Do social polarization and stochastic shocks matter for convergence speed of income?

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Abstract

This paper seeks to address two neglected aspects of convergence dynamics of cross-country per capita income. First, we allow evolutionary path of per capita income to contain stochastic shocks which may not converge fast enough to the long-run mean. Under this condition, we show that the conventional inference on σ convergence can be enlarged with more predictive power if one assumes, along with the necessary condition of β convergence, that the stochastic shocks are covariance stationary. Second, we argue that for economies to (conditionally) converge, they need to be sufficiently cohesive so that the growth of stochastic shocks is not sustained through complex socio-economic interactions. Empirical examination is carried out by analyzing time series properties of state per capita income in India and performing convergence analysis by conditioning a constructed social cohesion index based on indicators collected from the National Sample Survey. It is demonstrated that when the economy faces monotonic social segmentation, persistence of stochastic shocks considerably affect speed of per capita output convergence.

Key words: Social cohesion, convergence dynamics, long-memory, social distance, non-linear convergence speed.

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1 Introduction

Both traditional theory of output convergence (based on the celebrated Solow-Swan model) and its recent extension (following on the success of endogenous growth theory) suffer from the important limitation that the relevance of slowly convergent shocks to the long-run mean is disregarded while outlining conditions under which (conditional) β and σ convergence[1] may occur among nations. Indeed, if one integrates literature from economic history, political economy, sociology and economic growth, one would find that non-mean convergent stochastic shocks are often found to be present in a segregated and socially alienated society and its magnitude of persistence is often found to be higher in the former than in a socially cohesive and stable society.

Presence or absence of convergence is not a completely economic phenomenon. If individuals' productivity in economic sense matter for aggregate national productivity, then it is essential to recognize the importance of social condition of individuals under which he produces. Relative social position of individuals does affect productivity in a relative sense as individuals interacting in a stable and sustainable society produce externalities which are both socially and economically beneficial (for a recent survey, see for instance, Clark et al., 2008). The equilibria reached at under such societies are indicative of the high level of productivity growth which distinguishes itself from the outcome of a segregated society.

The sparse empirical studies have shown that polarized societies, as measured by ethnic fractionalization or income inequality, seem to be more prone to adopting growth-retarding policies. Moreover, social polarization may not only be responsible for coordination failure but is often thought to be associated with socio-political instability, which is by itself harmful to growth (e.g., Alesina et al., 1999). Majority of research, debates and policy discussions thus far have concentrated on developed societies, offering very little insights both with respect to rigorous theoretical and empirical analyses. In an era of rapid globalization and high internationalization of world economies, the effect of social polarization can have serious consequences for developing economies, especially because these economies' immediate objective is to achieve high growth and to be on the quality ladder of growth-success of developed economies. Second, some developing economies lend excessive emphasis on high growth for strategic political gains and building an effective deterrent to security threats from neighbors. In either case, growth without social limit is unstable and unsustainable.

In addition, even if one compares the optimization objectives of developed and developing worlds the principal motive appears to remain the same, i.e., optimize growth subject to resource constraints along with securing a cohesive society, developing economies like India, face additional challenges. However, the priorities differ significantly for developing countries for two important reasons. First, along the growth trajectory, it is always difficult to jointly optimize growth and social cohesion[2] especially when the growth trajectory concerns pure economic gains from achieved convergence for developing economies. Second, once a steady state growth is achieved and high growth momentum is maintained (as in most developed economies), the joint optimization of growth and cohesion becomes relatively easier since the social planner needs to focus more on re-distribution of resources in the society to make it more stable and cohesive. In view of these unique reasons, it is necessary to understand how persistent lack of cohesion in developing economies affects both short and long-run objectives of high and sustainable growth.

Akerlof (1997) and Gradstein and Justman (2002) argued that individuals' utility in a society are interdependent and such interdependence generate externalities which typically slow down movements towards socially beneficial equilibria and in most extreme cases, they will create

[1] Broadly, when the dispersion of real per capita income across a group of economies falls over time, there is σ convergence. When the partial correlation between growth in income over time and its initial level is negative, there is β convergence.

[2] We follow Chan et al. (2006) and define social cohesion 'as a state of affairs concerning both the vertical and the horizontal interactions among members of a society, as characterized by a set of attitudes and norms that include trust, a sense of belonging, and willingness to participate and help, as well as the behavioural manifestations'.

long-run low-level equilibrium traps that are far from socially optimal. This microeconomic result has important implication for macroeconomic theory of convergence - that convergence of per capita income at cross-country level needs to be conditioned on social classes and distinctions. Arguably, socially cohesive societies create favourable conditions, for instance via education, whereas segmented societies tend to alienate themselves from optimum growth. Additionally but importantly, a stochastic shock always finds its way to long-run persistence in a transition and socially volatile than in a developed and relatively stable society. It is the nature of the survivability of shocks which can impact the extent and speed of convergence. To the knowledge of the authors, this aspect of convergence dynamics has not yet been studied in the literature.

The empirical analysis is carried out for India where we examine the convergence properties of state real GDP per capita over two decades. Among several developing countries, India is a unique case because of persisting high growth momentum and equal pace of growth of social alienation. Growth without proper re-distribution among various strata of society in India has provided impetus to recent debates and discussion both in academic and policy circles. Given our theoretical arguments, it will be interesting to study convergence in state per capita GDP while stochastic shocks and high degree of lack of social cohesion is persistent. There is a growing number of studies in India that have focused on the issue of regional growth and convergence in per capita real income across the states (see for instance, Aiyer, 2001; Bandopadhyay, 2011; Sinha and Sinha, 2000). Bandopadhyay (2011), and Bandopadhyay (forthcoming), for instance, employ both non-parametric and parametric methods to examine convergence dynamics and Aiyer (2001) employs panel data technique to examine convergence hypothesis. These and similar other studies employ a variety of methodological tools (e.g., panel unit root, cointegration, stochastic kernel density, etc.) which disregard the effects of slow and non-mean converging stochastic shocks along with social segmentation. We aim to fill this void in the research undertaken in this paper.

Although our emphasis would be on demonstrating how convergence speed is determined by social segmentation, the implications of our finding would be straightforward. As we will argue in the paper, alienated societies nurture non-mean convergent shocks more than highly-convergent shocks. The latter is a characteristic feature of cohesive societies. To inhibit the proliferation of stochastic shocks it is essential that the economies and societies need to be stable and increasingly cohesive, which in the long-run help in achieving desirable convergence speed across sectors. To explicate further, we first build an analytical model by extending the conventional framework of convergence by mixing micro foundation to the macro setting (section 2). In the next step, we provide methods of testing such convergence (section 3). Empirical analysis carried out by studying inter-regional convergence pattern for India is presented next (in section 4). Finally in section 5, we conclude with main implications of our analytical and empirical results.

2 Framework

In this section, we build a simple model describing the interrelationship between social segmentation and economic growth convergence. We demonstrate that socially fragmented economies experience higher persistence of shocks than socially cohesive societies and that the magnitude of shock persistence determines the convergence rate of economies. Although the framework we describe is applicable in cross-country setting, it can be better understood within a regional economy framework of a nation, because elements of a subset are assumed to share affinities within a broader set. The agents within the set are expected to experience common steady behavior mainly due to their 'closeness' defined in both geographic and relational sense.

However, exceptions may occur and by utilizing the argument of social conditioning theory, divergence is a meaningful possibility in the sense that agents, even in a 'close' society maintain individualities. To the extent they internalize private and public information on their social standing, divergence of growth may occur. In this case, divergence, rather than convergence may be growth-enhancing and welfare maximizing. Such divergence may not create a chaotic and segregated society if the individuals compete in terms of productivity and knowledge-enhancement. However, human mind is seldom consistently affixed to idealistic states. Comparison does arise in human mind about their relative social and economic position. The competition and growth resulting from such a state may push the economy to low-level equilibrium trap, unless the social planner employs an equitable distribution plan over time. This argument has been stressed in Akerlof (1997) and Gradstein and Justman (2002) and has been the central argument among public policy analysts.

For the purpose of motivating our model, assume that the productivity, A of an individual $i : i = (1, \dots, n)$ is a function of his relative position in the society, denoted by utility U, and stochastic shocks (both endogenous and exogenous) (ϵ_t) present at time point $t : t = (1, \dots, T)$ of the economy. The individuals are assumed to enjoy both complete private and public information about his relative socio-economic position. This information set is denoted by Ω. Additionally assume that each individual is endowed with initial level of human capital h_0 and accumulated human capital from initial level denoted as $H_t = h_0 + e^{\lambda t}$, where λ is the efficiency gained over time through and the growth of human capital is denoted by $e^{\lambda t}$.[3] Thus, at time t, the productivity, A of individual i can be defined by

$$A_{it} = F(U_{it}, H_{it}; \Omega) \tag{1}$$

where $U_{it} = -ax_{it}^2 + bx_{it} + c - d(x_{it} - \bar{x})^2$. Denoting x as the consumption unit or the status producing variable, then the person loses utility in amount $d(x_{it} - \bar{x})^2$ from failing to conform to the standard of the others. This defines the relative social position, distance or the taste of conformity of the individual i following Akerlof (1997) which affects the productivity level A at time t. Moreover, x is assumed to have an additional intrinsic utility of $ax^2 + bx + c$, which is of quadratic structure conforming thus to the peculiarities of utility maximization theory. Since the utility function is of quadratic form, there would be only one equilibrium value of x, which occurs at $x = b/2a$. The problem confronting each individual i is to choose x_i contingent upon his social position, x_0 and his initial human capital, h_0. The individuals must form expectations about the position of his potential competitor in social exchange. With static expectations where the acquired social position of all the other individuals will coincide with their initial position, the i's expected acquired distance between himself and j will be $|x_i - x_{0j}|$. Denoting the initial social distance between individuals i and j as d_{ij}^e, it also defines the expected value of benefits in terms of productivity differential between i and j. While aggregated over individuals and over time, it would mean that the economy with large number of population and with defined two generations, old and new, will find themselves trapped under a catching up problem: new generation finds itself conforming to the productivity level of the older population. The catching up problem becomes prominent in the presence of stochastic shocks which survives certain period and affect both generations. Survivability of shocks in a society has to do with the progressive segregation and alienation, which ultimately affects the aggregate productivity at national level.

In line with conventional theory we construct now an output growth (loosely defined by per capita output) process which conditions expected social distance, d_{ij}^e and the information set, Ω.

Definition 1 ***Conditional convergence in productivity***: *The per capita output Y of state s and l converges if the long-term forecast of their difference conditional on d^e and Ω is zero at time t:*

$$\lim_{k\to\infty} E(Y_{s,t+k} - Y_{j,t+k} | d^e, \Omega) = 0$$

and its variance declines over time:

$$var(Y_{s,t+k} - Y_{j,t+k}) = \sigma < \infty$$

[3] At idealistic state, h_0 is assumed to be equal for all i emphasizing thus on the direct influence of social planner in maximizing welfare via education policy.

This definition is similar to Bernard and Durlauf (1995) but with an important addition that expected social distance over some economic functional must be zero and that every individual obtains complete and same private and public information, that is $lim\ d^e \to 0$ in probability and Ω which is decomposed of private and public information makes history dependence irrelevant. However, an economy is a breeding ground of stochastic shocks, some of them do escape certain periods and make economic system volatile. When social segmentation is acute, stochastic shocks take long time to taper off. This can affect the convergence speed of output between s and l at time t. We outline below a simple model which illustrates the importance of convergence speed of shocks for cross-country/regional productivity convergence. To motivate, we draw on Sala-i-Martin (1996) and Young et al. (2008). However, we extend the framework to long memory setting.

Since empirical studies often use natural logarithmic scale of per capita GDP, $\ln(Y_{it})$, we state the following dynamics

$$\ln(Y_{it}) = \alpha_i + (1+\beta)\ln Y_{i,t-1} + \Pi X_i^{'} + \epsilon_{it} \tag{2}$$

Manipulating (2) yields,

$$\ln(Y_{it}/Y_{i,t-1}) = \alpha_i + \beta \ln Y_{i,t-1} + \Pi X_i^{'} + \epsilon_{it} \tag{3}$$

where $i = 1, \ldots, N$, $\epsilon_{it} \sim iid(0, \sigma_u^2)$, α is fixed country effects and Xs are control or conditioning variables. In (3), a negative β means that convergence in output growth holds conditional on the defined distance and information set. From (3) the heterogenous steady-states are given by $-\frac{1}{\beta}(\Pi X_{ij}^{'} + \alpha_j)$. Using the variance of log income for all states for each time period t (where σ_t^2 = E[ln(Y_{it}-E(ln(Y_{it}))^2]):

$$\sigma_t^2 = \left(\frac{1}{N}\right)\sum_{i=1}^{N}[\ln(Y_{it}) - \mu_t]^2 \tag{4}$$

where μ_t = E[ln(Y_{it})] is the sample mean of log income. The sample variance approximates income variance when N is large. We now use (2) and (4) to describe the evolution of σ_t^2:

$$\sigma_t^2 \cong (1+\beta)^2\sigma_{t-1}^2 + \sigma_u^2. \tag{5}$$

The implication is that the cross-state variance of income at time t depends on its value at $t-1$ plus the cross-state variance of the idiosyncratic error, u. In (5) the system is difference equation stable only if $\beta < 0$. That is that average income growth rates of backward economies are definitely greater than those of advanced economies, which is empirically well-supported. However, allowing for different values for α and X_i, $\beta < 0$ would imply conditional β-convergence. Intuitively, this indicates that the average growth rate of income of an economy is an increasing function of its distance from its balanced growth level of income. Given $-1 < \beta < 0$, the steady-state variance of income is given by,

$$(\sigma^2)^s = \frac{\sigma_u^2}{[1-(1+\beta)^2]} \tag{6}$$

Combining (5) and (6) one obtains,

$$\sigma_t^2 = (1+\beta)^2\sigma_{t-1}^2 + \left[1-(1+\beta)^2\right](\sigma^2)^s \tag{7}$$

This is a first order difference equation with constant coefficients having the following solution:

$$\sigma_t^2 = (\sigma^2)^s + (1+\beta)^{2t}\left[\sigma_0^2 + (\sigma^2)^s\right] + \gamma(1+\beta)^{2t} \tag{8}$$

where γ is an arbitrary constant. As long as $-1 < \beta < 0$, we have $|1+\beta| < 1$ which implies that

$$\lim_{t\to\infty} (1+\beta)^{2t} = 0 \tag{9}$$

Stability of σ_t^2 is ensured because it implies that,

$$\lim_{t\to\infty} \sigma_t^2 = (\sigma^2)^s \tag{10}$$

The implication is that the variance will increase or decrease towards its steady state value depending on the initial variance σ_0^2.

We investigate next how slowly-decaying demographic shocks affect conditions for income convergence. For the purpose, we model state-specific income by an $I(m)$ process where fractional values of m, the integration parameter in the auto-covariance function (defined for lag length k: $G(k) \sim C(k)k^{2m-1}$ as $k \to \infty$ and $C(k) \neq 0$) displays varying convergence rates of shocks. Recalling that the variance of income is calculated for all states taken together (that is for the cross-sectional terms) and for each time period t, one may obtain then the time series of cross-sectional variance for each time period. In this case m represents the integration parameter such that if the value of m is in the interval [0.5, 1) the series is nonstationary though mean reverting. If $m \geq 1$ it is nonstationary and non-mean reverting. Stationary (long memory) occurs if m belongs to the interval (0, 0.5).

Proposition 1 *When* $\lim d^e \to 0$ *and* $m < 1/2$*, convergence in output between* s *and* l *is stable in the sense of* σ *convergence in addition to the condition that* $\beta < 0$.

Proof:
For the purpose, we modify equation (7) and model temporal difference between σ_t^2 with a fractal structure:

$$(1-L)^m \sigma_t^2 = [(1+\beta)^2 - 1]\sigma_{t-1}^2 + \left[1 - (1+\beta)^2\right](\sigma^2)^s \tag{11}$$

where L is the backshift operator and d is the integration parameter such that $(1-L)^m$ can be approximated by binomial expansion and where $(1-L)^m = \sum_{j=0}^{\infty} h_j L^j$ with $h_j = (j+1)^{m-1}$ is the impulse-response function of the effect of stochastic shock. Re-writing (11), one obtains,

$$\sigma_t^2 = (1-L)^{-m}[(1+\beta)^2 - 1]\sigma_{t-1}^2 + (1-L)^{-m}[\left[1 - (1+\beta)^2\right](\sigma^2)^s] \tag{12}$$

The solution of this equation now appears as:

$$\sigma_t^2 = \sigma^{2(s)} + (1+\beta)^{2t}(1-L)^{-m}[\sigma_0^2 + \sigma^{2s}] + \gamma(1+\beta)^{2t}(1-L)^{-m}(1-L)^{-m}[\left[1-(1+\beta)^2\right](\sigma^2)^s] \tag{13}$$

Clearly, the stability of the above system, i.e., σ convergence will occur not only with $-1 < \beta < 0$ but also with additional constraint that m must be mean reverting, $-0.5 < m \leq 0$. Therefore economies can be β converging in income growth towards one another while, at the same time, random shocks would push them apart. However, if $m > 1/2$, persistence in social alienation continues, that is, the expected distance d^e in the society grows monotonically. $Q.E.D$

It should be noted that from the above that stability condition (both with and without stationary long-memory shocks) holds true on the condition that the society is stable and cohesive enough to disallow slow or non-convergence of shocks to the long-run mean. When d^e increases monotonically (limit being 1), σ-convergence may not occur even with β being negative as the segmented society becomes the breeding ground for the proliferation of shocks, which ultimately pushes the economy to the low-level equilibrium. Under this purview, one can imagine three types of situation: first, a stable and cohesive society, where normal conditions of convergence prevail (that is $m < 1/2$, $d^e = 0$, and $\beta < 0$) so that inter-regional/country differences in dispersion in income declines monotonically. Second, there is a socially segmented society, facing chaotical economic dynamics, where divergence, rather than convergence is the possibility. Third, there are economies in transition, which over a time duration have experienced a transition of d^e from 1 (alienation) towards 0 (cohesion), and the long-memory shock, m transiting from >1/2 (non-stationary long-memory) to <1/2 (stationary long-memory). In the following section, we construct an empirical test of convergence based on stochastic long-memory classification as well as their transitional dynamics.

3 Convergence tests

In this section, we discuss three main test procedures that account for the presence of slow and non-mean convergence rate of stochastic shocks, transitional dynamics, and the extent of non-linearity in the understanding of speed of convergence in output.

3.1 Stochastic long-memory and output convergence

The first one, as we assume is relevant for convergence analysis is the role of stochastic shocks. Indeed, it is both theoretically and empirically interesting to study how the speed of convergence of stochastic shocks in a time series, such as per capita output, affects the evolution of the series in the long-run. To this effect, one can follow either (semi-)parametric or non-parametric approaches. In what follows, we will discuss the (semi-)parametric approach to estimate the speed of convergence first. Second, an outline of the recent development in non-parametric domain, viz., non-linear half-life will be provided to obtain information on the local convergence speed of output.

The literature concerning test of convergence in parametric follows two principal approaches: first, the coefficient of the initial level of output (β) in explaining per capita output growth between period t and $t+T$ (T being sufficiently large) is negative. An analogous empirical test procedure often employed in this setting is to investigate if multivariate output series contain stochastic unit root, that is whether they follow common stochastic trend. An alternative way is to classify the cross-sectional output series into convergence classes of shocks (that is if subsets of states are characterized by stationary long-memory, short-memory, and non-stationary long-memory). Since each of these classes possesses distinct transitional dynamics to steady state, long-memory convergence approach appear to fit most of the theoretical models and are intuitively akin to conventional empirical economic growth analysis. Since long-memory class of models accommodate the extreme cases of unit root and trend stationary processes, we employ this method for our empirical investigation.

A recent (semi-parametric) approach to test for long-memory in the presence of detrending and demeaning is Shimotsu (2008) and Shimotsu and Phillips (2005). Let $I_x(\lambda_j)$ denote the periodogram of a series x_t based on a discrete Fourier transform $F_x(\lambda_j)$ at frequency $\lambda_j = \frac{2\pi j}{T}$ for $j = 0, ..., T-1$ such that $I_x(\lambda_j) = F_x(\lambda_j)F_x^*(\lambda_j)$ with $F_x^*(\lambda_j)$ being the complex conjugate of $F_x(\lambda_j)$ defined as

$$F_x(\lambda_j) = \frac{1}{\sqrt{2\pi T}} \mid \sum_{t=1}^{T} x_t e^{it\lambda_j} \mid^2 \tag{14}$$

The discrete Fourier transform $F_x(\lambda_j)$ can be used to define a Whittle estimator of d obtained by minimizing the objective function below with respect to d:

$$W(G, m) = \frac{1}{d} \sum_{j=1}^{\nu} (\ln(G\lambda_j^{-2m}) + \frac{I_x(\lambda_j)\lambda_j^{2m}}{G}), G \in (0, \infty) \tag{15}$$

where ν is the number of frequencies used in the estimation. A well known Whittle estimator valid under non-stationarity is Exact Local Whittle (ELW) estimator of Shimotsu and Phillips (2005). This estimator has been shown to be consistent and has the same $N(0, 1/4)$ limit values for all values of d. It is 'exact' because it relies on exact algebraic manipulation and is different from the conventional Local Whittle estimator which is based on an approximation of Whittle likelihood function and is not a good general-purpose estimator when the value of d may take on values in the non-stationary zone beyond $\frac{3}{4}$.. However, the ELW estimator has also been shown to possess some undesirable properties. As demonstrated in Shimotsu (2008), if an unknown mean (initial value) is replaced by its sample average, simulation suggests that the ELW estimator is inconsistent for $d > 1$. Therefore we use the new estimator suggested by Shimotsu (2008): Feasible ELW (FELW), 2-step Feasible Exact Local Whittle (2FELW). These estimators are also computed with prior detrending (FELWD, 2FELWd) of data as suggested by Simotsu (2008). All LW, ELW, FELW, FELWD, 2FELW and 2FELWD estimators are used to estimate d where ν is chosen as $\nu = T^{0.6}$ as suggested by Shimotsu (2008).

3.2 Transitional dynamics in convergence test

While the above test provides an idea about the extent of deviation of empirically established convergence speed from the non-mean convergent stochastic shocks, it was not possible to study the transitional dynamics that might affect the convergence speed. In view of this, in the next step, we look for common class in transitional dynamics among a set or subset of agents (which may be regions, states or countries). Phillips and Sul (2009) develop a nonlinear dynamic factor model of the form

$$\log Y_{it} = \alpha_{it} + X_{it}t = \beta_{it}\mu_t \tag{16}$$

where the component α_{it} embodies transitional dynamics for real effective capital in the tradition of neoclassical growth model and the $X_{it}t$ captures the idiosyncratic time paths of technological progress. The dynamic factor formulation $\beta_{it}\mu_t$ involves a growth component, μ_t, that is common across individuals, and individual transition factors (β_{it}) that measure how individual economic performance relates over time to μ_t. In neoclassical growth framework, steady state common growth for log Y_{it} may be represented in terms of a simple linear deterministic trend $\mu_t = t$. Then

$$\beta_{it} = X_{it} + \frac{\alpha_{it}}{t} \to X_i; t \to \infty \tag{17}$$

so that X_i determines the growth rate of economy i in the steady state. The quantity β_{it} therefore plays a key role as a transition parameter in this framework (see Phillips and Sul, 2009 for details).

3.3 Non-linearity and half-life

In the previous two cases, we discussed how convergence speed may vary while one accounts for transitional dynamics of per capita output and the presence of non-mean converging stochastic shocks. Using these procedures, one can identify the cluster of countries (or regions) which share same pattern of growth. But, how does non-linearity affect the each country's convergence process? In the case of convergence of per capita income among various regions in a country, one would then try to understand if the presence of possible non-linear feedback and growth of stochastic shocks can determine the speed of convergence of output for each region is faster/slower than is empirically established. Moreover, we are also interested in understanding the adjustment process of real GDP per capita (y_t) towards its long-run level y provided that stochastic shocks are stationary and the economy is cohesive. Increasing deviations of y_t

from y occurs when shocks transits from stationary to non-stationarity and the society becomes increasingly non-cohesive.

To understand this, we employ a non-linear half-life test for convergence (Shintani, 2006). Since the half-lives are the most frequently used summary measure of persistence in the literature, we will mainly focus on this type of measure in this paper. The half-life of deviations in our case is the number of years required for the deviation at an initial level to dissipate by half. For an autoregressive process with long memory, the half life can be defined by the derived impulse response function $[(1-\rho L)^d]^h = h/2$, then $h = \ln(1/2)/\ln|(1-\rho L)^d|$ such that the half life and so the speed of convergence will not only depend on the sign and magnitude of ρ but also on the convergence of d.

To accommodate non-linear features, we have assumed smooth transition autoregressive model (STAR) for y_t such that y_t could be described by the class of non-linear autoregressive (AR) models $y_t = F(y_{t-1}) + \varepsilon_t$ where $F(y_{t-1})$ is a non-linear conditional mean function $E(y_t|y_{t-1})$. Then, the non-linear impulse response function (IRF) is given by $IRF_n(y_0, \delta) = F_n(y_0 + \delta) - F_n(y_0)$ where δ is the amount of shock to output series. The first derivative of the conditional mean function $F(y_{t-1})$ is proportional to the one step ahead non-linear IRF for small δ, since $DF(y_0) = \lim\limits_{\delta \to 0} \frac{F(y_0+\delta)-F(y_0)}{\delta}$, then local half-life at y_0 is defined by $h(y_0) = \frac{\ln(1/2)}{\ln|DF(y_0)|}$. This measure is used in the empirical section to provide the rate and shape of convergence of y_t to its long-run level.

4 Empirical analysis

In this section, we provide results of convergence tests based on the methods discussed in Section 3. The speed of convergence will be analyzed in light of the social and transitional dynamics, the analytical framework of which has been outlined in Section 2. For the purpose of empirical illustration, we have used state level per capita GDP spanning over three decades (1970-2006). The data have been obtained from Reserve Bank of India for various years. As has been argued before, the choice of India for our empirical examination is important in light of recent growth success story, especially after the liberalization period initiated in 1991. The pre-liberalization period is marked with strict control and regulation. Along with income growth, the Indian society has also expressed rapid transition in terms of cohesion. Commentators have often argued that the high growth of income per capita has resulted in divided society having sharp distinction in income inequality over the years. To test if income convergence has occurred among the Indian states, we condition income growth according to social status, which is measured by education cohesion and a constructed measure based on consumption inequality (reflecting more of social, then economic characteristics). The latter measure also captures features of social distance argument forwarded by Akerlof (1997).

To lend social dynamics to convergence debate, it is necessary to provide how Indian society has evolved over the years. We are interested here to understand if per capita income growth is following a rise/fall of social cohesion. A measure of cohesion is warranted and many international organizations recently have been attempting to build this multi-dimensional concept into a single measurable index. One of the important ways to measure cohesion and social polarization would to build an index based on per capita consumption and educational attainment distance. While the former is a convenient tool for welfare analysis, the usefulness of the latter has been recognized in the aftermath of endogenous growth theory's success.

Accordingly, in Table 1, we present the estimates of cohesion index based on per capita consumption expenditure and educational attainment levels obtained from the National Sample Survey (NSS) for two specific periods, viz., 1993 and 2004. The index for each category is calculated by inverting the value of $(x-min)/(max-min)$, where x corresponds to state average consumption or education. max and min are maximum and minimum values corresponding to each category where maximum values correspond to lack of cohesion. It is expected that after liberalization, the social distance among states per capita consumption and educational level would decline over time.

In Table 1, values greater than 0.5 represent polarized societies and less than 0.5 represent cohesive society. It appears that for all states and union territories, there has not been significant differences in social cohesion between 1993-94 and 2004-05 although a marginal increase in the cohesion index is found for both consumption and educational based measures. Overall, it is evident that all Indian states and territories are characterized more by social alienation than by high degree of cohesion, although some states have fared relatively better (for instance, Punjab, Manipur and Kerala) than the rest. It will be interesting see, if this social classification is consistent with or attributes largely to the persistence of stochastic shocks, which eventually affects speed of convergence of state per capita GDP.

Table 1: Social Cohesion Index for 1993 and 2004

	Consumption based		Education based	
	1993	2004	1993	2004
Andaman	0.664	0.899	0.610	0.605
Andhra Pradesh	0.169	0.253	0.26	0.144
Arunachal	0.136	0.346	0.000	0.337
Assam	0.070	0.159	0.470	0.429
Bihar	0.000	0.000	0.135	0.029
Chandigarh	0.732	1.000	0.643	1.000
Dadarnagar	0.055	0.299	0.277	0.233
Delhi	1.000	0.865	1.000	0.991
Damandiu	0.442	0.632	0.675	0.723
Goa	0.438	0.737	0.760	0.795
Gujarat	0.238	0.337	0.445	0.413
Haryana	0.274	0.446	0.332	0.335
Himachal	0.225	0.398	0.404	0.466
Jammu	0.299	0.413	0.438	0.315
Karnataka	0.159	0.221	0.393	0.375
Kerala	0.352	0.675	0.857	0.800
Lakshadweep	0.428	0.850	0.556	0.438
Madha Pradesh	0.108	0.098	0.216	0.130
Maharasthra	0.281	0.385	0.570	0.577
Manipur	0.074	0.179	0.616	0.685
Meghalaya	0.258	0.296	0.421	0.434
Mizoram	0.389	0.584	0.755	0.822
Nagaland	0.347	0.712	0.749	0.749
Orissa	0.025	0.009	0.217	0.228
Pondicherry	0.308	0.438	0.735	0.621
Punjab	0.410	0.572	0.502	0.464
Rajasthan	0.172	0.206	0.120	0.000
Sikkim	0.170	0.216	0.513	0.315
Tamil Nadu	0.209	0.367	0.497	0.519
Tripura	0.223	0.136	0.566	0.437
Uttarpradesh	0.105	0.135	0.196	0.072
West Bengal	0.171	0.251	0.441	0.325

Source: Authors'calculations based on 55^{th} and 61^{st} round of NSS consumption expenditure data.

The distributional dynamics of social cohesion for 1993 and 2004 is presented in Figure 1. The left panel of Figure 1 presents Kernel density plots for social cohesion based on consumption expenditure distance for 1993 and 2004, whereas education based measure of social cohesion is presented in the right panel of Figure 1. The thick lines in each figure represents the estimated density which is plotted against normal distribution (thin lines) along with their distributed standard deviations. Two notable features emerge: first, the density plots of social cohesion based on both consumption and education are skewed to the left except the education based measure in 1993. Second, cohesion distributions for the year 2004 display distinct bi-modality, implying possible presence of convergence clubs/clusters. From no cluster in 1993 to distinct clusters in 2004 imply that the transitional dynamics in Indian society is getting concentrated on low-level and high-level equilibria trap. This feature may significantly affect convergence pattern of output, the analytical framework of which has been presented in Section 2. However, density plots may not fully capture the transitional dynamics of output from low to high level equilibrium. An alternative test procedure has been proposed by Phillips and Sul (2009). The results are presented in Table 2.

Phillips and Sul (2009) test of transitional dynamic behavior allows us to classify state-level per capita output of Indian into cluster and sub-clusters. In Table 2, the overall test shows that the null of no convergence is rejected at 10 percent level. In the first club (see the left hand panel, headed initial classification) consists of four states where transitional dynamic component or fitted regression coefficient. All clubs have fitted coefficients which are negative (see the second column), thereby rejecting convergence and revealing evidence of divergence. For clubs 1 through 3, although point estimates are all significantly negative, they are also significantly less than 2.0. So there is strong evidence of conditional divergence and compelling evidence of level convergence within each of these clubs. The second panel reports the tests conducted to determine whether any of the original subgroups can be merged to form larger convergence clubs. We consider adjacent subgroups in the original classification and each cell in the panel reports the fitted regression coefficient and corresponding HAC standard error. As can be observed the three sub-groups are taken to form separate convergence clubs. The results from transitional dynamics support our findings of long-memory characteristics, in that all major Indian states have been experiencing divergent growth processes, conditional of course on social dynamics.

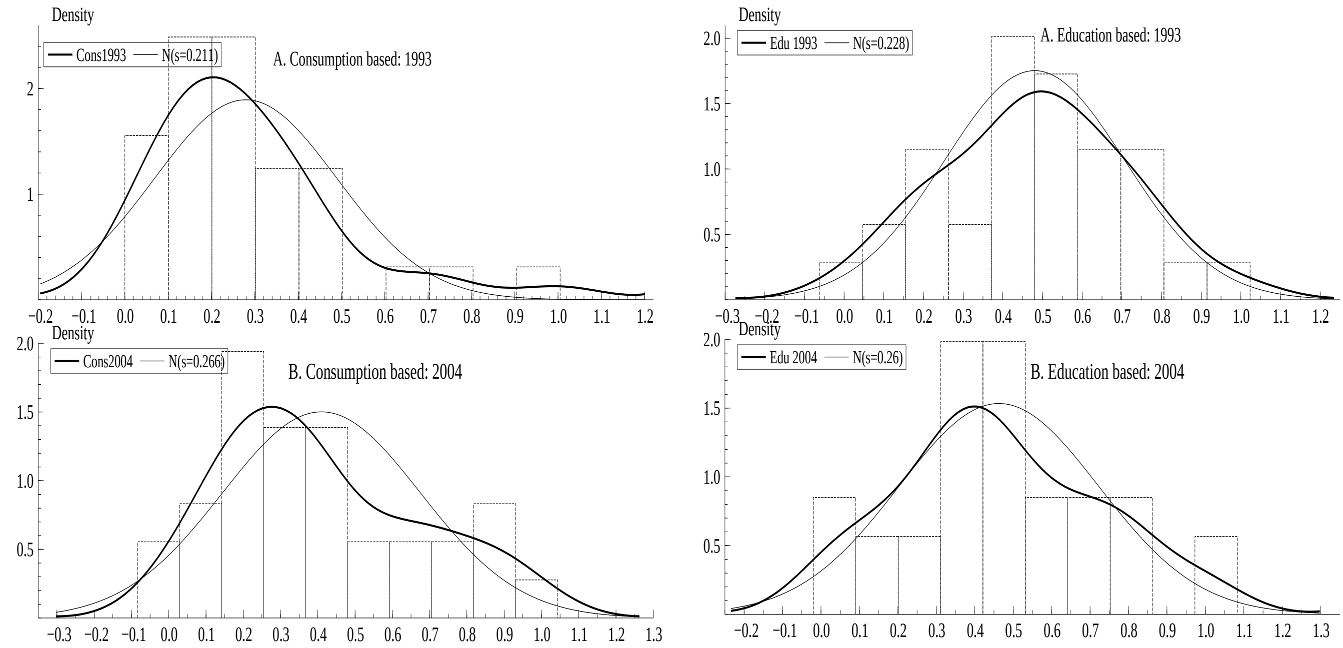

Figure 1: Distribution of cohesion index. [Left]: Consumption based. [Right]: Education based.

Table 2: Convergence and transitional dynamics

	Initial classification	Test of club merging
Club 1 [4]	-0.772 (0.020)	club 1+2: 0.498 (0.006)
Club 2 [5]	-0.155 (0.059)	club 2+3: 0.588 (0.011)
Club 3 [7]	-0.667 (0.007)	

Note: Figures in parentheses (...) are standard errors.

We next present results of long-memory test for 15 major Indian states for the period 1988-2006. For the purpose we report exact likelihood and its modification as in Shimotsu and Phillips (2005) and Shimotsu (2008). The results are presented in Table 3. Note that if the value of d, the integration parameter representing memory properties of per capita GDP, is less than 0.5, we call this a short-memory or covariance stationary process. Values greater than 0.5 are long-memory and such shocks may take long-time to converge or may not converge at all. From Table 3, it is clear that only Punjab has long-memory value less than 0.5, that is it is a covariance stationary process. Comparing this value with the corresponding figure in Table 1, it is apparent that Punjab is one of the most consistent states in terms of social cohesion, the other being Kerala. Combining the results of long-memory in output and cohesion, it is thus evident that highly cohesive societies contain stationary long-memory shock, the exception being Kerala where the long-memory value is 0.942 indicating the possible persistence of exogenous shocks. For the remaining states, both cohesion and long-memory estimates display 'polarized society and volatile economies'.

As invoked in Section 1, an important issue that a researcher would like to understand is while conditioning stochastic shocks and social dynamics, how does each state's per capita income behave in terms of convergence to their own steady state? A similarity of convergence dynamics to the respective steady-states would indicate possible clusters, sub-clusters, level convergence or divergence. Non-linear half-life convergence theory has been adopted to suit our purpose where per capita GDP for state i is allowed to converge conditionally to the steady-state level. Our purpose would be to observe whether the speed of convergence is linear or non-linear. The finding of the latter would mean that the estimated convergence speed based on linearization principle around steady state income level may underestimate the true value of convergence. Rather, the presence of non-linearity would imply the existence of social dynamics and slowly-converging stochastic shocks, which eventually make the speed of convergence slower than is empirically established.

Looking at the Figures (2-9), it is evident that except Assam (left panel of Figure 2), Haryana (left panel of Figure 4), and Punjab (left panel of Figure 7), none of the 12 states provide any evidence of linear local convergence. In fact, most states, for instance Andhra Pradesh (left panel of Figure 2), Gujarat 9Figure 3) and similar others provide evidence non-linear convergence till certain range and non-linear divergence for others. The combined presence of non-linear local convergence and divergence for any time series, such as per capita income, implies that various structural economic-social systems are at work. It also provides evidence of structural change that has significantly affected the evolutionary pattern of growth of output. Looking at the results of convergence clusters and sub-clusters and the results of divergence from Table 2, it is not surprising to find non-linearity and different local convergence speeds across Indian states. The results further strengthen our finding in Figure 1 about the bi-modality in the social cohesion distribution at the recent period. Taken together, it is evident that state level per capita income in India do not lend to unique convergence dynamics. Rather, persistent social dynamics and stochastic shocks are affecting the speed of convergence. Since the speed is non-linear it rules out any unique policy rule for all states.

Table 3: 2-step feasible Exact Likelihood estimates of long-memory parameter (Note: H_0: d = 0. The optimum chosen bandwidth = 0.60.)

States	2-step FELW
Andhra Pradesh	0.880
Assam	0.876
Bihar	1.169
Gujarat	1.139
Karnataka	0.674
Haryana	0.748
Kerala	0.942
Madhya Pradesh	1.257
Maharasthra	0.623
Orissa	0.630
Punjab	0.473
Rajasthan	0.874
Tamil Nadu	0.770
Uttar Pradesh	0.565
West Bengal	1.495

5 Conclusion

In this paper, we attempted at shedding light on convergence dynamics while explicitly accommodating social distance among the set of required conditions of σ convergence. We integrated social choice, political economy and economic growth theory and provided analytical result showing that convergence of stochastic shocks in output is essential for ensuring convergence in output along with the condition that the social distance must be minimal and cohesion in the society is sustainable and stable. The central idea of the paper was to provide a micro foundation to the macro setting where micro foundation is built on constructing the relative social position of that society against others.

Our empirical results point at the capital importance of stochastic shocks by showing that per capita income among majority of Indian states have been diverging intrinsically with interesting transitional growth dynamics. The implication is that conditioning social distance in conventional convergence analysis sheds new light into the stability of convergence and transitional dynamics of income growth over time. Our finding that there is no evidence of conditional convergence in state GDP per capita income is consistent with the broad literature which emphasizes on the crucial role of polarization. Given the similar nature of the engines of growth across the (rich) Indian states, this is contrary to what one would expect. However, in light of our analytical framework and theoretical results it appears relevant.

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Appendix

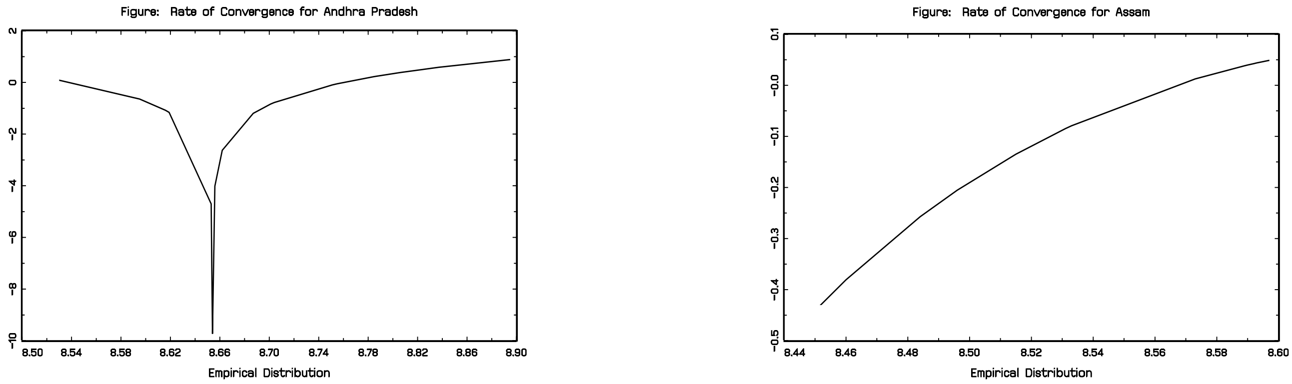


Figure 2: Local speed of convergence. [Left]: Andhra Pradesh. [Right]: Assam

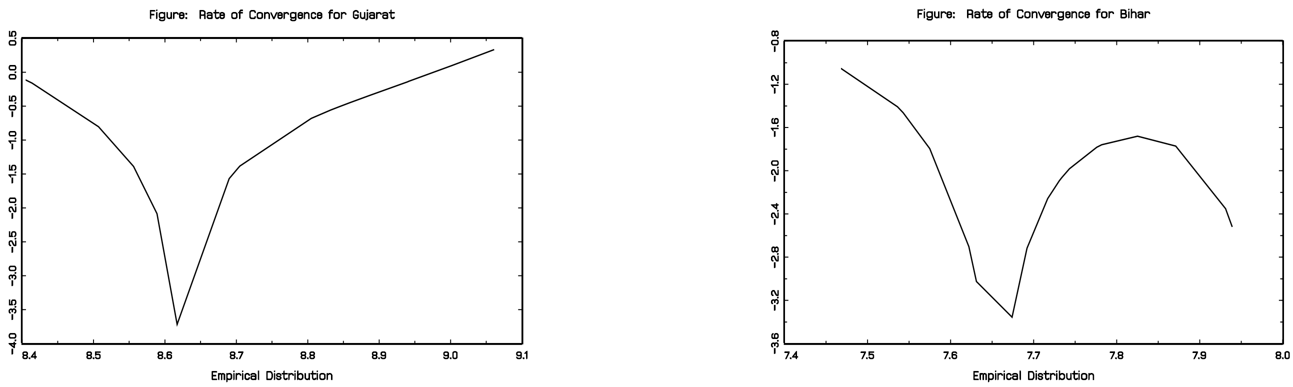


Figure 3: Local speed of convergence. [Left]: Gujarat. [Right]: Bihar

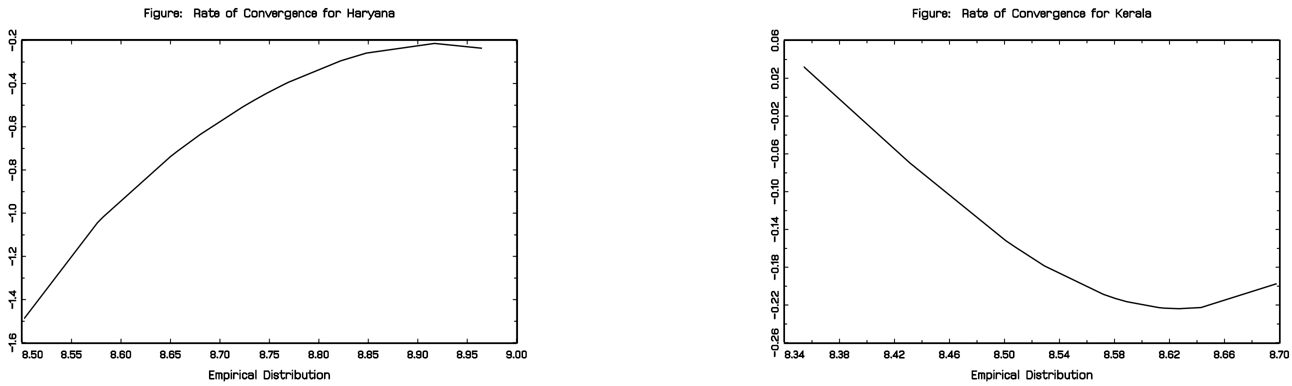


Figure 4: Local speed of convergence. [Left]: Karnataka. [Right]: Kerala

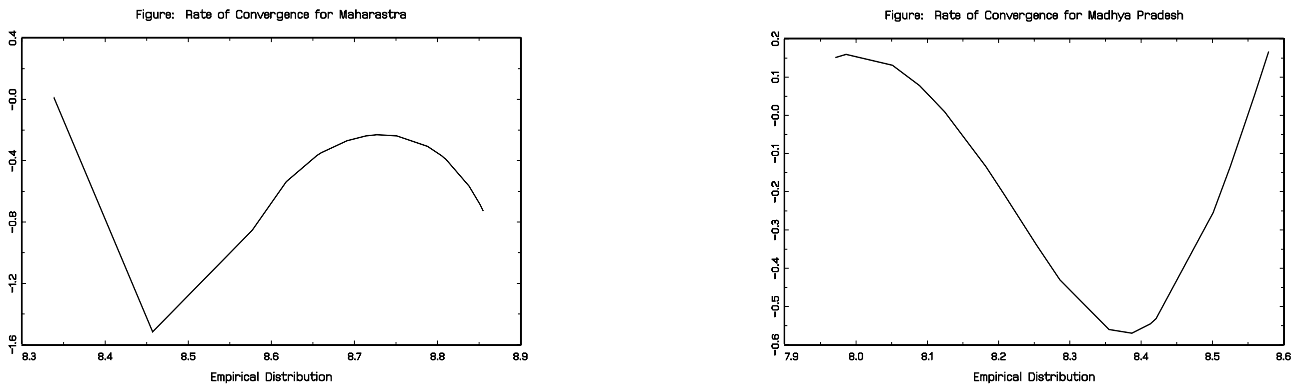


Figure 5: Local speed of convergence. [Left]: Maharasthra. [Right]: Madhya Pradesh

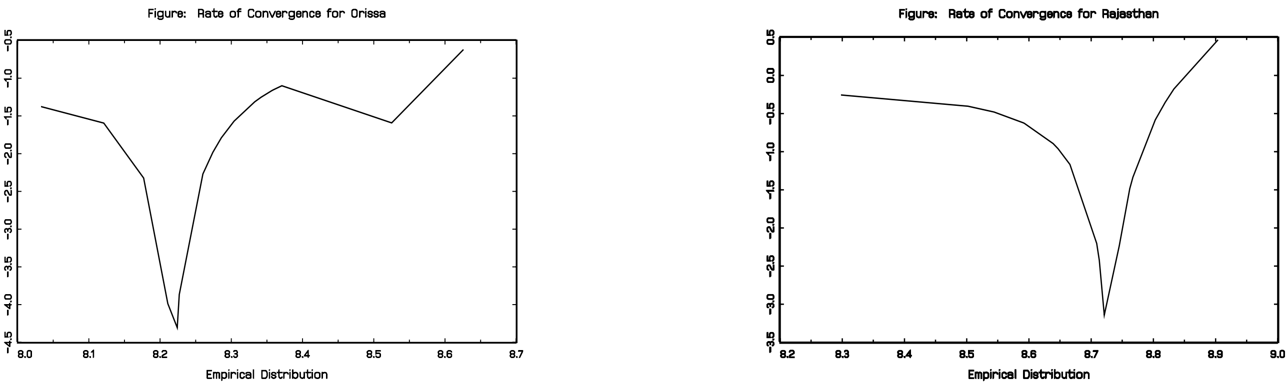


Figure 6: Local speed of convergence. [Left]: Orissa. [Right]: Rajasthan

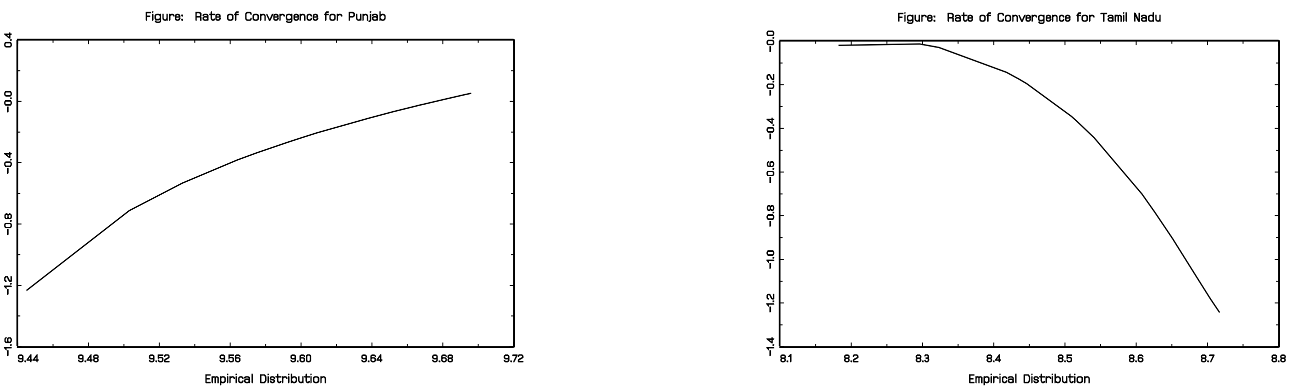
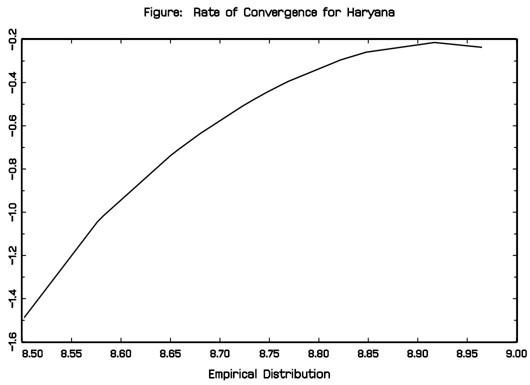


Figure 7: Local speed of convergence. [Left]: Punjab. [Right]: Tamil Nadu



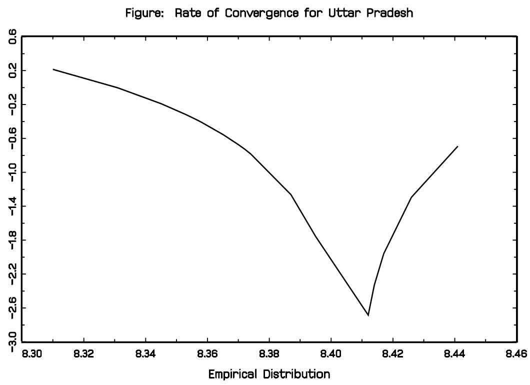


Figure 8: Local speed of convergence. [Left]: Haryana. [Right]: Uttar Pradesh

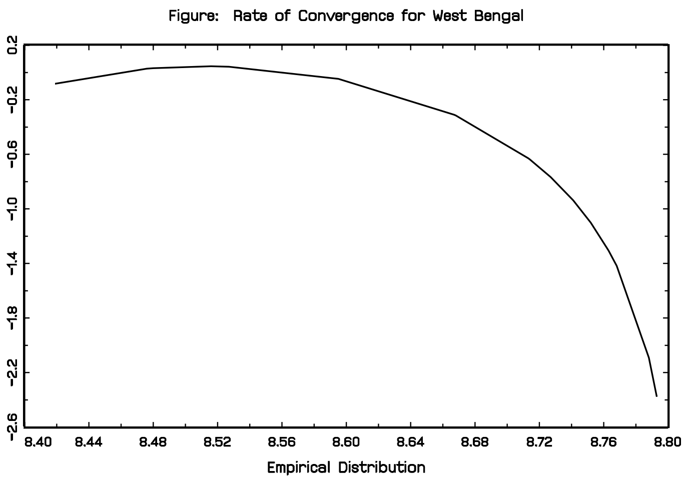


Figure 9: Local speed of convergence: West Bengal