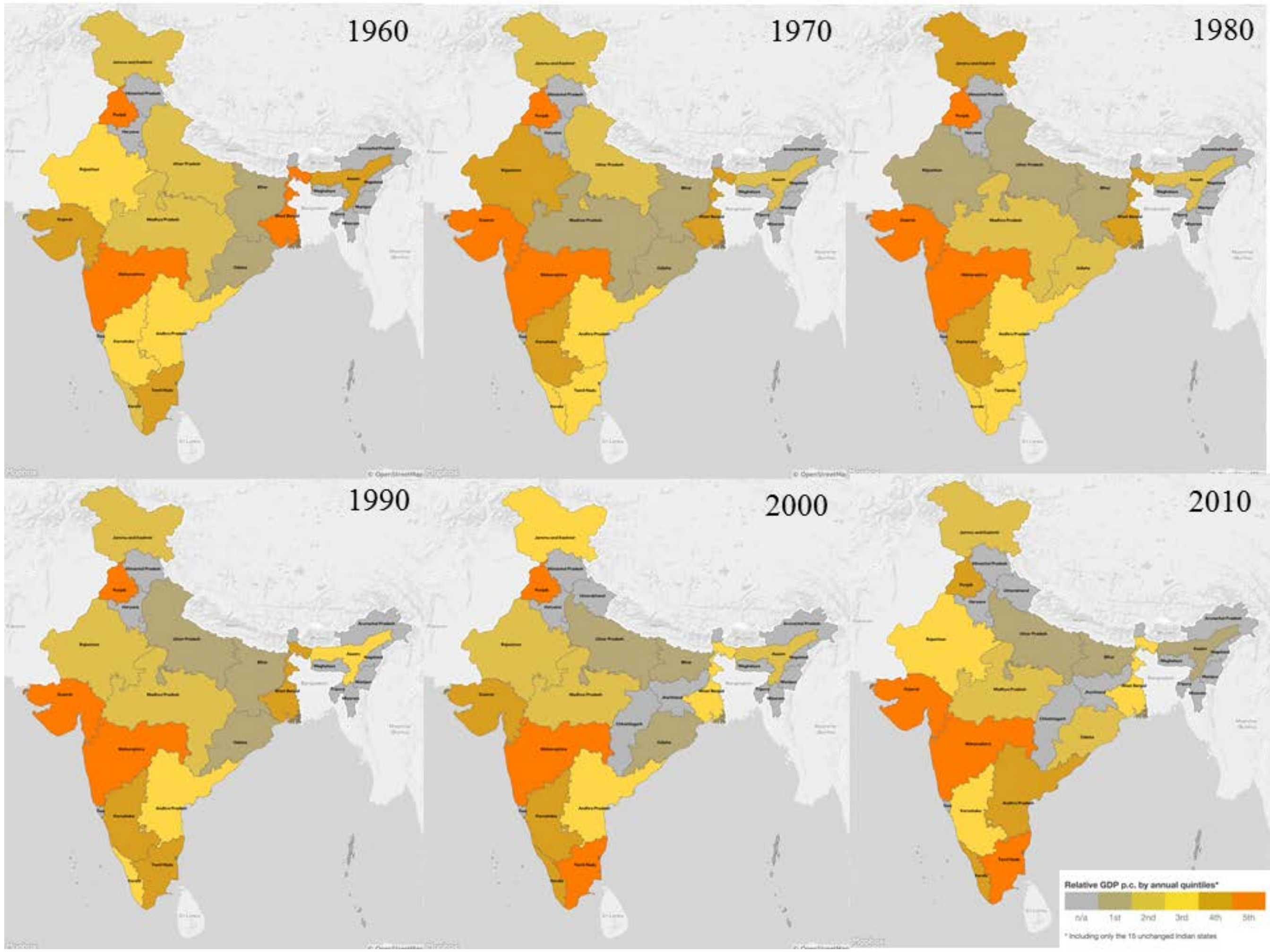

Figure 2: India, relative GDP per capita of 15 Indian states 1960-2011

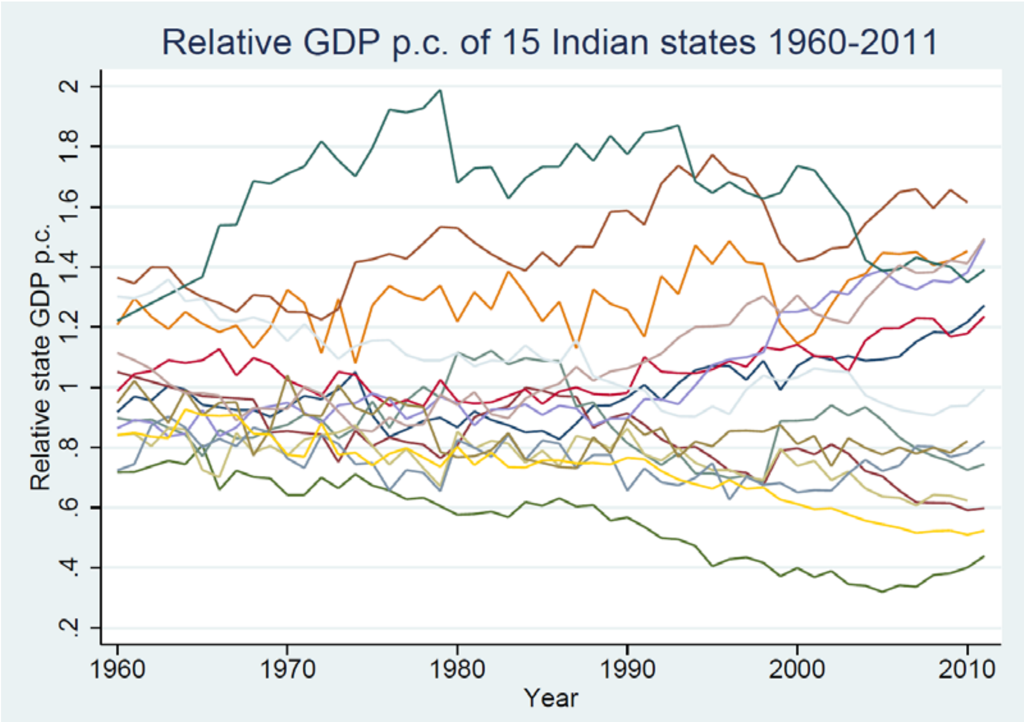

Figure 3: Sigma convergence