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State Heterogeneity, Redistributive Policy and Pro-Poor Growth: Evidence from India with a special reference to Education

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Abstract

Does redistributive policy make economic growth pro-poor? We investigate this for India by using a set of axiomatic pro-poor growth indices and deprivation measures that are computed using nationally representative sample survey data from 1983 to 2011-12. Estimation using a linear panel shows that redistributive policies have a positive and significant impact on pro-poor growth, and a negative impact on poverty. The results are consistent irrespective of the initial conditions of the state, across income groups and for an alternative measure. An endogenously determined threshold level of education, estimated from a non-linear threshold panel model reveals that policy impacts are asymmetric for states that have attained a minimum threshold level of education.

Keywords: Pro-poor growth, Redistributive Policy, Education, Threshold Panel, India

JEL Classification: D63, H53, I32, I38

State Heterogeneity, Redistributive Policy and Pro-Poor Growth: Evidence from India with a special reference to Education

Amartya Paul[1] and Srikanta Kundu[2]

1. Introduction

The Indian economy has gone through various phases of growth since independence.[3] In recent times, between 2003-04 and 2007-08, the average annual growth rate was more than 8%, which lasted for an extended period till 2010.[4] The high growth phase is coincided with increasing levels of income inequality and declining poverty (Pal and Ghosh, 2007; Datt et al., 2020; Deaton and Dreze, 2002; Chancel and Piketty, 2017). Direct income data from India Human Development Survey (IHDS) reveal that income inequality, measured using the Gini index, has increased from around 0.521 to 0.545 between 2004-05 and 2011-12.[5] The consumption inequality also shows an increasing trend from 0.385 to 0.393 during this period (see, Table A1). It has been highlighted on many occasions that in the case of India and the world, even in a robust growth spell, benefits of growth do not always translate into growth of personal incomes, especially for the vulnerable class. Recent literature on the distributional consequences of growth has therefore called for a robust evaluation of economic performance. This includes the country's overall achievement in improving aggregate welfare, as well as how gains from growth (or losses from contractions) are shared among different sub-national units, groups or individuals (World Bank, 2020; Klasen, 2003).

In a federal structure like India, sub-national units or states, have their own discretionary power of designing and implementing policies. This can largely be motivated by some state specific characteristics such as political interest of the respective ruling parties of the state, present condition and several historical factors, *inter-alia*, initial level of endowment, poverty and education. Therefore, institutional differences, primarily originated by this federal structure, would generate substantial heterogeneity in terms of policy preferences and thereby state's performance. A set of indicative results derived from our initial exercise possibly

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[3] The annual growth rate ranged from about 1.1 per cent to 9.6 per cent during the period 1983 to 2012.

[4] We primarily use the Indian National Sample Survey data for this work (see details in section 3.1). We restrict our analysis till 2011-12 because required consumer expenditure data beyond this period is not available. Though a new survey round was conducted in 2017-18, the data has not been released yet.

[5] Author's own calculation. Similar estimates are provided by Azam and Bhatt (2016).

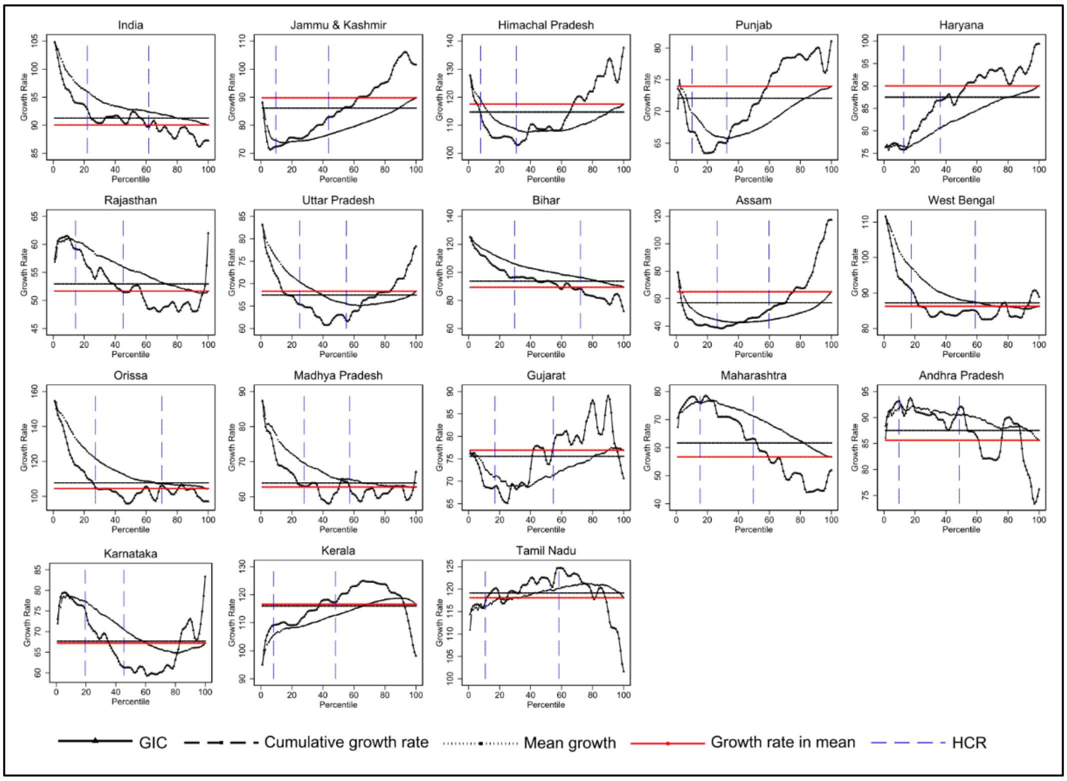
confirms this hypothesis. Considering all the available large sample household consumer expenditure (HCE) data from National sample survey (NSS) covering a long period between 1983 to 2011-12, we measure the extent of benefit from economic growth for the poor by using a set of alternative measures of pro-poor growth (Ravallion and Chen, 2003; Essama-Nssah, 2005; Kakwani and Son, 2008; Duclos, 2009). The estimated indices indicate instances of heterogeneity in pro-poorness of growth at sub-national level.[6]

A glimpse of our finding is provided in Figure 1 below. We use popular growth incidence curves (GIC) introduced by Ravallion and Chen (2003) which plots the growth in income of each percentile ranked by income as against the population percentiles for a particular growth spell. Results indicate, state performances are substantially heterogeneous. Further, economically better off states like Gujarat, Kerala, Punjab and Haryana have shown evidence of anti-poorness even when the country level experience was pro-poor while poor states like Bihar, West Bengal, Orissa and Madhya Pradesh have shown evidence of pro-poorness. Interestingly, there are fundamental differences in terms of the state characteristics and specific economic policies taken by these states. For instance, historically Kerala's achievement in socioeconomic indicators, such as literacy and health are statistically significantly better than Gujarat while Gujarat has done a lot better in terms of infrastructure development. Clearly, one is more towards welfare policies or affirmative actions and the other puts emphasis on market-oriented policies that accelerates economic growth.

However, existing evidence that have emerged from the widespread discussions on growth versus redistribution debate provide substantial ambiguity about the role that growth plays – it is not exactly clear whether it facilitates or impedes progress toward reduction in inequality. For example, Deininger and Squire (1998) using a novel cross-country asset data found a negative association between inequality in the initial distribution and long term growth rates. However, Barro (2000) using a three stage least estimator shows the relationship between income inequality and growth varies across rich and poor countries. In poor countries higher inequality tends to decelerate growth while it encourages in rich countries.

[6] Table A2 provides summary results. To save space, detailed State wise estimates are not provided.

Figure 1: State wise growth incidence curves between 1983 and 2011-12



Note: Real income growth rates at 1960 constant prices are plotted against the ranked population percentiles. We find similar state level heterogeneity for other different growth spells as well. Qualitatively, results did not alter when median is considered instead of mean.

The evidence in support of redistributive policies are also complex and the effectiveness, as argued in the literature, may vary due to numerous factors. In developing countries where the population density around poverty line is significantly high, any rank preserving redistributive transfer is expected to enhance aggregate welfare. Theoretically, through a direct channel such transfers increase real disposable income of the deprived class and indirectly it enhances nutrition, health, and education outcomes among poor households. However, due to imperfect targeting, extensive leakages, lack of accountability among implementing authorities, such policies do not always reach to the intended groups and as a result fails to produce desirable outcomes (see Alesina and Rodrik, 1994; McKay, 2002; Mosley et al., 2004; Anderson et al., 2018).

Given this background, we focus on redistributive policies and attempt to contribute in three strands of literature. First, we test if aggregate state policies drive the growth process pro-poor or not. We do this by building a unique state level panel data set using seven rounds of Indian national sample survey data spaced between 1983 and 2011-12. Second, we also seek to contribute on this long-going growth versus development debate by showing evidence that reveals redistributive policies at any level enhances economic welfare. Third, we also examine how level of education in a state determines performances of government policies leading to heterogeneous outcomes in terms of inclusiveness of growth.

Our work immensely draws upon two seminal works by Datt and Ravallion (1998) and Ravallion and Datt (2002) that raised similar questions but examined it from a different perspective. We complement and attempt to contribute by extending their work in three ways. First, while they consider Foster-Greer-Thorbecke (FGT) class of poverty measures to capture 'pro-poorness', we use a set of direct measures of pro-poor growth based on the recent development of the literature (Ravallion and Chen, 2003; Essama-Nssah and Lambert, 2009; Kakwani and Son, 2008; Duclos, 2009). Second, their work considers productivity to determine the role of the state, which, arguably, can be influenced by individual's performance. Here, the state's role is confined to, just as an enabling factor ignoring the fact that the state has a role to play as a federal institution as well, through their policy construction and implementation. We therefore, emphasize on the policy effects implemented by the state by making a clear distinction between affirmative and market-oriented policies. Third, we examine this heterogeneity by employing an econometric model which would find a policy threshold level and see the policy effectiveness above and below the threshold point.

Our findings suggest that controlling for state level socioeconomic and macroeconomic factors, redistributive policies significantly enhances the possibilities of growth to be more pro-poor. We also find systematic negative effects on incidence of poverty. However, results on overall inequality are not conclusive. Further, our results are consistent for economically deprived class of population for whom the welfare policies are primarily undertaken. Results are also consistent for an alternative measure of redistributive policy. It shows strong evidence of positive impact on pro-poor growth when initial levels of state endowments are controlled for. This means, irrespective of state's initial condition, any development policy even taken at an aggregate level, makes economic growth more inclusive. Furthermore, our estimates from linear panel reveal higher education has a significant impact while primary and secondary schooling does not seem to have an effect on our outcome variables. This leads us to test our hypothesis in a non-linear framework as it might be the case that may be a certain level of education helps in better policy utilization of states and thereby makes the growth process more inclusive. To address this, we make use of a static threshold panel model where estimated values from a threshold variable are interacted with our main variable of interest. Estimation results convey that the impact of welfare policies are asymmetric below and above a certain threshold value that is endogenously determined through a grid search method.

The remainder of the paper is structured as follows. Section 2 gives a brief background and discusses the literature that are related to this study. Section 3 presents the data, description of variables and the summary statistics. Section 4 introduces the estimation strategy and the baseline linear model. Main results are reported in Section 5. In Section 6 non-linear panel threshold models are laid out along with the findings. Section 7 draws some policy conclusions and raises some questions that might open avenues of future research in the domain of policy effectiveness on inclusive growth.

2. Background and Related Literature

Measurement of Inclusive growth

According to Ali and Son (2007), inclusive growth refers to 'growth coupled with equal opportunities'. However, beyond this there is ambiguity and there is no common definition of inclusive growth in this domain. Till date, the primary interpretation of inclusive growth with regard to the definitions, conceptualization and measurements, heavily relies on pro-poor growth and it is almost impossible to make a distinction between these two concepts (Ali and Son, 2007; Habito, 2009; Rauniyar and Kanbur, 2010).[7]

The approach to the measurement of pro-poor growth focuses on sustainable poverty reduction as manifested in the Sustainable Development Goals (SDG-1).[8] Numerous studies have argued that it is not growth alone but the quality of growth that makes the poverty reduction sustainable (IMF and UN, 2000; Klasen, 2003; Stiglitz et al., 2017). Pro-poor growth is the concept that deals with this 'quality' aspect of growth. More precisely, it evaluates the impact of economic growth on welfare by taking into account the distributional effects of growth. In this context, the nexus between growth, poverty and inequality has been widely discussed and significant attempts have been made to provide definitions and measurements of pro-poor growth such as: Kakwani et al. (2000), Ravallion and Chen (2003), Essama-Nssah (2005), Kakwani and Son (2008), Duclos (2009).

The major line of demarcation among these contributions seem to have boiled down to the generic debate between 'absolute' versus 'relative' approach. Ravallion and Chen (2003) defines growth is pro-poor if it reduces poverty. By this definition, the only condition is reduction in poverty during a growth spell. It does not matter however small may be the

7 In this study, we would be using both the terms, inclusive growth and pro-poor growth, interchangeably.

8 Among the 17 SDGs that United Nations have formulated, Goal 1 preaches Zero Poverty and Goal 10 addresses reduced inequality. For sustainable poverty reduction, both these goals are important to attain

decrease is. As opposed to this, Kakwani et al. (2000) defines pro-poor growth in both 'absolute' and 'relative' terms. According to the relative definition, it is pro-poor if the poor class gets proportionally more benefit than the non-poor class. In other words, a particular growth episode will be called 'pro-poor' in relative sense if there is redistribution in favour of the poor due to the growth.[9] Therefore, the relative concept implies that growth would reduce poverty and simultaneously improve relative inequality.

On the other hand, the 'absolute' definition identifies growth as pro-poor if the absolute benefit of the poor from growth is equal to, or greater than the absolute benefit of the non-poor. This is the strongest definition of pro-poor growth.[10] According to this definition the absolute inequality in the economy will fall during a growth process. Therefore, the fundamental requirement for growth to be pro-poor in relative sense is inequality must to go down. From a developing country's perspective absolute poverty reduction generally gets the utmost priority as a distributive policy objective whereas in developed countries largely relative approach is given importance because the presence of relative poverty and inequality is more prominent there. Duclos (2009) argues that the relative pro-poorness of growth may be substantiated if relative inequality has negative impact on growth and causes political and social instability, increases unequal opportunities, social exclusion or say it has an adverse effect of overall deprivation. Thus, the choice between these two definitions needs serious considerations of several positive and normative dimensions (Klasen, 2003; Duclos, 2009).

Another important distinction in this strand of literature is the use of the anonymity axiom between these measures. The axiom says that *two distributions are equivalent whenever one distribution is obtained from the other by a permutation*. This approach does not take into account the identity of a person or say household. For example, in our context, a universal policy would be assessed based on the aggregate welfare change in the distribution without considering identity of a particular person or households before and after their growth experience. On the other hand, non-anonymity approach allows us to compare income of a person at a specific quantile in current time period with income of that person at the same quantile in the subsequent period of time. Therefore, it is easily understandable that for such an exercise we need longitudinal data which is beyond our scope in the current exercise as NSS surveys do not track same households over years. Hence, we create quantiles under the

[9] Similarly, in case of negative growth (or contraction), the condition for pro-poorness is that the loss from contraction should be proportionally less for the poor compare to the non-poor.

[10] This definition can also incorporate negative growth in similar way: it is pro-poor if the absolute loss is less for the poor than the non-poor.

assumption that these quantiles represent the broad characteristics of respective income classes and their level of deprivation (or say achievement).

Government spending and inclusive growth

The early literature on growth and inequality used to be dominated by the influential Kuznets inverted-U hypothesis (Kuznets, 1955). However, systematic empirical evidence from cross-country studies suggest that this hypothesis has limited validation (see Adelman, 1973; Saith, 1983). Recent studies including World Bank report indicate that the target of inclusiveness cannot be achieved by economic growth alone unless redistributive policies are taken within countries. Lakner et al. (2014), Yoshida et al. (2014) argued that even with optimistic growth rate it will not be possible to eliminate world poverty without redistribution of income. A combination of growth with redistribution is the plausible way for sustainable poverty reduction (Ravallion, 2001; Son and Kakwani, 2008; Kalwij and Verschoor, 2007).

Redistributive policies through government spending towards a targeted population may directly increase the real disposable income of the poor households. On the other hand, redistributive welfare policies may increase the productivity and income of the poor by providing the better education, health, nutrition and other infrastructure Paternostro et al. (2005). However many empirical findings reveal that the benefit of welfare policies does not reach to poor households due to improper targeting and leakages. As for example, much of the benefits of health and education policies are taken by the middle income groups. Furthermore, researchers with opposite view, have argued that countries with higher indirect tax base may face an inflationary pressure while financing the government spending. This, ultimately reduces the purchasing power of the bottom class of the people. Therefore, implementing redistributive policies does not always act as a magic bullet. Wagle (2012) suggest, the direction and the effectiveness of redistributive policies largely depend on how pro-poorness is measured and the type of sample one uses for evaluation.

3. Data, Variables and Descriptive Statistics

Data

We use household consumer expenditure survey data (CES), conducted by the Indian National Sample Survey Office (NSS) for the computation of pro-poor growth indices and other deprivation indicators. The large, nationally representative survey, which comes in every five years, provides detailed socioeconomic and demographic information including household consumption expenditure, caste, household type, religion, household size, individual's level of education, among many. CES data is time tested, widely used and more importantly the Planning Commission (now NITI Aayog) uses estimated expenditure figures that comes from these surveys to calculate official poverty statistics which forms the basis of various transfers of central and state governments.

In particular, we use the CES rounds of 38 (1983), 43 (1987-1988), 50 (1993-1994), 55 (1999-2000), 61 (2004-2005), 66 (2009-2010) and 68 (2011-2012).[11] The sample consists of over one lakh households in all the rounds. Using these seven rounds of NSS-CES data, we construct a unique state level panel of 17 major Indian states that contains estimated indices of pro-poor growth, FGT class of poverty indices, Gini as a measure of overall inequality and other important control variables, such as, proportion of backward caste population, percentage of illiterates, years of schooling, average monthly per capita consumption expenditure and average level of education in the state.

Important to note, unlike other consumer expenditure surveys, NSS 55th round used a different questionnaire to record household expenditure data. In this round, same households were asked to report expenditures for both 30-day and 7-day recall periods whereas in other CES rounds the same information was collected from different households. Additionally, this round also collected data on "low frequency items" for the last 365-day period substituting the usual 30-day reporting. The difference in recall periods across rounds is expected to create a downward bias specifically for the bottom tail of the distribution. To avoid potential estimation bias that may occur due to this, we include an additional control variable for this round in all our model specifications.

We use poverty lines that are officially published by the planning unit of Ministry of Statistics and Programme Implementation, Government of India. A consistent absolute poverty measure should reflect the cost of a fixed standard of living over the years and across sectors (Ravallion et al., 1994). The Indian poverty threshold is derived by using calorie norms of 2400 kilocalorie per capita per day for rural sector and 2100 kilocalorie per capita per day for urban sector. A typical poverty line is set for rural and urban areas separately on the basis of the level of average monthly per capita expenditure at which these "minimum requirement" calorie

[11] After 2011-12, though surveys are conducted but the data has not been released yet by the government.

norms are attained. Therefore, by definition, real poverty lines should allow us to compare incidences of poverty over years and across sub-national units. Note, we use household monthly per capita consumption expenditure (MPCE) for the computation of state level pro-poor growth measures and other dependent variables.[12] In order to compare the consumption expenditure figures over time, we use consumer price index for agricultural labourer (CPI-AL) and for industrial worker (CPI-IW) as the price deflator for rural and urban sector respectively, fetched from the Handbook of statistics on Indian economy, Reserve bank of India (RBI).

Moving on to our main interest variable, we collect information on state's developmental and non-developmental expenses from RBI annual studies on state finances and various budget documents of respective state governments. Corresponding state level series, deflated by the respective price indices, were mapped with our constructed panel dataset. Data on Net State Domestic Product (NSDP) at constant prices were collected from the Central Statistical Organization (CSO). Population figures from census data is used to generate per head share of respective variables. Further, we gather information related to crimes from "Crime in India" reports of the National Crime Records Bureau (NCRB) at the Ministry of Home Affairs.

Descriptive Statistics

Table A2 presents the summary statistics of all the variables used in the regressions including outcome and our main interest variables. By construction, PEGR uses FGT class of indices. Therefore following standard notation, α can be interpreted as the 'deprivation aversion' parameter. With increase in α, that is if higher weights are given to the deprived class of population, the average value of the PEGR decreases implying the chances of pro-poorness would be less as average income growth - the critical value for pro-poor growth judgment - will remain same. For example, the corresponding mean values of PEGR and per capita income growth in Table A2 tells us the country level average values of the index and mean income respectively for the entire period of study. At α=0, the evidence suggests that the growth process has been pro-poor. However, with α >0, it is clearly anti-poor.

[12] Consumption expenditure is used as a proxy of income assuming that it posits a monotonic relationship with per capita income. Arguably, consumption distribution is a better measure of living standard than income. Further, this is a standard practice in the empirical literature especially in developing countries context, where, in most cases, systematic income data are not available. See Deaton and Kozel (2005), Anand and Ravallion (1993) and Ravallion et al. (1994) for more details and discussions.

Variables

Outcome: Measures of inclusive growth and deprivation

A set of alternative pro-poor growth indices are estimated following Kakwani et al. (2000), Ravallion and Chen (2003) and Kakwani and Son (2008). Primarily we use these three measures as the main outcome variables in our causal analysis. By construction, Ravallion and Chen (2003)'s measure, named Rate of pro-poor growth (RPPG), uses Watts index while Kakwani and Son (2008)'s Poverty equivalent growth rate (PEGR) uses a social welfare function in its generic form. Kakwani and Son (2008) argues that PEGR is valid for all poverty indices that follows fundamental axioms of poverty.

We use FGT class of indices for the estimation of PEGR largely because of three reasons. First, FGT has been used in this domain of literature for a long time now and thus it is time tested, robust and abides by all the poverty axioms (Foster et al., 1984, 2010). Second, it is easy to compute using the available STATA-DASP program given by Araar and Duclos (2013). Third, it takes care of the adjustment in inequality simultaneously with poverty. Important to note, both Ravallion and Chen (2003) and Kakwani and Son (2008) satisfy monotonicity axiom which is fundamental to the pro-poor growth measure – the reduction in indicators of deprivation should be a monotonically increasing function of the proposed index. However, Kakwani and Pernia's earlier index (Kakwani et al., 2000) fails to fulfill such basic axiomatic requirements (Kraay, 2006; Duclos, 2009). Although we use Kakwani et al. (2000) as one of our dependent variables but in line with what has been highlighted in the literature by others, we too do not find any systematic causal evidence with this index and hence we do not report results from those regressions.[13]

In addition to the set of pro-poor growth indices, as mentioned earlier, we also use standard poverty measures – Head count ratio (HCR), Poverty gap ratio (PGR) and Squared poverty gap ratio (SPGR) – to gauge the impact on poverty along with the Gini index that estimates the effect on overall inequality. Note, for computation of these indices monthly per capita consumption expenditure (MPCE) is used as a proxy of income.

Main interest variable: Social sector expenditure

[13] Results can be obtained on request

State's developmental and non-developmental finances, consisting of resources expended by the state governments according to their policy priorities and capacity is used as the measure of redistributibe policy. As documented in various state finances report, published by the RBI, social service expenditure (SSE) contains the largest part of the total social sector expenditure expended by the respective state governments. It is accounted under three separate heads – revenue expenditure, capital expenditure (or outlay) and loans and advances in state governments.[14] In this study, we use that part of SSE which exclusively accounts for the total revenue expenditure.

Arguably, revenue expenditure is accepted as a good proxy of state capacity and because SSE constitutes highest share in revenue expenditure, it should capture the maximum variation in revenue expenditure and thereby capacity of the state. Social service spending largely comprises of expenses incurred to the following: education, medical and public health, family welfare, welfare of backward castes, social security, among many. Education and health related expenses constitutes more than 50 percent of the total SSE. This clearly indicates that these are the groups that captures major variation in SSE (see Figure A1). However, we do not use dis-aggregated group level expenses, instead restrict our main interest variable to aggregate social service spending as we are mainly interested in the overall impact of redistributive policies.

Controls

Drawing from the existing literature and taking into account the Indian context, we use a number of state-specific socioeconomic, education related and political variables as controls in our model. There exists a rigid hierarchy in terms of individuals' socioeconomic status, called 'caste' groups, in India. Scheduled castes and Scheduled tribes (SC/ST) are considered to be the most economically deprived class of people. Presence of these groups with higher number in states may attract deliberate targeting and that can drive disproportionate monetary allocation from the state. Similar arguments can be drawn for Muslims which constitutes a major religious group, and considered to be economically backward than the dominant religious groups, the Hindus. Acemoglu et al. (2014) highlight the inclusion of education related controls can capture the effect of institutions when direct measures are not included in

[14] State finances: A study of budgets" is a stand-alone report (since 1999-00) by Indian federal bank which provides detailed information on state finances gathered using various budget documents of the state governments. It can be found here: https://www.rbi.org.in/Scripts/publications.aspx (accessed on July 31, 2020).

the model. Also, differences in levels of education might lead to differential capacity utilization of welfare policies. We construct six education related categories that include percentage of people who have no formal education, and percentage of people who have attained at least 5, 8, 10, 12 and more than 12 years of schooling in a particular state. An additional control to capture state's average level of education is also included in our model.

The absence of robust economic and political institutions, leading to higher transaction costs, increased leakages and thereby less accountability among local implementing authorities, can hinder the effectiveness of welfare policies (Besley and Burgess, 2000; Besley et al., 2005). To ensure these mechanisms do not otherwise impact our causal effects, we use a variable that controls for the quality of the economic institutions at state level. NCRB reports state level information on the percentage of property recovered by the police which would potentially capture the effectiveness of the institutions that oversee local law and order (governance) in states. Lastly, we include a variable on party ideology following Chhibber and Nooruddin (2004) and Dash and Raja (2014), who provide ideology scores for all national and major regional parties. As argued above, ideological differences across political parties can form the basis of formulation and implementation of redistributive policies. For example, Chhibber and Nooruddin (2004) identify the differences in government expenditures across states are largely driven by the existing party systems. In addition, we also include a centre/state party dummy that takes 1 if same party is in power in both centre and in state, and 0 otherwise. This is introduced to capture the potential political friction that might occur due to differences in centre and state party's ideology. We include these variables as controls to ensure that our estimates are not driven by any other alternative mechanisms.

4. Empirical Strategy

Baseline linear model

Our first approach to estimating the causal effects of redistributive policy on welfare outcomes is to posit a panel data model for the respective outcome variables. The baseline model for the same is specified as:

$$Y_{it} = \alpha + \beta_1 lnSSE_{it-1} + \beta_2 lnSSE_{it-1}^2 + \sum_{j=3}^{15} \beta_{j.} X_{ijt} + \gamma_i t + u_{it} \qquad (1)$$

Equation (1) can be written in a vector-matrix notation as –

$$Y_{it} = X_{it}'\beta + u_{it} \qquad (2)$$

Where Y_{it} represents our outcome variable of interest for state i at time t. $\beta = (\alpha\ \beta_1 \cdots \beta_{15}\ \gamma_1 \cdots \gamma_{17})'$ is the (33 x 1) vector of parameters of interest including a constant term and separate trend coefficients for all states. X_{it} is the vector of explanatory variables containing ln*PCSSE*, squared ln*PCSSE*, a set of controls, trend for each state and a vector of ones. We include a square term of our main variables to allow for potential non-linear effects of PCSSE. Additionally, we include state specific time trend dummies to control for potential time trended omitted variables.

As all our dependent variables represent development outcomes and arguably there is time delayed effects to any exogenous variation for such outcomes, we consider a one period lag for social sector spending. A one period lag represents a gap of five year time period analogous to releases of various large sample NSS data rounds. Intuitively, once a particular policy is announced, it does not get implemented with immediate effect in a large country like India. In addition to the administrative bottlenecks, there are numerous market frictions that makes the delay happen. Therefore, it would be reasonable to assume, if at all any policy has an impact, it should have at least some reflection on the target outcomes within the period of five years.

In a panel data framework, each state may have specific time invariant unobserved characteristics. Hence, the error term, u_{it}, can generally be written as: $u_{it} = \mu_i + v_{it}$

It is likely that the unobserved state fixed effects, μ_i, are correlated with the explanatory variables leading to biased and inconsistent estimates while using ordinary least square. Hence equation (2) can be augmented by including state dummies as

$$Y_{it} = X_{it}'\beta + \mu_i + v_{it} \qquad (3)$$

where the random error term, $v_{it} \sim iid\ (0, \sigma_v^2)$ are uncorrelated with the regressors. To avoid over parameterisation we have considered a fixed effect estimation β eliminating all μ_i by *within* transformation. Note, the heteroscedasticity corrected standard errors from the regression are clustered at the state level. We include additional controls and required explanatory variables in our baseline model mainly for robustness checks. We discuss this in respective sections.

5. Baseline Results

Main results

Table 1 presents causal effects of state level welfare policies on inclusiveness of growth and indicators of deprivation. The estimated coefficients of pro-poor growth, poverty and in-equality are shown in column (1) to (4), (5) to (7) and in (8) respectively. We get positive and significant effects on pro-poor growth. This implies, controlling for other potential confounding factors, if social spending increases, the impact on RPPG would go up by 2.536 units. Note that a positive coefficient on the pro-poor growth indices does not directly allow us to claim the growth process was “inclusive”. This is because, the judgment - pro-poor or anti-poor - exclusively depends on the norms that is set on the basis of some critical values, say the mean or median rate of growth. It would rather be fair to argue that such positive values of the coefficients imply, the chances of becoming a growth process ‘inclusive’ are more if such redistributive policies are taken by state governments.

We find similar positive and significant impacts for PEGR. The results are consistent with higher values of α but as expected it declines with increase in α. This implies, the chances of becoming a growth process pro-poor are less if the degree of deprivation is higher among the bottom class of people. In other words, with higher inequality in the income distribution, the distributional impact of economic growth, adjusted for levels of inequality and poverty, is likely to be less pro-poor.

Coming to additional set of deprivation measures, we find that the impact is negative for the set of poverty indices. This signifies that if states adopt a new welfare measure in addition to the current ones, or say, allocate additional funds to an existing program, that would reduce incidence of poverty in the economy magnifying the chances of growth to be more inclusive. Again like the previous findings with PEGR, we see that the magnitude of the coefficients reduces with higher α, corroborating the fact that introduction of inequality in the deprivation measure would reduce the chances of pro-poorness.

Further, as explained in equation 3, we allow non-linearity in our model and capture it by introducing a quadratic term for SSE. Estimated coefficients of the non-linear predictor would allow us to infer about the nature of the relationship. Theoretically, a positive sign of the estimated coefficient indicates the relationship is convex and a negative sign would mean otherwise. The results suggest a convex relationship with our primary outcome variables and a concave relationship for the class of poverty measures, conveying the fact that other things held constant, marginal increase in social spending has a positive and significant impact on the changes in pro-poor growth.

The negative significant coefficients for lagged MPCE gives an interesting insight (see Table A3). MPCE is the average consumption level occurred in last 30 days. Because it represents average expenditure of the entire distribution, it is highly likely that it would be dominated by the expenditures from upper tail of the distribution. For example, benefits from a growth episode is likely to increase the income of the rich way more than the poor. Therefore, in terms of 'inclusiveness' this would make the episode anti-poor. The negative coefficients on MPCE indicates the same. Moving on to other education related factors, we do not find systematic evidence for primary schooling, however, higher education seems to be a positive determinant of pro-poor growth. Positive impact of lagged NSDP suggests overall increase in state GDP might be important. However, the effect size is significantly lower than the impact of social sector expenditure. Results from a two sided mean test presented in the bottom row of A3 confirms this.

Table 1: Impact of state policies on pro-poor growth and deprivation (Full sample)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	RPPG	$PEGR_{\alpha=0}$	$PEGR_{\alpha=1}$	$PEGR_{\alpha=2}$	HCR	PGR	SPGR	Gini
Panel A: Unrestricted model								
Ln$PCSSE_{t-1}$	2.536***	3.998***	3.874***	3.799***	-2.699**	-0.413**	-0.135**	0.0154
	(0.645)	(1.106)	(1.061)	(1.001)	(1.084)	(0.154)	(0.062)	(0.069)
Ln$PCSSE_{t-1}^2$	0.121***	0.188***	0.183***	0.179***	-0.128**	-0.0199**	-0.0067*	0.0006
	(0.032)	(0.054)	(0.053)	(0.050)	(0.054)	(0.008)	(0.003)	(0.003)
R-squared	0.88	0.87	0.87	0.88	0.89	0.91	0.89	0.77
Panel B: Restricted model								
Ln$PCSSE_{t-1}$	4.043***	5.615***	5.363***	5.356***	-3.765***	-0.454**	-0.123	-0.0622
	(0.575)	(0.928)	(0.847)	(0.809)	(0.797)	(0.183)	(0.079)	(0.107)
Ln$PCSSE_{t-1}^2$	0.185***	0.254***	0.244***	0.244***	-0.172***	-0.0190**	-0.0048	-0.0030
	(0.027)	(0.043)	(0.040)	(0.038)	(0.038)	(0.009)	(0.004)	(0.005)
R-squared	0.51	0.51	0.52	0.53	0.77	0.76	0.72	0.45
Panel C: Restricted model								
Ln$PCSSE_{t-1}$	4.043***	5.615***	5.363***	5.356***	-3.765***	-0.454***	-0.123*	-0.0622

	(0.575)	(0.885)	(0.819)	(0.788)	(0.680)	(0.154)	(0.068)	(0.094)
Ln$PCSSE_{t-1}^2$	0.185***	0.254***	0.244***	0.244***	-0.172***	-0.0190**	-0.0048	-0.0030
	(0.028)	(0.044)	(0.040)	(0.039)	(0.033)	(0.008)	(0.003)	(0.005)
R-squared	0.51	0.51	0.52	0.53	0.77	0.77	0.73	0.46
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State specific trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of state	17	17	17	17	17	17	17	17
Observations	102	102	102	102	102	102	102	102

Note: Panel A provides unrestricted model with all controls. Panel B and C are restricted model with limited controls. Heteroscedasticity corrected standard errors clustered at state level are provided in parentheses for Panel A and B. Standard errors in Panel C are bootstrapped and clustered with 500 repetitions. Regression tables with all controls are provided in appendix table A3, A17, A18. ***p<0.01, ** p<0.05, * p<0.1.

Heterogeneous impact across income class

Typically redistributive policies are undertaken as a measure of affirmative action (Drèze and Sen, 2013). Therefore, the gains from such redistributive policies are expected to be heterogeneous across and within the targeted income classes or disadvantaged groups. Ideally, the bottom class of people or the disadvantaged groups for whom the affirmative policies are primarily formulated should gain more benefit than the non-poor. However, literature provides mixed evidence in support of such achievements. Numerous studies have highlighted that due to various market frictions such as agents rent seeking behaviour, elite capture, transaction cost and political clientelism programs often do not create desired outcome (Afridi et al., 2017; Maiorano et al., 2018; Bardhan and Mookherjee, 2012). So it is important to test if increase in social spending at aggregate level has any differential impact on pro-poor growth and deprivation that are estimated at the sub-group level identified as income class and socioeconomic caste groups.

Table 2 provide results for the bottom 20 percent and bottom 40 percent income class of population respectively. Overall, there is no qualitative change in terms of direction of the causality. However, in Table A4 and in Table A5 marginal effects for HCR, PGR, SPGR and PEGR show relatively higher magnitude. Therefore, increase in social spending has slightly higher effects for the poorest 20 percent than the poorest 40 percent population. In addition, it can be seen that for HCR the impact is quite high. This is primarily because in context of large developing countries like India, the density of the distribution around the poverty line is quite high. As a result any transfer will have a reflection on poverty measured in terms of head count ratio but not on the depth or spread of it. In accordance with previous full sample results, we observe higher education (percentages of persons with 12 years of schooling) has a positive impact on pro-poor growth and for illiteracy the impact is negative on FGT class and positive on RPPG (see Table A5).

Table 2: Heterogeneous impact of state policies across income class

Variables	(1) RPPG	(2) $PEGR_{\alpha=0}$	(3) $PEGR_{\alpha=1}$	(4) $PEGR_{\alpha=2}$	(5) HCR	(6) PGR	(7) SPGR	(8) Gini
				Panel A: Bottom 20%				
Ln*PCSSE*t−**1**	3.421***	4.725***	4.363***	4.202***	-8.078***	-1.972***	-0.548**	0.0249
	(0.95)	(1.40)	(1.37)	(1.24)	(2.03)	(0.52)	(0.21)	(0.13)
Ln*PCSSE*t−$\mathbf{1}^2$	0.164***	0.226***	0.208***	0.200***	-0.377***	-0.092***	-0.026**	0.001
	(0.05)	(0.07)	(0.07)	(0.06)	(0.10)	(0.03)	(0.01)	(0.01)
				Panel B: Bottom 40%				
Ln*PCSSE*t−**1**	2.253***	3.622***	3.522***	3.590***	-3.769**	-1.712**	-0.448*	0.0203
	(0.56)	(1.15)	(1.11)	(1.08)	(1.49)	(0.60)	(0.24)	(0.11)
Ln*PCSSE*t−$\mathbf{1}^2$	0.107***	0.173***	0.168***	0.171***	-0.174**	-0.080**	-0.022*	0.001
	(0.03)	(0.06)	(0.05)	(0.05)	(0.07)	(0.03)	(0.01)	(0.01)
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State specific trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of state	17	17	17	17	17	17	17	17
Observations	102	102	102	102	102	102	102	102

Note: Heteroscedasticity corrected standard errors clustered at state level are provided in parentheses. Regression tables with all controls are provided in appendix table A4, A5 *** p<0.01, ** p<0.05, * p<0.1.

Effects of Liberalization

India started adopting pro-market policies from mid-1980s and the pace of policy change was accelerated in the beginning of 1990s when implementation of market oriented policies were given explicit preference over state intervention for redistributive policies. Literature has marked this as the beginning of the change in attitudes towards policy making as well as the concept of ‘state’ as a federal institute. Literature on the effect of liberalization provides mixed evidence. For instance, Bhalla (2003) argued that as a result of the major economic reforms in 1991, the rate of economic growth accelerated, so as the reduction in poverty and inequality. As per his estimation, the reduction in poverty is primarily due to the growth not inequality. A meager one tenth of the reduction comes from inequality, while rest of it accounts to higher growth that has solely occurred due to the economic reforms. On the contrary, Pal and Ghosh (2007), Sen and Himanshu (2004a,b) and Deaton and Dreze (2002); Deaton (2003a,b,c) provide estimates that suggest poverty and inequality has actually increased in the post liberalization period. The ambiguity creates a perfect background for us to examine the effect of liberalization on the set of outcome variables that we have at hand.

Table 3 provides first set of results on the impact of liberalisation. Here, liberalisation is constructed as a dummy variable which takes 0 and 1 for the pre and post liberalization period respectively. We observe an overall negative impact of liberalisation on the inclusive growth and a modest impact on poverty. We see the coefficients are positive and significant for HCR and PGR. However, the impact is statistically indistinguishable from zero for FGT and Gini index.

Further, we interacted per capita social sector expenditure with liberalization dummy just to see whether PCSSE has any differential impact in pre and post liberalisation period. To do that we create another dummy variable, putting 1 for the states that had higher PCSSE than the country average and 0 elsewhere. We observe in Panel B, Table 3, the coefficients for the interaction between pre-liberalisation and above average PCSSE is positive and significant, suggesting the growth process was way more inclusive for states with higher social spending in pre-liberalization period. In contrast, we find in the post liberalisation period the impact on 'inclusiveness' is negative for states with below average PCSSE, and the impact is indistinguishable from zero for states with above average PCSSE.

Table 3: Effects of liberalization (Full sample)

Variables	(1) RPPG	(2) $PEGR_{\alpha=0}$	(3) $PEGR_{\alpha=1}$	(4) $PEGR_{\alpha=2}$	(5) HCR	(6) PGR	(7) SPGR	(8) Gini
Panel A: Overall impact								
$\mathrm{Ln}PCSSEt{-}1$	1.541*	1.794	2.011**	2.145**	-0.938	-0.1900	-0.048	0.0637
	(0.733)	(1.103)	(0.908)	(0.831)	(0.954)	(0.136)	(0.051)	(0.076)
$\mathrm{Ln}PCSSEt{-}1^2$	0.0730*	0.0821	0.0936**	0.0996**	-0.043	-0.0092	-0.003	0.0029
	(0.035)	(0.053)	(0.044)	(0.040)	(0.046)	(0.007)	(0.003)	(0.004)
Liberalization	-0.0718*	-0.159***	-0.135***	-0.119***	0.127***	0.0161*	0.006	0.0035
	(0.037)	(0.040)	(0.031)	(0.030)	(0.031)	(0.009)	(0.004)	(0.004)
Panel B: Interaction effects								
$\mathrm{Ln}PCSSEt{-}1$	2.574***	2.866**	2.875***	2.907***	-1.734*	-0.320**	-0.0913	-0.011
	(0.779)	(0.993)	(0.960)	(0.924)	(0.969)	(0.149)	(0.059)	(0.103)
$\mathrm{Ln}PCSSEt{-}1^2$	0.121***	0.132**	0.134**	0.135***	-0.0799	-0.015*	-0.0045	-0.001
	(0.037)	(0.048)	(0.046)	(0.044)	(0.047)	(0.007)	(0.003)	(0.005)
I(PCSSE> μ*PCSSE*) * I(Year<1991)	0.253***	0.248***	0.203***	0.178***	-0.184***	-0.031***	-0.010*	-0.018**
	(0.042)	(0.049)	(0.053)	(0.052)	(0.034)	(0.009)	(0.005)	(0.007)
I(PCSSE < μ*PCSSE*) * I(Year>1991)	-0.063**	-0.104***	-0.091**	-0.080**	0.086***	0.010	0.004	-0.0003
	(0.024)	(0.034)	(0.031)	(0.034)	(0.028)	(0.009)	(0.005)	(0.003)
I(PCSSE> μ*PCSSE*) * I(Year>1991)	-0.0044	-0.060	-0.062	-0.0520	0.0522	0.006	0.0025	-0.003
	(0.038)	(0.052)	(0.048)	(0.052)	(0.046)	(0.014)	(0.007)	(0.004)

Note: Heteroscedasticity corrected standard errors clustered at state level are provided in parentheses. Regression tables with all controls are provided in appendix table A10, A11. *** p<0.01, ** p<0.05, * p<0.1.

Robustness checks

A series of robustness checks are performed to ensure our causal estimates are qualitatively correct. We construct an alternative measure of social spending first and rerun all our models. In addition to that, we also test whether differential initial condition in the beginning years has any impact on our outcome variables.

Alternative measure of social spending

An alternative measure of social spending is constructed using total development expenditure of the state as a share of total revenue expenditures. As reported in the state budgets, development expenditure is an aggregation of expenses incurred to social services, economic services and general economic services. It comes under the head of revenue expenditure which comprises of developmental and non-developmental expenditures. By definition development expenditure is broader than social spending. Thus, we expect the evidence might not be as strong as the previous ones but even if we get some effects using this, it would be fair to argue that in general welfare policies has positive impact on our outcome variables.

Table 4: Impact of development expenditure on pro-poor growth and deprivation

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Variables	RPPG	$PEGR_{\alpha=0}$	$PEGR_{\alpha=1}$	$PEGR_{\alpha=2}$	HCR	PGR	SPGR	Gini
Full Sample	Ln*(DE/RE)*t−1	0.177**	0.268***	0.259***	0.243**	-0.249**	-0.052**	-0.021*	0.010
		(0.08)	(0.09)	(0.09)	(0.09)	(0.10)	(0.02)	(0.01)	(0.01)
Bottom 20%	Ln*(DE/RE)*t−1	0.236***	0.273***	0.278***	0.269***	-0.519***	-0.147***	-0.500**	-0.014
		(0.06)	(0.06)	(0.08)	(0.08)	(0.13)	(0.04)	(0.02)	(0.01)
Bottom 40%	Ln*(DE/RE)*t−1	0.137**	0.254***	0.232***	0.229***	-0.186	-0.152*	-0.061*	-0.009
		(0.06)	(0.06)	(0.06)	(0.06)	(0.14)	(0.08)	(0.03)	(0.01)
State fixed effect		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State specific trend		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of state		17	17	17	17	17	17	17	17
Observations		102	102	102	102	102	102	102	102

Note: Heteroscedasticity corrected standard errors clustered at state level are provided in parentheses. Regression tables with all controls are provided in appendix table A6, A7 and A8. *** p<0.01, ** p<0.05, * p<0.1.

Table 4 presents our findings. Like previous specifications, we use a five year lag for our main independent variable and we find similar positive and significant coefficients for pro-poor growth and negative impact on poverty.[15] For education related variables, consistent with the previous results we see a positive effects on more than 12 years of schooling on pro-poor

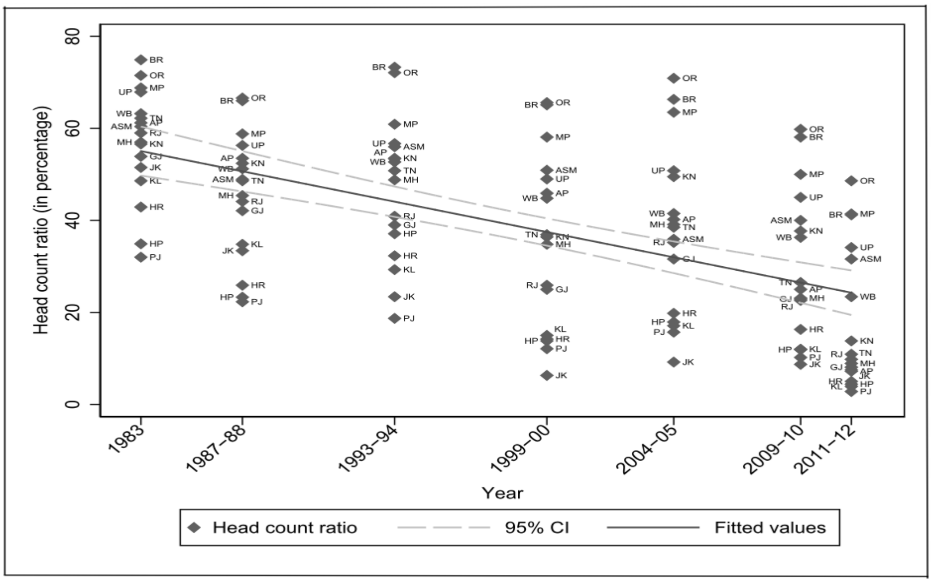
[15] Note, only for this model specification, we had to drop the square term as it turned out that they are perfectly correlated

growth. Similar findings in terms of the direction of causality can be seen for the poorest 20 percent and 40 percent of the population.

Initial condition

Glaeser et al. (2004), Acemoglu et al. (2019) among many others, have argued that initial endowments of an economy (such as human capital, wealth, per capita income, institution quality etc.) might have an impact on growth as well as on the better welfare of the economy. Although literature has examined the determinants of growth but one can see that there is a strong connection between levels of prosperity and levels of deprivation. The connection between the initial level of endowments and subsequent growth or between economic growth and changes in poverty is often quite strong (Sen 2012). Thus, while the literature has succeeded to a large extent to causally show the drivers of growth and deprivation, it remains an empirical question whether results are robust even when the level effect of initial endowments are controlled for. For example, in Figure 2, in the initial years Punjab and Kerala, two richest states in India, were among the bottom five which had lowest incidence of poverty. Interestingly, in 2011-12 both the states remain in the bottom in terms of the ratio of people living below poverty line, clearly indicates a possible impact of initial endowments. Therefore, a pertinent exercise would be to test whether our results holds true irrespective of the effect of initial endowments.

Figure 2: State wise poverty trends in India (1983 to 2011-12)



Note: Scatter plot showing state level poverty ratios between 1983 to 2011-12. A linear fitted plot is drawn to get the secular trend with 95 percent confidence interval, shown as the solid and dashed line respectively. Tendulkar poverty line figures adjusted with appropriate consumer price indices have employed to compute state level poverty ratios. Household consumer expenditure data from various NSS quinquennial rounds are used to generate the above figure.

Table 5 provides results where we include an initial dummy in Equation 3 based on three criteria – (a) states which had per capita income greater than the country average in 1983 (b) states which had higher poverty elasticity to growth than the average in 1983 and (c) states which had per capita net state domestic product higher than the national average. We consider those states as better off which qualify all three criteria and gets a score of three. Then we create an initial dummy variable and interact it with lagged values of the real MPCE. Coefficients of the interaction term turns out to be negative similarly to what we observed in our earlier results. Importantly, our main results do not get contaminated except for a marginal reduction in effect size. This allows us to conclude the fact that effect of welfare policies does not depend on the initial level of economic condition, although it might be more favourable to inclusive growth in states which had greater levels of higher education and less illiteracy. Similar line of arguments can also be drawn for poverty.

Table 5: Impact of state policies controlling for initial conditions of states

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	RPPG	PEGRα=0	PEGRα=1	PEGRα=2	HCR	PGR	SPGR	Gini
LnPCSSEt−1	2.172**	3.462**	3.406**	3.342**	-2.694**	-0.468**	-0.164**	-0.0038
	(0.760)	(1.262)	(1.272)	(1.259)	(1.015)	(0.161)	(0.075)	(0.067)
LnPCSSEt−1^2	0.107**	0.167**	0.165**	0.161**	-0.128**	-0.0221**	-0.0078*	-0.0002
	(0.040)	(0.064)	(0.064)	(0.064)	(0.051)	(0.008)	(0.004)	(0.003)
LnMPCEt−1 * Initial dummy	-0.794***	-1.202***	-1.059***	-1.031***	0.297**	0.015	-0.0034	0.0041
	(0.210)	(0.291)	(0.229)	(0.197)	(0.136)	(0.022)	(0.011)	(0.034)
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State specific trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of state	17	17	17	17	17	17	17	17
Observations	102	102	102	102	102	102	102	102

Note: Heteroscedasticity corrected standard errors clustered at state level are provided in parentheses. Regression tables with all controls are provided in appendix table A9. *** p<0.01, ** p<0.05, * p<0.1.

6. Testing role of education in a non-linear setting

It is therefore evident that government has an important role to play in terms of redistribution of income and inclusiveness of growth (see, Alesina and Rodrik (1994)). The previous analysis has discussed extensively how state government can improve pro-poor growth in terms of its social sector expenditure in the case of India. However, there are various conditions on which the impact of government spending towards inclusiveness varies (Wagle, 2012). These conditions include the sector where the spending is allocated, how well it is targeted, corruption and leakages, state institutional conditions, government size, among many. Many authors have tried to find out various optimal conditions for the effectiveness of such government spending.

In this part, we examine how the level of education in a state determines the efficacies of government policies leading to heterogeneous outcomes in terms of inclusiveness of growth. In particular, does possessing a minimum level of education make the impact of redistributive policies more effective on pro-poor growth? To the best of our knowledge, no study has considered education level as a threshold/benchmark in examining the potential channels of government expenditure towards pro-poorness of the states, especially in the context of India. Additionally, while the previous studies have considered growth, poverty and inequality separately, our composite indices of pro-poor growth capture a combined effect of the three. However, there is ample evidence in the literature that suggests the impacts of education on personal earnings – and thereby reduction in poverty – is positive and significantly large in developed countries (Hofmarcher, 2021; Brunello et al., 2009). In developing countries context, Tilak (2007) presents evidence for India that shows the contribution of secondary and higher education in development has a significant role to play for poverty reduction and for improving other welfare outcomes, such as per capita income, economic growth, infant mortality, and life expectancy. The proponents of '*Redistribution with Growth'*, Chenery et al. (1974), argue that public policy should promote education as an instrument to achieve more equitable distribution of growth, human capital and social benefits.

Therefore, we further analyze whether level of education has any role to channelize the impact of state governments' policies towards the poor or not. To test this, we employ a non-linear threshold panel model where different categories of education that was earlier used in the baseline model are considered as threshold variable separately. The choice of threshold variable differentiates all states into two groups depending on whether the threshold variable is above or below a specific value, known as threshold value. The novelty of this model is that the threshold value is considered as unknown parameter and estimated from the model itself. Hence, in our context, if the threshold effect exists, i.e., if the relationship between policy variable and the outcome variable alter below and above a critical level of education, we can conclude that the policy effects are asymmetric for a certain level of education.

Static panel threshold model

Following Tong and Lim (1980) and Tsay (1986), Hansen (1999) extends threshold regression specification in case of static panel model based known threshold variable. The single-threshold model in panel data is given as

$$y_{it} = \begin{cases} X'_{it}\beta_1 + \mu_i + v_{it}, & q_{it} \leq \gamma \\ X'_{it}\beta_2 + \mu_i + v_{it}, & q_{it} > \gamma \end{cases} \quad (4)$$

where q_{it} is the known threshold variable. In our case we have considered several indices of education level of the states and per capita consumption expenditure as threshold variables. γ is the unknown threshold value, to be estimated, that divides the equation into two regimes with coefficients vectors β_1 and β_2. X_{it} is a vector of k number of regressors. The parameter μi is the country specific fixed effect as discussed in the linear fixed effect model, while v_{it} is the error term. Alternatively, we can write Equation (4) with the help of an indicator variable I(·).

$$y_{it} = \beta'_1 X_{it} I(q_{it} \leq \gamma) + \beta'_2 X_{it} I(q_{it} > \gamma) + \mu_i + v_{it} \quad (5)$$

where I(·) is an indicator variable taking value 1 if the argument inside parenthesis is true and takes 0, otherwise. To write the Equation (4) in much compact way, we define

$$X_{it}(q_{it}, \gamma) = \begin{pmatrix} X_{it} I(q_{it} \leq \gamma) \\ X_{it} I(q_{it} > \gamma) \end{pmatrix}$$

and $\beta = (\beta'_1\ \beta'_2)'$ such that

$$y_{it} = \beta' X_{it}(q_{it}, \gamma) + \mu_i + v_{it} \quad (6)$$

To identify the parameter vector for each regime it is assumed that the elements of X_{it} and the threshold variable q_{it} are not time invariant. It is also assumed that the error term is independently and identically distributed with mean 0 and variance σ^2, *i.e.*, $v_{it} \sim iid(0, \sigma^2)$.

As μ_i is correlated with the regressor under fixed effect model, it is required to eliminate the country specific mean to estimate the parameter vector β. Let Y^* and X^* denote the within group deviations of Y and X respectively in the matrix notation, given γ the least square estimates of β can be written as

$$\hat{\beta} = \{X^*(\gamma)' X^*(\gamma)\}^{-1} \{X^*(\gamma)' Y^*\}$$

The sum of squared errors is

$$S_1(Y) = \hat{v}^*(\gamma)'\hat{v}^*(\gamma) \qquad (7)$$

where $\hat{v}^*(\gamma)$, the OLS residual of Equation (4), depends on the threshold value γ.

To estimate γ one can search over the threshold variable q_{it} and estimate γ as

$$\hat{\gamma} = \arg min\, S_1(Y)$$

where S_1 is the residual sum of square of the threshold model.

It is also important to note that, the usual static threshold panel model deals with a single intercept though two regime has been considered for the slope coefficients. In our model we have consider separate intercept term for each regimes. Here we first estimate the threshold value following Hansen (1999) and once the threshold value is estimated we re-estimate the model including separate intercept.

Asymptotic distribution of threshold estimate and testing for threshold

Hansen (1999) proposed a non-rejection region of the threshold value using a likelihood ratio test on γ. The null hypothesis of H_0: $\gamma = \gamma_0$ against the alternative H_1: $\gamma \neq \gamma_0$ is tested using

$$LR_1(\gamma) = (S_1(\gamma) - S_1(\hat{\gamma}))/\hat{\sigma}^2$$

where $\hat{\sigma}^2$ is the residual variance of the model with the threshold value $\hat{\gamma}$, *i.e.*, $\hat{\sigma}^2 = S_1(\hat{\gamma})/(n \times (\mathrm{T}-1))$. Hansen (1999) has provided the asymptotic critical values using the formula $C(\alpha) = -2\log(1-\sqrt{1-\alpha})$ where α represents level of significance. More specifically 1%, 5% and 10% critical values are given as 10.59, 7.35 and 6.53 respectively. This test can also be used for testing the existence of a nonlinear threshold model. Rejection of the null hypothesis for all possible values of γ_0 implies that non-existence of such threshold. We draw the sequence of LR statistic for all possible values of γ_0. A failure of rejection of null hypothesis for at least one γ_0 implies an existence of threshold model. Similarly, the confidence interval of the threshold value can be found from the range of γ_0 where null hypothesis cannot be rejected.

Results from threshold panel model

As discussed, we now test whether the criteria for growth to be inclusive is asymmetric across determining factors. Literature has highlighted that the main limitation of linear models are the basis on which the groups are separated. It is found to be quite ad-hoc in nature. States has their own differences depending on numerous macro characteristics as well as some innate ones that are difficult to capture. A uniform policy across states might not be effective and even if it is effective it might be advantageous for a certain group of people. Determining at what level or where exactly these policies are effective is important. The advantage of the model is that these cut off points are entirely determined through an endogenous process that uses a gradient search method. Therefore the results should have more validity. Note, our present data structure do not allow us to go beyond national level since within cross-section we do not have sufficient number of observations. Therefore, we restrict our analysis to country level estimation.

First, it is important to test whether such a threshold or cut-off does exist below and above which the relationship alters. Figure A2 in the appendix presents results of the likelihood test of linearity against a two regime threshold model considering literacy as the threshold variable for the effectiveness of social spending on pro-poor growth.[16] We follow Enders et al. (2007) that provides an inverted LR statistic and an asymptotic critical value based on the bootstrap method. Null hypothesis of single regime linear model has been rejected in favour of a threshold model for all the threshold variables.[17]

Literacy

Table 6 provides estimated results of the static threshold panel model. The first threshold variable is percentage of literate people in a particular state. We find that the estimated threshold value (denoted as $\hat{\lambda}_{LIT}$) for pro-poor growth indices – RPPG, PEGRα_i, FGTα_i are 50.6, 53, 53, 55.3, 61.8, 61.8 and 62.9 respectively and it is 60 for Gini. It is important to note, states like Kerala, Punjab, Himachal Pradesh, Jammu & Kashmir, Tamil Nadu, Karnataka and West Bengal lies above the threshold level and Bihar, Uttar Pradesh, Rajasthan, Haryana, Orissa, Assam are found to be states which remains in below.

The coefficients are positive and significant for all the pro-poor growth indices when average education level is greater than $\hat{\lambda}_{LIT}$. However, for Gini the coefficient is negative and significant above 60. The marginal effects reduces as α increases, signifying with higher inequality within the poor class makes the policies marginally less effective. Similarly, for the coefficients on the square of lag social sector spending, the impact is still positive and significant signifying a strong convex relationship. Results are statistically significant at 1 percent level. Now, moving on to the results for below the threshold group, as expected we do not find any statistically significant result which means on average the policies have no impact on pro-poor growth when literacy is less than $\hat{\lambda}_{LIT}$.

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[16] We also have the similar LR test results for rest of the model specifications. It can always be provided on request.
[17] Results can always be provided on request

Years of schooling

The next set of results, presented in Panel B, Table 6 are for 8 years of schooling. The threshold value $\hat{\lambda}_{YS}$ hovers around 12 for pro-poor growth indices. Qualitatively causal impacts are consistent and similar as to our earlier exercise on literacy. We then use average education of the state, defined as the mean level of education of a particular state measured in terms of the years of schooling. We rerun all our models and find that the estimated threshold value hovers around 3.5 (see Table 6, Panel C). Marginal effects for social spending corresponding to PEGR indices are positive and significant at 1 percent level and it is negative for poverty ratio. States which lies above the estimated threshold value would, in all likelihood, utilize the benefits of welfare program more and that in turn would make the growth process more inclusive. An opposite argument can be drawn according to the results we observe for Gini index for literacy. Further, like the previous results in Panel A and B, here as well we observe a convex relationship. In contrast, states which belong to the low average education group, did not get similar advantage from distributive policies adopted by respective states. Important to note, although statistically insignificant but coefficients are negative.

Gender gap in education

Next, we introduce a separate variable called gender gap in education and do a similar exercise considering that as the threshold variable. Although it is argued in the literature many a times that there has been improvement in education in terms of school enrollment, attendance and dropout rates, however, descriptive statistics from a simple gender gap metric, measured in terms of female to male literacy ratio, tells that the existing gap is still pretty large. About 26 girls out of 100 boys did not receive any form of education in India on average in last thirty years. Therefore it can be hypothesized that with higher gender gap in education in an economy, the effectiveness of social policies might differ due to numerous reasons such as asymmetric bargaining power, heterogeneous power relations, to name a few. Note, a higher value of our gender gap variable would actually mean female versus male gap is lower. For example, the value 0.6 would mean out of 100 males, 60 females are literate.

In Table 6 we present our findings. It can be seen that largely we get similar result like the previous models in terms of the direction of causality and statistical significance, except for the coefficient corresponding to the square of per capita social sector spending. However, interestingly the effect size is higher for $GENEDU_{it} > \hat{\lambda}_{GENEDU}$. A joint F-test is done to check for the difference which turns out to be significant in all cases. However, overall the results are systematic and consistent with our earlier findings. At lower group results are largely statistically insignificant, meaning on average policies are not effective beyond a cut-off which is around 0.71 in case of $GENEDU_{it}$. For the above threshold group, all are significant and positive for pro-poor growth measures.

Table 6: Estimation results of single threshold panel model

Variables	(1) RPPG	(2) $PEGR_{\alpha=0}$	(3) $PEGR_{\alpha=1}$	(4) $PEGR_{\alpha=2}$	(5) HCR	(6) PGR	(7) SPGR	(8) Gini
Panel A: Threshold variable - Literacy (LIT)								
Threshold value ($\hat{\lambda}_{LIT}$)	50.6	53.0	53.0	53.0	55.3	61.8	61.8	60.0
$\text{Ln}PCSSE_{t-1} * I(LIT_{it} > \hat{\lambda}_{LIT})$	2.744***	4.327***	4.600***	4.790***	-2.395**	1.123***	0.645***	-0.270*
	(0.552)	(1.279)	(0.916)	(0.794)	(1.107)	(0.364)	(0.199)	(0.150)
$\text{Ln}PCSSE_{t-1} * I(LIT_{it} < \hat{\lambda}_{LIT})$	-0.919	-0.826	-0.814	-0.712	-0.362	0.095	0.099	-0.098
	(1.770)	(2.238)	(2.060)	(2.097)	(2.598)	(0.442)	(0.186)	(0.125)
$\text{Ln}PCSSE^2_{t-1} * I(LIT_{it} > \hat{\lambda}_{LIT})$	0.130***	0.203***	0.218***	0.227***	-0.112*	0.0579***	0.0328***	-0.0139*
	(0.027)	(0.063)	(0.045)	(0.040)	(0.055)	(0.018)	(0.010)	(0.007)
$\text{Ln}PCSSE^2_{t-1} * I(LIT_{it} < \hat{\lambda}_{LIT})$	-0.0384	-0.0342	-0.0330	-0.0293	-0.0207	0.0033	0.0040	-0.0046
	(0.082)	(0.105)	(0.098)	(0.099)	(0.123)	(0.021)	(0.009)	(0.006)
Panel B: 8 years of schooling (Y S)								
Threshold value ($\hat{\lambda}_{YS}$)	12.37	11.60	12.37	12.37	12.58	8.41	13.99	14.88
$\text{Ln}PCSSE_{t-1} * I(YS_{it} > \hat{\lambda}_{YS})$	3.174***	5.244***	5.809***	5.789***	-3.212*	-0.414**	0.273**	0.1360
	(1.026)	(1.261)	(1.142)	(0.993)	(1.628)	(0.183)	(0.111)	(0.263)
$\text{Ln}PCSSE_{t-1} * I(Y\,S_{it} < \hat{\lambda}_{YS})$	0.910	0.522	0.713	0.8150	-1.062	-0.781	-0.0796	-0.0491
	(0.676)	(1.080)	(0.859)	(0.911)	(1.242)	(1.589)	(0.070)	(0.082)
$\text{Ln}PCSSE^2_{t-1} * I(YS_{it} > \hat{\lambda}_{YS})$	0.150**	0.244***	0.275***	0.274***	-0.151*	-0.0199**	0.0140**	0.0066
	(0.051)	(0.062)	(0.057)	(0.050)	(0.083)	(0.009)	(0.006)	(0.013)
$\text{Ln}PCSSE^2_{t-1} * I(YS_{it} < \hat{\lambda}_{YS})$	0.0452	0.027	0.0358	0.0399	-0.0516	-0.037	-0.0040	-0.0024
	(0.032)	(0.051)	(0.042)	(0.044)	(0.059)	(0.072)	(0.003)	(0.004)
Panel C: Mean years of schooling (MYS)								
Threshold value ($\hat{\lambda}_{MYS}$)	3.5	3.7	3.7	3.7	3.7	3.7	4.1	4.5
$\text{Ln}PCSSE_{t-1} * I(MYS_{it} > \hat{\lambda}_{MYS})$	2.638***	4.963***	5.238***	5.699***	-2.692*	-0.125	0.348	0.3040
	(0.690)	(1.649)	(1.164)	(1.100)	(1.498)	(0.353)	(0.411)	(0.245)
$\text{Ln}PCSSE_{t-1} * I(MYS_{it} < \hat{\lambda}_{MYS})$	-2.3320	0.0343	-0.6100	-0.6230	-0.2870	0.0071	0.0874	0.1140
	(2.299)	(2.087)	(1.739)	(1.552)	(1.974)	(0.461)	(0.239)	(0.124)
$\text{Ln}PCSSE^2_{t-1} * I(MYS_{it} > \hat{\lambda}_{MYS})$	0.125***	0.235**	0.250***	0.273***	-0.126	-0.0052	0.0178	0.0154
	(0.035)	(0.082)	(0.058)	(0.055)	(0.075)	(0.018)	(0.021)	(0.013)
$\text{Ln}PCSSE^2_{t-1} * I(MYS_{it} < \hat{\lambda}_{MYS})$	-0.1030	0.0033	-0.0261	-0.0273	-0.0156	-0.0005	0.0035	0.0051
	(0.107)	(0.097)	(0.082)	(0.073)	(0.093)	(0.021)	(0.011)	(0.006)
Panel D: Gender gap in education (GENEDU)								
Threshold value ($\hat{\lambda}_{GENEDU}$)	0.712	0.712	0.712	0.712	0.712	0.750	0.750	0.753
$\text{Ln}PCSSE_{t-1} * I(GENEDU_{it} > \hat{\lambda}_{GENEDU})$	3.822***	6.149***	6.091***	6.124***	-3.992**	-0.451	-0.108	-0.0201
	(0.780)	(1.038)	(0.735)	(0.601)	(1.392)	(0.325)	(0.135)	(0.132)
$\text{Ln}PCSSE_{t-1} * I(GENEDU_{it} < \hat{\lambda}_{GENEDU})$	2.537*	4.373***	4.077***	3.728**	-2.2540	-0.2670	-0.0391	0.1130
	(1.362)	(1.442)	(1.311)	(1.426)	(1.760)	(0.563)	(0.255)	(0.136)
$\text{Ln}PCSSE^2_{t-1} * I(GENEDU_{it} > \hat{\lambda}_{GENEDU})$	0.186***	0.298***	0.296***	0.297***	-0.193**	-0.0217	-0.0053	-0.0010
	(0.040)	(0.051)	(0.037)	(0.030)	(0.070)	(0.017)	(0.007)	(0.007)
$\text{Ln}PCSSE^2_{t-1} * I(GENEDU_{it} < \hat{\lambda}_{GENEDU})$	0.120*	0.204***	0.190***	0.174**	-0.1060	-0.0131	-0.0023	0.0053
	(0.062)	(0.066)	(0.061)	(0.067)	(0.083)	(0.026)	(0.012)	(0.006)
p-value: joint F-test of difference	0.103	0.012	0.002	0.001	-	-	-	-

Note: Heteroscedasticity corrected standard errors clustered at state level are provided in parentheses. Regression tables with all controls are provided in appendix table A12, A13, A14, A15. *** p<0.01, ** p<0.05, * p<0.1.

Results of Threshold Panel with Endogenous Threshold Variables

Although in all our non-linear specifications so far, we have allowed the model to determine the threshold values endogenously, one may argue that the threshold variables (q_{it}) can itself be endogenous. This is plausible as significant proportion of the SSE goes to education and this in turn might lead to the problem of reverse causality. However, in reality, as our outcome variable, main interest variable and the threshold variable are determined simultaneously, the threshold variable would potentially be endogenous. Thus, in our final specification, we consider a threshold panel model where the threshold variables are considered as endogenous variables. This specification is used as a robustness exercise of the non-linear model we have estimated. It is quite evident in the literature that an increase in income of the poor people affects the level of education and quality of education by increasing the education expenditure of the poor or by reducing the school dropout rate. Hence, before coming to the conclusion of the asymmetric impact of government expenditure on the pro poorness, we have re-estimated the stated nonlinear model as a confirmatory regression model considering threshold variables as endogenous. Table A16 in appendix reports the estimated results of the threshold panel model with endogeneity in threshold variables.[18] The impacts are found to be asymmetric at least in the cases where literacy rate and eight year of schooling of states are considered as threshold variables. It has been found that the impact of social sector expenditure on pro poor growth indices are statistically significant in case when the threshold variable crosses the threshold value. The impact is not statistically different for both the categories in cases when poverty and inequality are considered as dependent variables. Hence, the impact of social sector expenditure on inclusiveness is asymmetric below and above some selected educational attainment of the states.

[18] The detail estimation results will be available on request.

7. Conclusion

The paper applies linear as well as non-linear panel data models to gauge the causal effects of redistributive policy, which states' often undertake as a measure of welfare, on pro-poor growth. The linear model confirms that the impacts are positive and significant on the measures of pro-poor growth, and negative and significant on the measures of FGT class of poverty. However, the impact remains largely indistinguishable from zero across specifications for overall inequality. The findings are systematic and consistent across specifications, heterogeneous income classes and for an alternative classification of redistributive policy. Moreover, our results are robust to state's initial condition *i.e* the effect of aggregate redistributive policy does not depend on the initial level of state endowment. The policy of economic liberalisation has a negative effect on pro-poor growth in general.

The baseline linear model, however, does not show consistent results with regard to the education. If we were to conclude on the basis of this, we would be inclined to view the evidence as indicating the absence of any significant relationship between redistributive policy, inclusive growth and the education. However, as hypothesized, it could be the case that education has an asymmetric impact and the linear model might not be appropriately capturing some important nonlinearities. The panel threshold model relaxes the linearity assumption and extend it to a non-linear framework which tests the effect of the policy variable below and above a certain threshold value. The model allows one to endogenously determine this threshold value by minimizing the corresponding residual sum of squares. Results indicate, the existence of education thresholds and their estimated values are statistically valid. The effectiveness of the redistributive policy is largely heterogeneous below and above that estimated threshold value. On average, the policy effectiveness in states with literacy rates in the neighbourhood of 55% and more, or when more than 11% and 10% of the population having 8 years and 10 years of schooling respectively, the impact of state policies are positive and statistically significant.

Indian economy has known for several market frictions that often reduces the efficacy of the welfare programs at the local level. This largely attracts skepticism among policy makers and the implementing agencies about the effectiveness of the welfare programs which, in turn, pose questions on whether to adopt a growth oriented policy or something that is focused on development. However, our findings suggest even after controlling for potential confounding factors the effects are systematic and robust. Hence, any welfare policies at aggregate level can be useful especially for a developing country. The adoption of nonlinear threshold regression model helps us addressing the shortcomings of linear panel framework. We employ this nonlinearity in the context of achievement in education. The approach also allows us an endogenous test for the existence and significance of threshold level of education attainment in the state level redistributive policy and pro-poor growth relationship. This approach is an improvement in the sense that instead of specifying adhoc threshold points, it imposes it endogenously through a gradient search method.

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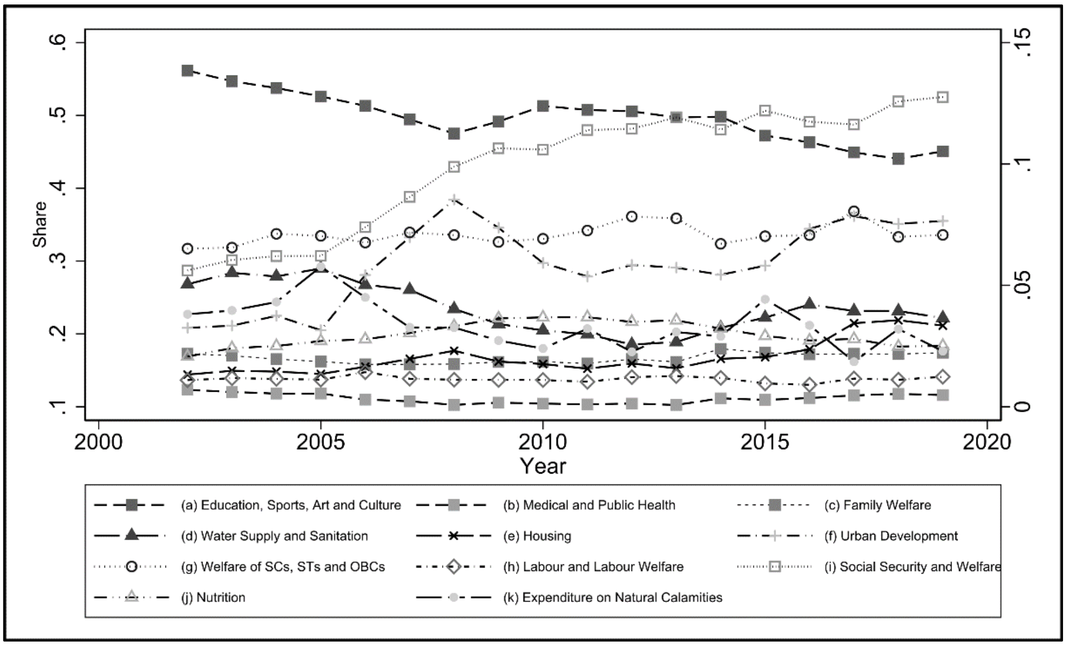
Appendix

Table A1: Trends in MPCE, Poverty and Inequality in India

Year	Expenditure per capita			Poverty head count			Inequality (Gini)		
	Rural	Urban	All India	Rural	Urban	All India	Rural	Urban	All India
1983	119.22	190.10	136.41	67.62	42.66	61.66	0.315	0.358	0.351
1987-88	164.76	275.70	196.74	57.44	33.44	50.69	0.329	0.396	0.382
1993-94	281.40	458.04	325.18	50.12	31.81	45.31	0.314	0.391	0.381
1999-00	485.87	854.70	578.61	47.87	26.31	42.45	0.299	0.354	0.359
2004-05	558.44	1052.62	683.42	41.83	25.71	37.21	0.335	0.384	0.385
2009-10	927.70	1785.81	1159.80	33.81	20.94	29.82	0.341	0.397	0.391
2011-12	1287.17	2477.01	1627.143	25.72	13.71	21.93	0.337	0.397	0.393

Note: The quinquennial rounds of NSS-HCE data are used for calculation. Monthly per capita consumption expenditure (MPCE) is taken as a proxy of income. Tendulkar Poverty line is used for poverty estimation. Respective consumer price indices (CPI-AL for rural and CPI-IW for urban with base year 1982 and 1986-87) are used to get real values.

Figure A1: Components of Social sector expenditure (2002-03 to 2019-20)



Note: Line graph showing share of various components of social service expenditure within revenue expenditure. The dashed lines with square markers showing the country level share of education and health in social service expenses of all the Indian states.

Table A2: Descriptive Statistics

	1987-1988		1993-1994		1999-2000		2004-2005		2009-2010		2011-2012	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Outcome variables												
Rate of pro-poor growth index	0.148	0.023	0.015	0.052	0.111	0.019	-0.076	0.053	0.075	0.038	0.112	0.015
Poverty equivalent growth rate, $\alpha = 0$	0.189	0.047	0.006	0.047	0.160	0.052	-0.064	0.051	0.106	0.056	0.208	0.042
Poverty equivalent growth rate, $\alpha = 1$	0.179	0.032	0.015	0.035	0.139	0.048	-0.058	0.037	0.099	0.051	0.190	0.050
Poverty equivalent growth rate, $\alpha = 2$	0.176	0.028	0.018	0.026	0.131	0.048	-0.064	0.045	0.094	0.048	0.181	0.053
Head count ratio	0.455	0.137	0.470	0.156	0.353	0.191	0.378	0.184	0.298	0.165	0.178	0.155
Poverty gap ratio	0.108	0.047	0.094	0.048	0.061	0.045	0.078	0.052	0.053	0.037	0.026	0.025
Squared poverty gap ratio	0.041	0.021	0.034	0.021	0.020	0.017	0.028	0.022	0.018	0.015	0.007	0.008
Gini Index	0.265	0.015	0.263	0.016	0.253	0.019	0.266	0.017	0.270	0.014	0.265	0.013
Main interest variables												
Per capita social sector expenditure (Rs. lakh)	0.003	0.001	0.005	0.002	0.012	0.003	0.014	0.004	0.030	0.007	0.038	0.009
Development expenditure to revenue expenditure	0.706	0.036	0.640	0.059	0.585	0.054	0.528	0.061	0.589	0.075	0.599	0.067
Education related variables												
Illiterate (%)	49.640	12.570	47.280	11.690	42.160	10.420	37.110	9.600	31.170	7.996	28.940	7.366
8 years of schooling	9.602	3.875	10.310	4.836	12.020	4.452	14.710	5.076	16.330	2.640	16.900	2.435
10 years of schooling	4.686	2.015	6.405	2.592	7.991	3.114	8.554	3.135	14.590	3.195	13.890	3.074
12 years of schooling	1.660	0.454	2.759	0.601	3.638	0.907	4.468	1.265	14.750	4.031	14.880	4.048
More than 12 years of schooling	2.193	0.754	2.382	0.544	3.157	0.715	4.408	1.473	22.640	6.336	24.930	6.834
Average education in State	2.707	0.847	3.149	0.852	3.670	0.881	4.317	0.931	4.943	0.904	5.224	0.887
Gender gap in education	0.676	0.129	0.676	0.129	0.724	0.108	0.766	0.094	0.814	0.076	0.818	0.070
State endowments												
Monthly per capita expenditure (real)	1.592	0.199	1.564	0.210	1.777	0.297	1.759	0.302	1.963	0.320	2.341	0.425
Per capita net state domestic product (Rs. lakh)	214.300	63.590	38.450	14.080	31.270	11.320	33.720	12.080	30.340	12.290	28.950	11.750
Social groups, Gender and other variables												
Scheduled caste/ Scheduled tribe	27.250	8.249	28.150	7.477	26.930	8.662	27.880	7.498	28.520	8.887	27.660	8.377
Religion: Muslim	12.720	13.880	9.965	7.420	13.090	12.480	13.550	13.560	14.230	14.660	14.980	15.160
Gender ratio	0.975	0.066	0.985	0.066	0.972	0.064	0.984	0.069	0.984	0.069	0.979	0.071
Urbanization	0.260	0.091	0.237	0.086	0.240	0.083	0.239	0.092	0.258	0.101	0.269	0.104
Political variables												
Centre/State party	0.471	0.514	0.529	0.514	0.176	0.393	0.412	0.507	0.294	0.470	0.353	0.493
Party ideology	2.824	1.185	2.706	1.047	2.575	1.211	2.608	0.995	2.706	1.263	2.512	0.983
Wealth recovered (%)	36.960	19.170	36.430	19.710	33.940	12.480	35.500	18.430	34.190	17.910	34.170	18.730

Note: Author's own calculation based on the constructed data from various sources. All monetary variables are at 1993-94 constant prices.

Table A3: Impact of state policies on pro-poor growth and deprivation (Full sample)

Variables	(1) RPPG	(2) $PEGR_{\alpha=0}$	(3) $PEGR_{\alpha=1}$	(4) $PEGR_{\alpha=2}$	(5) HCR	(6) PGR	(7) SPGR	(8) Gini
Ln$PCSSE_{t-1}$	2.536***	3.998***	3.874***	3.799***	-2.699**	-0.413**	-0.135**	0.0154
	(0.645)	(1.106)	(1.061)	(1.001)	(1.084)	(0.154)	(0.062)	(0.069)
Ln$PCSSE_{t-1}^2$	0.121***	0.188***	0.183***	0.179***	-0.128**	-0.0199**	-0.0067*	0.001
	(0.032)	(0.054)	(0.053)	(0.050)	(0.054)	(0.008)	(0.003)	(0.003)
Ln$NSDP_{t-1}$	0.0659**	0.0857**	0.0881**	0.0865**	-0.0353	-0.0114	-0.00417	-0.0094**
	(0.028)	(0.036)	(0.034)	(0.031)	(0.032)	(0.007)	(0.004)	(0.004)
Illiterate	-0.006*	-0.008	-0.008	-0.007	0.005	0.000	0.000	0.0016***
	(0.003)	(0.006)	(0.005)	(0.004)	(0.005)	(0.001)	(0.00)	(0.00)
8 years of schooling	0.003	0.006	0.004	0.004	-0.003	-0.001	0.000	0.00133*
	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)	(0.001)	(0.001)	(0.001)
10 years of schooling	0.0001	-0.0023	-0.0005	-0.0020	-0.0011	0.0006	0.0004	-0.0011**
	(0.005)	(0.009)	(0.008)	(0.008)	(0.007)	(0.002)	(0.001)	(0.001)
12 years of schooling	-0.0014	-0.0040	-0.0042	-0.0017	0.0030	-0.0020	-0.0011	0.0027***
	(0.005)	(0.008)	(0.008)	(0.007)	(0.009)	(0.002)	(0.001)	(0.001)
More than 12 years of schooling	0.0070***	0.0092**	0.0077**	0.0073**	-0.0023	0.0002	0.0002	-0.0004
	(0.002)	(0.004)	(0.003)	(0.003)	(0.004)	(0.001)	(0.000)	(0.000)
Average education in state (in years)	-0.0352	-0.0515	-0.0479	-0.0517	-0.0248	0.0013	0.0018	-0.0036
	(0.058)	(0.086)	(0.074)	(0.068)	(0.092)	(0.022)	(0.010)	(0.008)
Ln$MPCE_{t-1}$	-0.610***	-0.905***	-0.793***	-0.773***	0.0744*	-0.0607	-0.0345**	0.0214
	(0.069)	(0.085)	(0.099)	(0.107)	(0.113)	(0.029)	(0.016)	(0.013)
Scheduled Caste/Scheduled Tribe	0.0015	-0.0023	-0.0018	-0.0028	0.0026	-0.0005	-0.0004	0.0008***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.000)
Religion: Muslim	0.0013	0.0009	0.0016	0.0016	0.0001	-0.0001	-0.0001	-0.0003
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)
Wealth recovered(%)	-0.0006	-0.0010	-0.0010	-0.0013	0.0006	0.0003	0.0001	0.0001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Party ideology	-0.0018	-0.0042	-0.0035	-0.0004	0.0003	-0.0001	-0.0002	0.0003
	(0.007)	(0.011)	(0.010)	(0.010)	(0.008)	(0.002)	(0.001)	(0.001)
Centre/State party	0.0166	0.0064	0.0052	0.0065	-0.0070	-0.0037	-0.0017	-0.0024
	(0.021)	(0.029)	(0.025)	(0.021)	(0.023)	(0.005)	(0.002)	(0.003)
Urbanization	0.0341	-0.0691	-0.0922	-0.0890	0.0141	0.0175	-0.0069	-0.0158
	(0.313)	(0.420)	(0.373)	(0.370)	(0.407)	(0.095)	(0.046)	(0.040)
Gender ratio	0.3010	0.3000	0.3250	0.3800	-0.0117	0.0253	-0.0024	-0.0118
	(0.384)	(0.568)	(0.456)	(0.415)	(0.510)	(0.110)	(0.047)	(0.046)
Year 1999	0.154***	0.197***	0.173***	0.170***	-0.0928***	-0.0378***	-0.0156***	-0.0182***
	(0.024)	(0.032)	(0.027)	(0.024)	(0.024)	(0.006)	(0.003)	(0.003)
Constant	12.61***	20.60***	19.73***	19.44***	-13.28**	-1.917**	-0.577*	0.496
	(3.185)	(5.281)	(5.054)	(4.719)	(5.089)	(0.736)	(0.293)	(0.342)
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State specific trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	102	102	102	102	102	102	102	102
Number of states	17	17	17	17	17	17	17	17
R-squared	0.88	0.87	0.87	0.88	0.89	0.91	0.89	0.77
p-value:Ln$PCSSE_{t-1}$>Ln$NSDP_{t-1}$	0.000	0.000	0.001	0.001	-	-	-	-

Note: Heteroscedasticity corrected standard errors clustered at state level are in parentheses. P-values from a one sided mean test are provided in the bottom row. *** p<0.01, ** p<0.05, * p<0.1

Table A4: Impact of state policies on pro-poor growth and deprivation (Bottom 20 percent)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	RPPG	$PEGR_{\alpha=0}$	$PEGR_{\alpha=1}$	$PEGR_{\alpha=2}$	HCR	PGR	SPGR	Gini
Ln$PCSSE_{t-1}$	3.421***	4.725***	4.363***	4.202***	-8.078***	-1.972***	-0.548**	0.0249
	(0.95)	(1.40)	(1.37)	(1.24)	(2.03)	(0.52)	(0.21)	(0.13)
Ln$PCSSE_{t-1}^2$	0.164***	0.226***	0.208***	0.200***	-0.377***	-0.0919***	-0.0256**	0.0012
	(0.05)	(0.07)	(0.07)	(0.06)	(0.10)	(0.03)	-(0.01)	-(0.01)
Ln$NSDP_{t-1}$	0.042	0.0649*	0.0476	0.0415	-0.102*	-0.0244*	-0.0091	0.0016
	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.01)	(0.01)	(0.01)
Illiterate	-0.0053	-0.0044	-0.0075	-0.0071	0.0081	0.0024	0.0011	0.000
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
8 years of schooling	0.0050	0.0073	0.0065	0.0068	-0.0061	-0.0014	0.0001	0.0004
	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
10 years of schooling	0.0005	0.0009	0.0000	-0.0008	0.0094	0.0019	0.0007	-0.0001
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
12 years of schooling	0.0028	0.0029	0.0027	0.0033	0.0117	-0.0014	-0.0015	-0.0001
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
More than 12 years of schooling	0.0056	0.0064	0.0059	0.0069	-0.0098	-0.0028	-0.0006	0.0000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Average education in state(in years)	-0.111*	-0.0987	-0.148*	-0.161**	0.205	0.0407	0.0135	0.0076
	(0.06)	(0.08)	(0.08)	(0.08)	(0.13)	(0.03)	(0.02)	(0.01)
Ln$MPCE_{t-1}$	-0.454***	-0.340**	-0.445***	-0.431***	-0.531**	-0.194***	-0.109***	0.0401
	(0.12)	(0.14)	(0.15)	(0.14)	(0.20)	(0.05)	(0.03)	(0.03)
Scheduled Caste/Scheduled Tribe	0.0019	0.0032	0.0011	0.000	-0.0031	-0.0016	-0.0009	0.0006
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Religion: Muslim	0.0025	0.0035	0.0025	0.0023	-0.0031	-0.0016*	-0.0008**	0.0001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Wealth recovered (%)	-0.0013	-0.0006	-0.0013	-0.0015*	0.0004	0.0004	0.0002	-0.0001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Party ideology	-0.0022	-0.0116	-0.0041	-0.0036	0.0112	0.0018	-0.0001	-0.0003
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.00)	(0.00)	(0.00)
Centre/State party	-0.0011	-0.0093	-0.0049	-0.0016	0.0157	0.0011	-0.0011	-0.0003
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)	(0.00)	(0.00)
Urbanization	0.171	0.263	0.144	0.138	-0.4	-0.154	-0.0753	0.0513
	(0.40)	(0.39)	(0.45)	(0.43)	(0.52)	(0.18)	(0.10)	(0.08)
Gender ratio	0.0856	-0.0869	-0.0456	-0.0159	0.183	-0.0253	-0.0418	-0.0697
	(0.37)	(0.53)	(0.49)	(0.49)	(0.88)	(0.22)	(0.09)	(0.08)
Year 1999	0.0989***	0.156***	0.124***	0.119***	-0.129**	-0.103***	-0.0578***	-0.0037
	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.01)	(0.01)	(0.00)
Constant	18.19***	24.92***	23.51***	22.76***	-42.25***	-9.999***	-2.647**	0.268
	(4.71)	(6.82)	(6.74)	(6.05)	(9.84)	(2.55)	(1.00)	(0.62)
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State specific trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	102	102	102	102	102	102	102	102
Number of State	17	17	17	17	17	17	17	17
R-squared	0.89	0.86	0.85	0.87	0.86	0.97	0.97	0.65
Ln$PCSSE_{t-1}$=Ln$NSDP_{t-1}$	-	0.004	-	-	0.001	0.002	-	-

Note: Heteroscedasticity corrected standard errors, clustered at state level, are given in parentheses. P-values from a two sided mean test are provided in the bottom row. *** p<0.01, ** p<0.05, * p<0.1

Table A5: Impact of state policies on pro-poor growth and deprivation (Bottom 40 percent)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	RPPG	$PEGR_{\alpha=0}$	$PEGR_{\alpha=1}$	$PEGR_{\alpha=2}$	HCR	PGR	SPGR	Gini
Ln$PCSSE_{t-1}$	2.253***	3.622***	3.522***	3.590***	-3.769**	-1.712**	-0.448*	0.0203
	(0.56)	(1.15)	(1.11)	(1.08)	(1.49)	(0.60)	(0.24)	(0.11)
Ln$PCSSE_{t-1}^2$	0.107***	0.173***	0.168***	0.171***	-0.174**	-0.0804**	-0.0215*	0.0006
	(0.03)	(0.06)	(0.05)	(0.05)	(0.07)	(0.03)	(0.01)	(0.01)
Ln$MPCE_{t-1}$	-0.437***	-0.583***	-0.526***	-0.544***	-0.254	-0.238**	-0.135**	-0.0435*
	(0.07)	(0.09)	(0.11)	(0.12)	(0.16)	(0.09)	(0.05)	(0.02)
Illiterate	-0.0062**	-0.0099	-0.0101	-0.0095	0.0148*	0.0057*	0.0018*	0.0006
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
8 years of schooling	0.0040	0.0048	0.0041	0.0048	0.0001	0.0005	0.0006	0.00119*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
10 years of schooling	-0.0003	0.0024	0.0014	-0.0001	-0.0062	-0.0008	0.0004	-0.0001
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
12 years of schooling	0.0019	-0.0036	-0.0026	-0.0008	0.0095	-0.0008	-0.0017	0.0006
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
More than 12 years of schooling	0.0081***	0.0102**	0.0089**	0.0083**	-0.0099**	-0.0022	-0.0001	0.0004
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Average education in state(in years)	-0.0837	-0.1010	-0.1070	-0.1080	0.0480	0.0183	0.0082	-0.0047
	(0.05)	(0.08)	(0.07)	(0.07)	(0.12)	(0.06)	(0.03)	(0.01)
Ln$NSDP_{t-1}$	0.0626**	0.0723*	0.0778**	0.0731*	-0.0525	-0.0460**	-0.0176*	-0.0047
	(0.02)	(0.04)	(0.04)	(0.03)	(0.04)	(0.02)	(0.01)	(0.00)
Scheduled caste/Scheduled tribe	-0.0004	-0.0023	-0.0024	-0.0033	0.0062**	-0.002	-0.001	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Religion: Muslim	0.0012	0.0021	0.0022	0.0020	-0.0038*	-0.0024*	-0.0009**	-0.0002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Wealth recovered (%)	-0.0006	-0.0011	-0.0013	-0.0016*	0.0014	0.0009	0.0004	0.0001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Party ideology	0.0021	-0.0055	-0.0025	-0.0003	0.0020	0.0009	-0.0007	0.0003
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
Centre/State party	0.0058	-0.0016	-0.0014	-0.0014	0.0014	-0.0019	-0.0021	-0.0014
	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.01)	(0.00)
Urbanization	0.0708	0.0017	0.0071	0.0326	0.0559	0.0175	-0.0253	0.0193
	(0.28)	(0.43)	(0.40)	(0.40)	(0.37)	(0.27)	(0.15)	(0.07)
Gender ratio	0.415	0.0397	0.235	0.26	-0.208	0.107	0.033	-0.0317
	(0.30)	(0.55)	(0.48)	(0.47)	(0.45)	(0.33)	(0.15)	(0.08)
Year 1999	0.155***	0.173***	0.166***	0.161***	-0.238***	-0.182***	-0.0744***	-0.0065
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.01)	(0.00)
Constant	11.77***	19.50***	18.82***	19.21***	-19.77**	-8.522***	-2.040*	0.314
	(2.72)	(5.65)	(5.36)	(5.18)	(6.98)	(2.87)	(1.12)	(0.49)
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State specific trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	102	102	102	102	102	102	102	102
Number of State	17	17	17	17	17	17	17	17
R-squared	0.93	0.88	0.88	0.88	0.96	0.97	0.95	0.67
Ln$PCSSE_{t-1}$=Ln$NSDPt-1$	0.001	0.007	0.007	0.005	0.023	0.013	0.084	0.819

Note: Heteroscedasticity corrected standard errors, clustered at state level, are given in parentheses. P-values from a two sided mean test are provided in the bottom row. *** p<0.01, ** p<0.05, * p<0.1

Table A6: Impact of development expenditure on pro-poor growth and deprivation (Full sample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	RPPG	$PEGR_{,=0}$	$PEGR_{,=1}$	$PEGR_{,=2}$	HCR	PGR	SPGR	Gini
$\text{Ln}(DE/RE)_{t-1}$	0.177**	0.268***	0.259***	0.243**	-0.249**	-0.052**	-0.021*	0.010
	(0.08)	(0.09)	(0.09)	(0.09)	(0.10)	(0.02)	(0.01)	(0.01)
$\text{Ln}MPCE_{t-1}$	-0.577***	-0.807***	-0.714***	-0.684***	0.046	-0.053*	-0.027*	-0.022
	(0.06)	(0.10)	(0.09)	(0.09)	(0.11)	(0.03)	(0.01)	(0.01)
Illiterate	-0.0071	-0.0099	-0.0099	-0.0086	0.0064	0.0004	0.0001	0.002***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
8 years of schooling	0.0044	0.0069	0.0054	0.0056	-0.0043	-0.0018	-0.001	0.001**
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
10 years of schooling	-0.0039	-0.0085	-0.0066	-0.0079	0.0027	0.0012	0.0001	-0.001*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
12 years of schooling	0.0045	0.0039	0.0040	0.0059	-0.0039	-0.0035	-0.0017	0.003***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
More than 12 years of schooling	0.0065***	0.0080***	0.0067***	0.0062**	-0.0014	0.0004	0.0003	-0.001*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Mean years of schooling in state	-0.0517	-0.0487	-0.0558	-0.0531	-0.0117	0.0095	0.0068	-0.003
	(0.05)	(0.09)	(0.07)	(0.07)	(0.07)	(0.02)	(0.01)	(0.01)
$\text{Ln}NSDP_{t-1}$	0.0432*	0.0620*	0.0612*	0.0637*	-0.0067	-0.0033	-0.0002	-0.0100***
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.01)	(0.00)	(0.00)
Scheduled caste/Scheduled tribe	0.0012	-0.0025	-0.0022	-0.0031	0.0025	-0.0005	-0.0004	0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Religion: Muslim	0.0011	0.0009	0.0015	0.0015	0.0002	-0.0001	-0.0001	-0.0003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Wealth recovered (%)	-0.0010	-0.0016**	-0.0016**	-0.0018*	0.0011	0.0004	0.0002	0.0001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Party ideology	-0.0003	-0.0004	-0.0003	0.0031	-0.0006	0.0002	0.0000	0.0003
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Centre/State party	0.0215	0.0188	0.0155	0.0178	-0.0123	-0.0034	-0.0012	-0.0023
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)
Urbanization	0.473*	0.6700	0.6100	0.6140	-0.4280	-0.0343	-0.0183	-0.0163
	(0.26)	(0.43)	(0.36)	(0.38)	(0.31)	(0.07)	(0.04)	(0.04)
Gender ratio	-0.0243	-0.173	-0.145	-0.0687	0.362	0.0969	0.026	-0.0172
	(0.40)	(0.65)	(0.51)	(0.48)	(0.34)	(0.09)	(0.04)	(0.04)
Year 1999	0.134***	0.171***	0.146***	0.145***	-0.0642**	-0.0309***	-0.0126***	-0.0193***
	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.01)	(0.00)	(0.00)
Constant	0.419	0.737	0.709	0.553	-0.142	0.0333	0.0212	0.242***
	(0.53)	(0.90)	(0.79)	(0.79)	(0.74)	(0.14)	(0.05)	(0.05)
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State specific trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of State	17	17	17	17	17	17	17	17
Observations	102	102	102	102	102	102	102	102
R-squared	0.85	0.82	0.82	0.83	0.88	0.92	0.89	0.78
$\text{Ln}(DE/RE)_{t-1}=\text{Ln}NSDP_{t-1}$	0.132	0.062	0.065	0.101	0.041	0.106	0.132	0.021

Note: Heteroscedasticity corrected standard errors, clustered at state level, are given in parentheses. P-values from a two sided mean test are provided in the bottom row. *** p<0.01, ** p<0.05, * p<0.1

Table A7: Impact of development expenditure on pro-poor growth and deprivation (Bottom 20%)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	RPPG	$PEGR_{\alpha=0}$	$PEGR_{\alpha=1}$	$PEGR_{\alpha=2}$	HCR	PGR	SPGR	Gini
Ln$(DE/RE)_{t-1}$	0.236***	0.273***	0.278***	0.269***	-0.519***	-0.147***	-0.500**	-0.014
	(0.06)	(0.06)	(0.08)	(0.08)	(0.13)	(0.04)	(0.02)	(0.01)
Ln$MPCE_{t-1}$	-0.427***	-0.271***	-0.383***	-0.367***	-0.787***	-0.251***	-0.122***	-0.033
	(0.09)	(0.09)	(0.10)	(0.09)	(0.15)	(0.06)	(0.04)	(0.03)
Illiterate	-0.0068	-0.0065	-0.0095	-0.0090	0.0123	0.0034	0.0014	-0.0001
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.00)	(0.00)	(0.00)
8 years of schooling	0.0079*	0.0104*	0.0093	0.0094*	-0.0062	-0.0015	0.000	0.0003
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
10 years of schooling	-0.0051	-0.0070	-0.0071	-0.0076	0.0216	0.0047	0.0015	-0.0002
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.00)	(0.00)	(0.00)
12 years of schooling	0.0113	0.0134	0.0125	0.0126	-0.0025	-0.0051	-0.0027**	-0.0003
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.00)	(0.00)	(0.00)
More than 12 years of schooling	0.0051	0.0059*	0.0052	0.0061*	-0.007	-0.002*	-0.0004	0.0001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Mean years of schooling in state	-0.146**	-0.133	-0.177**	-0.186**	0.164	0.0312	0.0116	0.0094
	(0.06)	(0.08)	(0.08)	(0.08)	(0.14)	(0.04)	(0.02)	(0.01)
Ln$NSDP_{t-1}$	0.00723	0.0271	0.0113	0.0074	-0.0691	-0.0142	-0.005	0.0037
	(0.03)	(0.03)	(0.04)	(0.04)	(0.06)	(0.01)	(0.01)	(0.01)
Scheduled caste/Scheduled tribe	0.0012	0.0022	0.0003	-0.0007	-0.0032	-0.0018	-0.0009	0.0006
	(0.00)	(0.01)	(0.01)	0.00	(0.01)	(0.00)	(0.00)	(0.00)
Religion: Muslim	0.0021	0.0030	0.0021	0.0020	-0.0036	-0.0017	-0.0008*	0.0001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Wealth recovered (%)	-0.0018*	-0.0011	-0.0018*	-0.002**	0.0015	0.0007*	0.0003*	0.0001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Party ideology	-0.0007	-0.0083	-0.0013	-0.0008	0.0019	-0.0002	-0.0005	0.0000
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.00)	(0.00)	(0.00)
Centre/State party	0.0036	-0.0002	0.0037	0.0071	-0.0153	-0.0062	-0.0029	0.0002
	(0.01)	(0.02)	(0.01)	(0.01)	(0.03)	(0.01)	(0.00)	(0.00)
Urbanization	0.748**	1.107***	0.914**	0.883**	-1.954**	-0.522***	-0.172*	0.0666
	(0.33)	(0.34)	(0.40)	(0.40)	(0.67)	(0.16)	(0.08)	(0.07)
Gender ratio	-0.365	-0.667	-0.591	-0.539	1.087	0.207	0.0285	-0.0623
	(0.38)	(0.57)	(0.55)	(0.54)	(1.13)	(0.27)	(0.09)	(0.07)
Year 1999	0.0707**	0.125***	0.0933**	0.0892**	-0.0826	-0.0890***	-0.0527***	-0.0017
	(0.03)	(0.03)	(0.03)	(0.03)	(0.06)	(0.02)	(0.01)	(0.01)
Constant	1.155*	1.137	1.511*	1.518*	0.087	0.317	0.206*	0.101
	(0.59)	(0.89)	(0.81)	(0.80)	(1.59)	(0.33)	(0.12)	(0.12)
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State specific trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of State	17	17	17	17	17	17	17	17
Observations	102	102	102	102	102	102	102	102
R-squared	0.85	0.79	0.78	0.80	0.77	0.96	0.97	0.66
Ln$(DE/RE)_{t-1}$=Ln$NSDP_{t-1}$	0.007	0.001	0.010	0.015	0.020	0.017	0.11	0.219

Note: Heteroscedasticity corrected standard errors, clustered at state level, are given in parentheses. P-values from a two sided mean test are provided in the bottom row. *** p<0.01, ** p<0.05, * p<0.1

Table A8: Impact of development expenditure on pro-poor growth and deprivation (Bottom 40%)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	RPPG	$PEGR_{\alpha=0}$	$PEGR_{\alpha=1}$	$PEGR_{\alpha=2}$	HCR	PGR	SPGR	Gini
$\text{Ln}(DE/RE)_{t-1}$	0.137**	0.254***	0.232***	0.229***	-0.186	-0.152*	-0.061*	-0.009
	(0.06)	(0.06)	(0.06)	(0.06)	(0.14)	(0.08)	(0.03)	(0.01)
$LnMPCE_{t-1}$	-0.401***	-0.554***	-0.484***	-0.493***	-0.425**	-0.268**	-0.126**	-0.033
	(0.06)	(0.08)	(0.07)	(0.07)	(0.18)	(0.10)	(0.05)	(0.02)
Illiterate	-0.0073	-0.0115	-0.0117	-0.0111	0.0169	0.0066	0.002	0.0005
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
8 years of schooling	0.0054*	0.0079	0.0067	0.0072	0.0017	-0.0002	-0.0001	0.0009
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
10 years of schooling	-0.0040	-0.0035	-0.0043	-0.0059	-0.0004	0.0017	0.0010	-0.0001
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	0.00	0.00
12 years of schooling	0.0069	0.0054	0.0057	0.0073	0.0048	-0.0048	-0.0034	0.0003
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
More than 12 years of schooling	0.0077***	0.0097***	0.0083***	0.0077***	-0.0085**	-0.0016	0.0001	0.0004
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Mean years of schooling in state	-0.0970**	-0.136	-0.134*	-0.132	0.0027	0.0198	0.0164	0.0009
	(0.04)	(0.08)	(0.08)	(0.08)	(0.11)	(0.05)	(0.03)	(0.01)
$\text{Ln}NSDP_{t-1}$	0.0451**	0.0353	0.0461	0.0431	-0.0528	-0.0310*	-0.0087	-0.0017
	(0.02)	(0.04)	(0.04)	(0.04)	(0.04)	(0.02)	(0.01)	0.00
Scheduled caste/Scheduled tribe	-0.0008	-0.0030	-0.0030	-0.0039	0.0060	-0.0024	-0.0015	0.0005
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Religion: Muslim	0.001	0.0017	0.0019	0.0017	-0.0042	-0.0024	-0.0009*	-0.0001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Wealth recovered (%)	-0.0009	-0.0016*	-0.0018*	-0.002**	0.0018	0.0012*	0.0005	0.0001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Party ideology	0.0037	-0.0040	-0.0005	0.0020	-0.0043	0.0000	-0.0003	0.0007
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
Centre/State party	0.0105	0.0034	0.0048	0.0057	-0.0180	-0.0064	-0.0018	-0.0004
	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.01)	(0.01)	(0.00)
Urbanization	0.474*	0.612	0.618*	0.665*	-0.736	-0.276	-0.0801	0.0361
	(0.23)	(0.36)	(0.34)	(0.37)	(0.43)	(0.22)	(0.12)	(0.06)
Gender ratio	0.138	-0.439	-0.214	-0.19	0.154	0.332	0.112	-0.0225
	(0.35)	(0.58)	(0.54)	(0.53)	(0.48)	(0.29)	(0.13)	(0.08)
Year 1999	0.140***	0.143***	0.140***	0.135***	-0.227***	-0.165***	-0.0664***	-0.0047
	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.02)	(0.01)	(0.01)
Constant	0.381	1.456	1.142	1.113	0.459	0.256	0.114	0.109
	(0.47)	(0.84)	(0.79)	(0.81)	(0.97)	(0.36)	(0.15)	(0.11)
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State specific trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of State	17	17	17	17	17	17	17	17
Observations	102	102	102	102	102	102	102	102
R-squared	0.91	0.85	0.84	0.84	0.95	0.97	0.96	0.67
$\text{Ln}(DE/RE)_{t-1}=\text{Ln}NSDP_{t-1}$	0.157	0.007	0.035	0.051	0.39	0.178	0.204	0.635

Table A9: Impact of state policies controlling for initial conditions of states

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	RPPG	PEGR$_{\alpha=0}$	PEGR$_{\alpha=1}$	PEGR$_{\alpha=2}$	HCR	PGR	SPGR	Gini
LnPCSSE$_{t-1}$	2.172**	3.462**	3.406**	3.342**	-2.694**	-0.468**	-0.164**	-0.0038
	(0.760)	(1.262)	(1.272)	(1.259)	(1.015)	(0.161)	(0.075)	(0.067)
LnPCSSE$_{t-1}^{2}$	0.107**	0.167**	0.165**	0.161**	-0.128**	-0.0221**	-0.0078*	-0.0002
	(0.040)	(0.064)	(0.064)	(0.064)	(0.051)	(0.008)	(0.004)	(0.003)
LnMPCE$_{t-1}$ * Initial dummy	-0.794***	-1.202***	-1.059***	-1.031***	0.297**	0.015	-0.0034	0.0041
	(0.210)	(0.291)	(0.229)	(0.197)	(0.136)	(0.022)	(0.011)	(0.034)
Illiterate	-0.0078*	-0.0107	-0.0105*	-0.0091*	0.0052	0.000	-0.0001	0.0015***
	(0.000)	(0.007)	(0.006)	(0.005)	(0.005)	(0.001)	(0.000)	(0.001)
8 years of schooling	0.0058	0.0105*	0.0078	0.0084	-0.0032	-0.001	-0.0002	0.0014*
	(0.000)	(0.006)	(0.006)	(0.006)	(0.005)	(0.001)	(0.001)	(0.001)
10 years of schooling	-0.0002	-0.0028	-0.0009	-0.0024	-0.0007	0.001	0.0005	-0.0011*
	(0.010)	(0.008)	(0.008)	(0.008)	(0.007)	(0.002)	(0.001)	(0.001)
12 years of schooling	0.00148	0.000	-0.00033	0.0021	0.002	-0.002	-0.0011	0.0027***
	(0.000)	(0.007)	(0.008)	(0.008)	(0.009)	(0.003)	(0.001)	(0.001)
More than 12 years of schooling	0.0073***	0.0096**	0.0081**	0.0076**	-0.0016	0.001	0.0004	-0.0003
	(0.000)	(0.004)	(0.003)	(0.003)	(0.004)	(0.001)	(0.001)	(0.000)
Mean years of schooling in state	-0.142**	-0.210*	-0.186**	-0.187**	-0.0175	-0.012	-0.0055	-0.0083
	(0.060)	(0.102)	(0.088)	(0.088)	(0.082)	(0.023)	(0.010)	(0.008)
LnNSDP$_{t-1}$	0.0445*	0.0545	0.0608*	0.0599**	-0.0365	-0.0153*	-0.0062	-0.0107***
	(0.020)	(0.033)	(0.032)	(0.028)	(0.027)	(0.008)	(0.004)	(0.004)
Scheduled caste	0.0002	-0.0043	-0.0036	-0.0045*	0.0029	-0.0006	-0.0004	0.0008**
	0.000	(0.003)	(0.003)	(0.002)	(0.003)	(0.001)	(0.000)	(0.000)
Religion: Muslim	-0.0004	-0.0017	-0.0006	-0.0006	0.0004	-0.0003	-0.0002	-0.0004*
	0.000	(0.002)	(0.002)	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)
Wealth recovered(%)	-0.0002	-0.0003	-0.0004	-0.0007	0.0004	0.0002	0.0001	0.0001
	0.000	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Party ideology	0.0035	0.0038	0.0036	0.0064	-0.0018	-0.0003	-0.0002	0.0003
	(0.010)	(0.015)	(0.013)	(0.012)	(0.007)	(0.002)	(0.001)	(0.001)
Centre/State party	0.0237	0.017	0.0142	0.0153	-0.00701	-0.003	-0.0011	-0.0020
	(0.020)	(0.028)	(0.024)	(0.021)	(0.020)	(0.005)	(0.002)	(0.003)
Urbanization	0.3950	0.4660	0.3770	0.3680	-0.0319	0.0525	0.0131	-0.0035
	(0.280)	(0.392)	(0.333)	(0.315)	(0.388)	(0.099)	(0.047)	(0.039)
Gender ratio	0.2140	0.1740	0.2160	0.2730	-0.0290	0.0035	-0.0131	-0.0193
	(0.460)	(0.669)	(0.552)	(0.527)	(0.487)	(0.112)	(0.049)	(0.045)
Year 1999	0.140***	0.177**	0.155***	0.152***	-0.0913***	-0.0393***	-0.0165***	-0.0187***
	(0.030)	(0.036)	(0.031)	(0.029)	(0.023)	(0.007)	(0.004)	(0.003)
Constant	11.25***	18.52**	18.03***	17.66***	-13.72**	-2.216**	-0.726*	0.2380
	(3.510)	(5.669)	(5.767)	(5.708)	(4.725)	(0.772)	(0.350)	(0.334)
Observations	102	102	102	102	102	102	102	102
R-squared	0.84	0.82	0.83	0.84	0.89	0.90	0.88	0.76
Number of State	17	17	17	17	17	17	17	17
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State specific trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A10: Effects of liberalization (Full sample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	RPPG	PEGR$_{\alpha=0}$	PEGR$_{\alpha=1}$	PEGR$_{\alpha=2}$	HCR	PGR	SPGR	Gini
Ln$PCSSE_{t-1}$	1.541*	1.794	2.011**	2.145**	-0.938	-0.1900	-0.0483	0.0637
	(0.733)	(1.103)	(0.908)	(0.831)	(0.954)	(0.136)	(0.051)	(0.076)
Ln$PCSSE_{t-1}^2$	0.0730*	0.0821	0.0936**	0.0996**	-0.043	-0.0092	-0.0025	0.0029
	(0.035)	(0.053)	(0.044)	(0.040)	(0.046)	(0.007)	(0.003)	(0.004)
Liberalization	-0.0718*	-0.159***	-0.135***	-0.119***	0.127***	0.0161*	0.0062	0.0035
	(0.037)	(0.040)	(0.031)	(0.030)	(0.031)	(0.009)	(0.004)	(0.004)
Ln$MPCE_{t-1}$	-0.411***	-0.464***	-0.420***	-0.443***	-0.278*	-0.105***	-0.0518***	-0.0311**
	(0.124)	(0.105)	(0.110)	(0.124)	(0.144)	(0.034)	(0.017)	(0.013)
Illiterate	-0.0045*	-0.005	-0.0054*	-0.0043*	0.0026	0.000	-0.0001	0.0016**
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.001)	(0.000)	(0.001)
8 years of schooling	0.001	0.003	0.001	0.002	0.000	-0.001	-0.0002	0.0014*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.001)	(0.001)	(0.001)
10 years of schooling	0.0001	-0.0022	-0.0004	-0.0019	-0.0012	0.0006	0.0004	-0.0011**
	(0.005)	(0.008)	(0.007)	(0.007)	(0.007)	(0.002)	(0.001)	(0.001)
12 years of schooling	-0.0015	-0.0042	-0.0043	-0.0018	0.0032	-0.0019	-0.0011	0.0027**
	(0.004)	(0.006)	(0.006)	(0.006)	(0.008)	(0.002)	(0.001)	(0.001)
More than 12 years of	0.0064***	0.0079***	0.0067***	0.0063**	-0.0013	0.000	0.0003	-0.0004
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.001)	(0.000)	(0.000)
Average education in State	-0.0027	0.0204	0.0129	0.0022	-0.0822	-0.0059	-0.0010	-0.0052
	(0.058)	(0.077)	(0.067)	(0.063)	(0.090)	(0.023)	(0.011)	(0.009)
Ln$NSDP_{t-1}$	0.0782***	0.113***	0.111***	0.107***	-0.0570*	-0.0141*	-0.0052	-0.0100**
	(0.026)	(0.031)	(0.029)	(0.028)	(0.029)	(0.008)	(0.004)	(0.004)
Scheduled caste/Scheduled	0.0020	-0.0013	-0.0009	-0.0020	0.0017	-0.0006	-0.0004	0.0008**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	-0.0004	(0.000)
Religion: Muslim	0.0010	0.0002	0.0011	0.0011	0.0007	0.0000	-0.0001	-0.0003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)
% of wealth recovered	-0.0004	-0.0004	-0.0005	-0.0008	0.0001	0.000	0.0001	0.0001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Party ideology	-0.0009	-0.0022	-0.0018	0.0010	-0.0012	-0.0003	-0.0003	0.0003
	(0.007)	(0.011)	(0.009)	(0.009)	(0.008)	(0.002)	(0.001)	(0.001)
Centre/State party	0.0221	0.0185	0.0154	0.0156	-0.0167	-0.0049	-0.0022	-0.0027
	(0.023)	(0.029)	(0.025)	(0.021)	(0.022)	(0.005)	(0.002)	(0.003)
Urbanization	-0.0669	-0.2930	-0.2820	-0.2570	0.1930	0.0401	0.0019	-0.0109
	(0.269)	(0.310)	(0.296)	(0.311)	(0.357)	(0.086)	(0.042)	(0.041)
Adult female to male ratio	0.325	0.353	0.37	0.4200	-0.0542	0.020	-0.0045	-0.0129
	(0.339)	(0.485)	(0.407)	(0.375)	(0.498)	(0.105)	(0.044)	(0.045)
Year 1999	0.187***	0.270***	0.235***	0.224***	-0.151***	-0.0451***	-0.0185***	-
	(0.028)	(0.039)	(0.033)	(0.031)	(0.024)	(0.007)	(0.004)	(0.003)
Constant	7.760*	9.329	10.34**	11.06**	-4.161	-0.727	-0.109	0.5970
	(3.949)	(5.679)	(4.656)	(4.271)	(4.821)	(0.729)	(0.268)	(0.397)
Observations	102	102	102	102	102	102	102	102
R-squared	0.89	0.90	0.90	0.90	0.91	0.91	0.89	0.77
Number of State	17	17	17	17	17	17	17	17
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State specific trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A11: Interaction effects of liberalization and state policies (Full sample)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	RPPG	PEGRα=0	PEGRα=1	PEGRα=2	HCR	PGR	SPGR	Gini
$LnPCSSE_{t-1}$	2.574***	2.866**	2.875***	2.907***	-1.734*	-0.320**	-0.0913	-0.0113
	(0.779)	(0.993)	(0.960)	(0.924)	(0.969)	(0.149)	(0.059)	(0.103)
$LnPCSSE_{t-1}^2$	0.121***	0.132**	0.134**	0.135***	-0.0799	-0.0152*	-0.0045	-0.0006
	(0.037)	(0.048)	(0.046)	(0.044)	(0.047)	(0.007)	(0.003)	(0.005)
$LnMPCE_{t-1}$	-0.641***	-0.685***	-0.603***	-0.601***	-0.115	-0.0777*	-0.0428**	-0.0151
	(0.156)	(0.185)	(0.188)	(0.191)	(0.176)	(0.040)	(0.019)	(0.013)
I(PCSSE > μ_{PCSSE})*I(Year<1991)	0.253***	0.248***	0.203***	0.178***	-0.184***	-0.031***	-0.010*	-0.018**
	(0.042)	(0.049)	(0.053)	(0.052)	(0.034)	(0.009)	(0.005)	(0.007)
I(PCSSE < μ_{PCSSE})*I(Year>1991)	-0.063**	-0.104***	-0.091**	-0.080**	0.086***	0.010	0.004	-0.0003
	(0.024)	(0.034)	(0.031)	(0.034)	(0.028)	(0.009)	(0.005)	(0.003)
I(PCSSE > μ_{PCSSE})*I(Year>1991)	-0.0044	-0.060	-0.062	-0.0520	0.0522	0.006	0.0025	-0.0025
	(0.038)	(0.052)	(0.048)	(0.052)	(0.046)	(0.014)	(0.007)	(0.004)
Illiterate	-0.0042*	-0.005	-0.0052*	-0.0042	0.0024	0.000	-0.0001	0.0016***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.000)	(0.000)
8 years of schooling	0.002	0.0024	0.0011	0.0019	0.0003	-0.001	-0.0002	0.0014*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.001)	(0.001)	(0.001)
10 years of schooling	0.0001	-0.0030	-0.0009	-0.0024	-0.0006	0.0007	0.0004	-0.0011*
	(0.005)	(0.008)	(0.007)	(0.007)	(0.008)	(0.002)	(0.001)	(0.001)
12 years of schooling	0.0005	-0.0036	-0.0034	-0.0012	0.0028	-0.002	-0.0011	0.0026***
	(0.004)	(0.006)	(0.006)	(0.006)	(0.008)	(0.002)	(0.001)	(0.001)
More than 12 years of schooling	0.0049**	0.0075***	0.0060***	0.0059**	-0.0011	0.000	0.0003	-0.0003
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)	(0.000)	(0.000)
Mean years of schooling in state	-0.00231	0.011	0.00752	-0.0037	-0.0744	-0.005	-0.0007	-0.0048
	(0.062)	(0.075)	(0.070)	(0.063)	(0.090)	(0.022)	(0.010)	(0.008)
$LnNSDP_{t-1}$	0.0798**	0.113***	0.111***	0.107***	-0.0568*	-0.0142*	-0.0052	-0.0100**
	(0.028)	(0.028)	(0.030)	(0.028)	(0.028)	(0.007)	(0.004)	(0.004)
Scheduled caste/Scheduled tribe	-0.0003	-0.004	-0.0030	-0.0038*	0.0037*	0.000	-0.0003	0.0009***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.000)	(0.000)
Religion: Muslim	0.0013	0.0006	0.0014	0.0014	0.0003	-0.0001	-0.0001	-0.0003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)
Wealth recovered (%)	-0.0004	-0.0004	-0.0005	-0.0008	0.0001	0.0002	0.0001	0.0001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Party ideology	-0.0033	-0.006	-0.0047	-0.0017	0.0018	0.000	-0.0001	0.0005
	(0.006)	(0.010)	(0.009)	(0.009)	(0.007)	(0.002)	(0.001)	(0.001)
Centre/State party	0.0108	0.0105	0.0080	0.0095	-0.011	-0.004	-0.0019	-0.0020
	(0.014)	(0.020)	(0.018)	(0.016)	(0.019)	(0.006)	(0.003)	(0.003)
Urbanization	-0.0921	-0.339	-0.313	-0.2880	0.228	0.045	0.0036	-0.0083
	(0.268)	(0.358)	(0.322)	(0.340)	(0.390)	(0.088)	(0.043)	(0.040)
Gender ratio	0.438	0.405	0.4280	0.4620	-0.0888	0.011	-0.0069	-0.0186
	(0.287)	(0.423)	(0.360)	(0.317)	(0.441)	(0.099)	(0.042)	(0.041)
Year 1999	0.171***	0.249***	0.219***	0.209***	-0.135***	-0.043***	-0.018***	-0.018***
	(0.028)	(0.038)	(0.035)	(0.034)	(0.026)	(0.007)	(0.004)	(0.003)
Constant	13.34***	15.23**	15.07***	15.24***	-8.546*	-1.433*	-0.3450	0.1880
	(4.226)	(5.287)	(5.109)	(4.977)	(4.840)	(0.755)	(0.300)	(0.539)
Observations	102	102	102	102	102	102	102	102
R-squared	0.91	0.91	0.91	0.91	0.92	0.92	0.90	0.79
NumberofState	17	17	17	17	17	17	17	17
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State specific trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Figure A2: Plot of likelihood ratio test of linearity against threshold panel

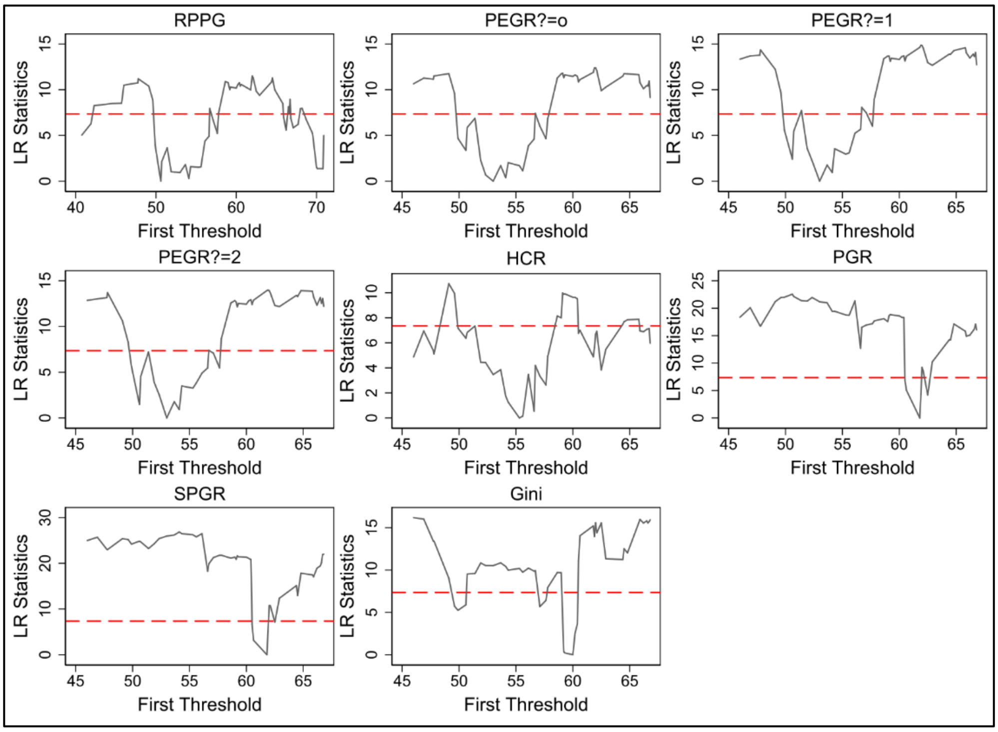


Table A12: Coefficients for threshold panel model with literacy as threshold variable

Variables	(1) RPPG	(2) PEGRα=*0*	(3) PEGRα=*1*	(4) PEGRα=*2*	(5) HCR	(6) PGR	(7) SPGR	(8) Gini
Threshold value ($\hat{\lambda}_{LIT}$)	50.6	53.0	53.0	53.0	55.3	61.8	61.8	60.0
Ln*PCSSE*t-*1* * I(*LIT*it >$\hat{\lambda}_{LIT}$)	2.744***	4.327***	4.600***	4.790***	-2.395**	1.123***	0.645***	-0.270*
	(0.552)	(1.279)	(0.916)	(0.794)	(1.107)	(0.364)	(0.199)	(0.150)
Ln*PCSSE*t-*1* * I(*LIT*it < $\hat{\lambda}_{LIT}$)	-0.919	-0.826	-0.814	-0.712	-0.362	0.095	0.099	-0.098
	(1.770)	(2.238)	(2.060)	(2.097)	(2.598)	(0.442)	(0.186)	(0.125)
Ln*PCSSE*t-*1*^{2} * I(*LIT*it > $\hat{\lambda}_{LIT}$)	0.130***	0.203***	0.218***	0.227***	-0.112*	0.0579***	0.0328***	-0.0139*
	(0.027)	(0.063)	(0.045)	(0.040)	(0.055)	(0.018)	(0.010)	(0.007)
Ln*PCSSE*t-*1*^{2} * I(*LIT*it < $\hat{\lambda}_{LIT}$)	-0.0384	-0.0342	-0.0330	-0.0293	-0.0207	0.0033	0.0040	-0.0046
	(0.082)	(0.105)	(0.098)	(0.099)	(0.123)	(0.021)	(0.009)	(0.006)
Ln*MPCE*t-*1*	-0.586***	-0.869***	-0.756***	-0.740***	0.0579	-0.0673**	-0.0380**	-0.0259**
	(0.074)	(0.079)	(0.085)	(0.086)	(0.119)	(0.027)	(0.013)	(0.011)
Illiterate	-0.0072*	-0.0099*	-0.0091*	-0.0073	0.0061	0.0026**	0.0012**	0.0012*
	(0.003)	(0.006)	(0.005)	(0.004)	(0.005)	(0.001)	(0.001)	(0.001)
8 years of schooling	0.0036	0.0070	0.0049	0.0059	-0.0025	-0.0004	0.0000	0.0010
	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)	(0.001)	(0.0004)	(0.001)
10 years of schooling	0.0005	-0.0007	0.0007	-0.0013	-0.0013	-0.0009	-0.0003	-0.0007
	(0.006)	(0.009)	(0.008)	(0.008)	(0.007)	(0.002)	(0.001)	(0.001)
12 years of schooling	-0.0014	-0.0046	-0.0042	-0.0010	0.0036	0.0008	0.0003	0.0020**
	(0.005)	(0.008)	(0.008)	(0.007)	(0.009)	(0.001)	(0.0004)	(0.001)
More than 12 years of schooling	0.0078***	0.0108**	0.0088**	0.008**	-0.0035	-0.0010	-0.0004	-0.0001
	(0.002)	(0.004)	(0.003)	(0.003)	(0.003)	(0.001)	(0.0003)	(0.000)
Mean years of schooling in state	-0.0813	-0.131*	-0.113*	-0.1060	0.0200	0.0299	0.0161	-0.0083
	(0.052)	(0.069)	(0.064)	(0.067)	(0.092)	(0.025)	(0.011)	(0.008)
Ln*NSDP*t-*1*	0.0493*	0.0551	0.0602*	0.0615*	-0.0182	-0.0127	-0.0048	-0.0097**
	(0.028)	(0.034)	(0.034)	(0.034)	(0.034)	(0.007)	(0.004)	(0.004)
Scheduled caste/Scheduled tribe	0.0012	-0.0030	-0.0026	-0.00375*	0.0022	-0.0005	-0.0004	0.0007**
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.0004)	(0.000)
Religion: Muslim	0.0011	0.0005	0.0012	0.0010	0.0011	0.0000	0.0000	-0.0004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.0002)	(0.000)
Wealth recovered (%)	-0.0009	-0.0014*	-0.0014*	-0.0015*	0.0008	0.0003	0.0001	0.0001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.0001)	(0.000)
Party ideology	-0.0040	-0.0073	-0.0062	-0.0024	0.0028	-0.0022	-0.0013	0.0005
	(0.007)	(0.011)	(0.010)	(0.010)	(0.011)	(0.002)	(0.001)	(0.001)
Centre/State party	0.0142	0.0053	0.0053	0.0070	-0.0063	-0.0017	-0.0007	-0.0022
	(0.021)	(0.028)	(0.024)	(0.021)	(0.023)	(0.004)	(0.002)	(0.002)
Urbanization	-0.0234	-0.219	-0.222	-0.211	0.121	0.197**	0.0837***	-0.0612
	(0.275)	(0.353)	(0.323)	(0.333)	(0.508)	(0.073)	(0.027)	(0.047)
Gender ratio	0.257	0.261	0.307	0.354	-0.0206	0.0052	-0.0127	-0.0066
	(0.411)	(0.563)	(0.457)	(0.422)	(0.440)	(0.090)	(0.034)	(0.050)
Year 1999	0.141***	0.171***	0.149***	0.148***	-0.0779**	-0.0405***	-0.0170***	-0.0183***
	(0.024)	(0.034)	(0.029)	(0.027)	(0.032)	(0.005)	(0.003)	(0.002)
*LIT*it dummy	19.90*	27.99**	29.19***	29.49***	-11.35	4.7810	2.5600	-0.775
	(9.953)	(10.661)	(9.404)	(9.980)	(14.116)	(3.272)	(1.494)	(0.996)
Constant	-5.197	-4.185	-4.417	-3.9	-1.331	0.62	0.591	-0.245
	(9.069)	(11.427)	(10.414)	(10.589)	(13.452)	(2.331)	(1.001)	(0.614)
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State specific trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of State	17	17	17	17	17	17	17	17
R-squared	0.88	0.87	0.88	0.89	0.89	0.94	0.93	0.79
Observations	102	102	102	102	102	102	102	102
Ln*PCSSE*t-*1**I(*LIT*it >$\hat{\lambda}_{LIT}$)=Ln*NSDP*t-*1*	0.000	0.004	0.000	0.000	0.047	0.007	0.005	0.104

Table A13: Coefficients for threshold panel model with 8 years of schooling as threshold variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	RPPG	$PEGR_{\alpha=0}$	$PEGR_{\alpha=1}$	$PEGR_{\alpha=2}$	HCR	PGR	SPGR	Gini
Threshold value ($\hat{\lambda}_{YS}$)	12.37	11.60	12.37	12.37	12.58	8.41	13.99	14.88
$\text{Ln}PCSSE_{t-1} * I(YS_{it} > \hat{\lambda}_{YS})$	3.174***	5.244***	5.809***	5.789***	-3.212*	-0.414**	0.273**	0.1360
	(1.026)	(1.261)	(1.142)	(0.993)	(1.628)	(0.183)	(0.111)	(0.263)
$\text{Ln}PCSSE_{t-1} * I(YS_{it} < \hat{\lambda}_{YS})$	0.910	0.522	0.713	0.8150	-1.062	-0.781	-0.0796	-0.0491
	(0.676)	(1.080)	(0.859)	(0.911)	(1.242)	(1.589)	(0.070)	(0.082)
$\text{Ln}PCSSE_{t-1}^2 * I(YS_{it} > \hat{\lambda}_{YS})$	0.150**	0.244***	0.275***	0.274***	-0.151*	-0.0199**	0.0140**	0.0066
	(0.051)	(0.062)	(0.057)	(0.050)	(0.083)	(0.009)	(0.006)	(0.013)
$\text{Ln}PCSSE_{t-1}^2 * I(YS_{it} < \hat{\lambda}_{YS})$	0.0452	0.027	0.0358	0.0399	-0.0516	-0.037	-0.0040	-0.0024
	(0.032)	(0.051)	(0.042)	(0.044)	(0.059)	(0.072)	(0.003)	(0.004)
$\text{Ln}MPCE_{t-1}$	-0.676***	-1.066***	-0.892***	-0.859***	0.157	-0.045	-0.0364**	-0.0246
	(0.083)	(0.118)	(0.113)	(0.103)	(0.120)	(0.034)	(0.017)	(0.015)
Illiterate	-0.0064**	-0.0094*	-0.0096***	-0.0084***	0.0053	0.000	0.0009*	0.0016***
	(0.003)	(0.005)	(0.003)	(0.003)	(0.004)	(0.001)	(0.000)	(0.000)
8 years of schooling	0.0025	0.007	0.0031	0.0039	-0.0012	-0.001	-0.00097	0.0005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.007)	(0.001)	(0.001)	(0.001)
10 years of schooling	0.0001	-0.0028	0.000	-0.0015	-0.0008	0.0003	0.0005	-0.0012**
	(0.005)	(0.008)	(0.007)	(0.008)	(0.007)	(0.002)	(0.001)	(0.001)
12 years of schooling	0.0028	0.004	0.0024	0.0040	-0.0015	-0.002	-0.0011	0.0026***
	(0.004)	(0.007)	(0.006)	(0.006)	(0.009)	(0.002)	(0.001)	(0.001)
More than 12 years of schooling	0.0036*	0.0029	0.0016	0.0018	0.0016	0.000	0.0001	-0.0004
	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)	(0.001)	(0.0004)	(0.000)
Mean years of schooling in state	-0.0443	-0.057	-0.0635	-0.0664	-0.0315	-0.004	0.0124	-0.0025
	(0.054)	(0.072)	(0.065)	(0.061)	(0.090)	(0.022)	(0.012)	(0.008)
$\text{Ln}NSDP_{t-1}$	0.0576**	0.0764**	0.0764**	0.0766**	-0.0313	-0.0122*	-0.004	-0.0088**
	(0.026)	(0.030)	(0.030)	(0.029)	(0.032)	(0.006)	(0.005)	(0.004)
Scheduled caste/Scheduled tribe	0.0014	-0.002	-0.0024	-0.0035*	0.0022	-0.001	-0.0006	0.0006*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)	(0.000)	(0.000)
Religion: Muslim	0.0003	-0.0008	0.0002	0.0003	0.0009	0.000	-0.0002	-0.0004*
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)
Wealth recovered(%)	-0.0004	-0.0007	-0.0007	-0.0010	0.0003	0.0002	0.0001	0.0001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Party ideology	0.0004	0.0024	-0.0001	0.0026	-0.0011	0.0012	-0.0006	0.0001
	(0.006)	(0.008)	(0.008)	(0.008)	(0.007)	(0.002)	(0.001)	(0.001)
Centre/State party	0.0174	0.006	0.0068	0.0080	-0.0083	-0.003	-0.0005	-0.0018
	(0.021)	(0.026)	(0.023)	(0.020)	(0.022)	(0.004)	(0.002)	(0.003)
Urbanization	0.0191	-0.0952	0.0434	0.0713	-0.101	0.041	0.0175	-0.0133
	(0.324)	(0.369)	(0.368)	(0.379)	(0.385)	(0.105)	(0.046)	(0.036)
Gender ratio	0.230	0.174	0.290	0.368	0.0578	0.014	0.0291	-0.0102
	(0.343)	(0.475)	(0.434)	(0.391)	(0.550)	(0.116)	(0.036)	(0.053)
YS_{it} dummy	12.27**	25.55**	27.14***	26.37***	-11.63	2.039	1.737**	0.9560
	(5.477)	(8.895)	(6.730)	(6.054)	(8.891)	(8.562)	(0.752)	(1.462)
Year 1999	0.143***	0.184***	0.153***	0.152***	-0.0832***	-0.0369***	-0.0152***	-0.0174***
	(0.020)	(0.026)	(0.020)	(0.018)	(0.023)	(0.006)	(0.003)	(0.003)
Constant	4.646	3.015	3.829	4.336	-5.076	-3.958	-0.399	-0.0069
	(3.660)	(5.431)	(4.267)	(4.515)	(6.367)	(8.655)	(0.394)	(0.428)
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State specific trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of State	17	17	17	17	17	17	17	17
R-squared	0.89	0.89	0.90	0.90	0.90	0.91	0.91	0.79
Observations	102	102	102	102	102	102	102	102
p-value: $\text{Ln}PCSSE_{t\_1} * I(YS_{it} > \hat{\lambda}_{YS}) = \text{Ln}NSDP_{t-1}$	0.007	0.001	0.000	0.000	0.066	0.041	0.025	0.589

Table A14: Coefficients for threshold panel model with mean years of schooling as threshold variable

Variables	(1) RPPG	(2) $PEGR_{\alpha=0}$	(3) $PEGR_{\alpha=1}$	(4) $PEGR_{\alpha=2}$	(5) HCR	(6) PGR	(7) SPGR	(8) Gini
Threshold value ($\hat{\lambda}_{MYS}$)	3.5	3.7	3.7	3.7	3.7	3.7	4.1	4.5
Ln*PCSSE*t-*1* * I(*MYS*it >$\hat{\lambda}_{MYS}$)	2.638***	4.963***	5.238***	5.699***	-2.692*	-0.125	0.348	0.3040
	(0.690)	(1.649)	(1.164)	(1.100)	(1.498)	(0.353)	(0.411)	(0.245)
Ln*PCSSE*t-*1* * I(*MYS*it < $\hat{\lambda}_{MYS}$)	-2.3320	0.0343	-0.6100	-0.6230	-0.2870	0.0071	0.0874	0.1140
	(2.299)	(2.087)	(1.739)	(1.552)	(1.974)	(0.461)	(0.239)	(0.124)
Ln*PCSSE*t-1^2 * I(*MYS*it >$\hat{\lambda}_{MYS}$)	0.125***	0.235**	0.250***	0.273***	-0.126	-0.0052	0.0178	0.0154
	(0.035)	(0.082)	(0.058)	(0.055)	(0.075)	(0.018)	(0.021)	(0.013)
Ln*PCSSE*t-1^2 * I(*MYS*it < $\hat{\lambda}_{MYS}$)	-0.1030	0.0033	-0.0261	-0.0273	-0.0156	-0.0005	0.0035	0.0051
	(0.107)	(0.097)	(0.082)	(0.073)	(0.093)	(0.021)	(0.011)	(0.006)
Ln*MPCE*t-*1*	-0.481***	-0.823***	-0.719***	-0.698***	-0.0032	-0.0706**	-0.0391**	-0.0203
	(0.103)	(0.081)	(0.069)	(0.063)	(0.093)	(0.026)	(0.015)	(0.012)
Illiterate	-0.00674*	-0.0074	-0.0076	-0.0058	0.0048	0.0005	0.0008	0.0019***
	(0.004)	(0.006)	(0.005)	(0.004)	(0.006)	(0.001)	(0.001)	(0.000)
8 years of schooling	0.0040	0.0060	0.0050	0.0062	-0.0007	-0.0006	0.00002	0.0014**
	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.001)	(0.0005)	(0.001)
10 years of schooling	-0.0001	0.0000	0.0015	-0.0006	-0.0037	0.0000	-0.0003	-0.0014**
	(0.006)	(0.009)	(0.009)	(0.009)	(0.007)	(0.002)	(0.001)	(0.001)
12 years of schooling	-0.0012	-0.0092	-0.0079	-0.0043	0.0096	-0.0005	0.0002	0.0026***
	(0.005)	(0.008)	(0.008)	(0.008)	(0.008)	(0.002)	(0.0006)	(0.001)
More than 12 years of schooling	0.0091***	0.0136**	0.0115**	0.0105**	-0.0069*	-0.0007	-0.0004	-0.0003
	(0.003)	(0.005)	(0.004)	(0.004)	(0.003)	(0.001)	(0.0002)	(0.0003)
Mean years of schooling in state	-0.124*	-0.133*	-0.129*	-0.124*	0.0428	0.0163	0.0136	-0.0029
	(0.069)	(0.074)	(0.063)	(0.062)	(0.089)	(0.026)	(0.011)	(0.009)
Ln*NSDP*t-*1*	0.0374	0.0474	0.0483	0.0483	-0.0064	-0.0063	-0.0040	-0.0091**
	(0.025)	(0.036)	(0.034)	(0.031)	(0.028)	(0.006)	(0.003)	(0.003)
Scheduled caste/Scheduled tribe	0.0012	-0.0040	-0.0040*	-0.0051**	0.00313*	-0.0005	-0.0001	0.0008**
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.0003)	(0.000)
Religion: Muslim	-0.0012	-0.0027	-0.0020	-0.0019	0.00281*	0.0003	0.0001	-0.0003*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.000)	(0.0002)	(0.0002)
Wealth recovered (%)	-0.0010	-0.0001	-0.0002	-0.0005	-0.0003	0.0001	0.0001	0.0001
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.0001)	(0.0001)
Party ideology	-0.0033	-0.0032	-0.0023	0.0005	-0.0002	-0.0003	-0.0008	0.0004
	(0.006)	(0.009)	(0.008)	(0.008)	(0.007)	(0.002)	(0.001)	(0.001)
Centre/State party	0.0054	0.0061	0.0043	0.0062	-0.0076	-0.0034	-0.0014	-0.0018
	(0.012)	(0.018)	(0.014)	(0.013)	(0.014)	(0.005)	(0.002)	(0.002)
Urbanization	0.0326	-0.102	-0.126	-0.0522	0.0636	0.0666	0.0713	-0.0094
	(0.285)	(0.416)	(0.376)	(0.369)	(0.395)	(0.091)	(0.050)	(0.048)
Gender ratio	0.221	0.193	0.226	0.292	0.0882	0.0459	-0.0088	-0.0054
	4)	(0.486)	(0.379)	(0.321)	(0.409)	(0.096)	(0.033)	(0.044)
Year 1999	0.128***	0.160***	0.136***	0.134***	-0.0631**	-0.0328***	-	-0.0168***
	(0.020)	(0.035)	(0.029)	(0.026)	(0.028)	(0.004)	(0.003)	(0.003)
*MYS*it dummy	27.08**	26.30***	31.07***	33.35***	-13.12	-0.8820	1.1520	0.87
	(11.153)	(7.625)	(6.330)	(6.338)	(9.138)	(2.643)	(2.209)	(1.453)
Constant	-12.67	0.691	-2.905	-3.059	-1.264	0.211	0.542	0.85
	(11.949)	(10.534)	(8.747)	(7.762)	(9.982)	(2.459)	(1.282)	(0.620)
Observations	102	102	102	102	102	102	102	102
R-squared	0.91	0.90	0.91	0.92	0.92	0.93	0.92	0.80
Numberof State	17	17	17	17	17	17	17	17
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State specific trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p-value: Ln*PCSSE*t_*1**I(*MYS*it>$\hat{\lambda}_{MYS}$)=*LnNSDP*$_{t-1}$	0.002	0.009	0.000	0.000	0.091	0.741	0.406	0.218

Table A15: Coefficients for threshold panel model with gender gap in education as threshold variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	RPPG	PEGRα=0	PEGRα=1	PEGRα=2	HCR	PGR	SPGR	Gini
Threshold value ($\hat{\lambda}_{GENEDU}$)	0.712	0.712	0.712	0.712	0.712	0.750	0.750	0.753
Ln$PCSSE_{t-1}$ * I($GENEDUit > \hat{\lambda}_{GENEDU}$)	3.822***	6.149***	6.091***	6.124***	-3.992**	-0.451	-0.108	-0.0201
	(0.780)	(1.038)	(0.735)	(0.601)	(1.392)	(0.325)	(0.135)	(0.132)
Ln$PCSSE_{t-1}$ * I($GENEDUit < \hat{\lambda}_{GENEDU}$)	2.537*	4.373***	4.077***	3.728**	-2.2540	-0.2670	-0.0391	0.1130
	(1.362)	(1.442)	(1.311)	(1.426)	(1.760)	(0.563)	(0.255)	(0.136)
Ln$PCSSE_{t-1}^2$ * I($GENEDUi_t > \hat{\lambda}_{GENEDU}$)	0.186***	0.298***	0.296***	0.297***	-0.193**	-0.0217	-0.0053	-0.0010
	(0.040)	(0.051)	(0.037)	(0.030)	(0.070)	(0.017)	(0.007)	(0.007)
Ln$PCSSE_{t-1}^2$ * I($GENEDUit < \hat{\lambda}_{GENEDU}$)	0.120*	0.204***	0.190***	0.174**	-0.1060	-0.0131	-0.0023	0.0053
	(0.062)	(0.066)	(0.061)	(0.067)	(0.083)	(0.026)	(0.012)	(0.006)
Ln$MPCE_{t-1}$	-0.718***	-1.030***	-0.945***	-0.923***	0.179*	-0.0354	-0.0231	-0.0164
	(0.103)	(0.134)	(0.120)	(0.108)	(0.102)	(0.024)	(0.014)	(0.018)
% of Illiterate	-0.0071**	-0.0095**	-0.0099***	-0.0085***	0.0085*	0.0005	0.0001	0.0018***
	(0.003)	(0.004)	(0.003)	(0.002)	(0.004)	(0.001)	(0.000)	(0.000)
8 years of schooling	0.0019	0.0047	0.0037	0.0044	-0.0028	-0.0014	-0.00041	0.0007
	(0.003)	(0.005)	(0.004)	(0.004)	(0.005)	(0.001)	(0.0005)	(0.001)
10 years of schooling	-0.0006	-0.0042	-0.0022	-0.0039	-0.0017	0.0005	0.0004	-0.0008
	(0.005)	(0.008)	(0.007)	(0.007)	(0.007)	(0.002)	(0.001)	(0.001)
12 years of schooling	0.0000	-0.0020	-0.0011	0.0014	0.0013	-0.0024	-0.0012	0.0021**
	(0.004)	(0.006)	(0.005)	(0.005)	(0.008)	(0.003)	(0.0012)	(0.001)
More than 12 years of schooling	0.0049***	0.0059*	0.0044*	0.0038*	-0.0012	0.0004	0.0003	-0.0003
	(0.001)	(0.003)	(0.002)	(0.002)	(0.003)	(0.001)	(0.0005)	(0.000)
Gender gap in education	-0.6120	-0.7460	-0.882*	-0.851**	0.8390	0.1320	0.0545	0.0357
	(0.401)	(0.535)	(0.476)	(0.399)	(0.550)	(0.184)	(0.102)	(0.075)
Ln$NSDPt$-1	0.0728***	0.101***	0.0964***	0.0968***	-0.0223	-0.0088	-0.0036	-0.0075**
	(0.017)	(0.023)	(0.022)	(0.019)	(0.025)	(0.006)	(0.002)	(0.003)
Scheduled caste/Scheduled tribe	0.0026	-0.0004	-0.0001	-0.0011	0.0020	-0.0005	-0.0004	0.0007**
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.001)	(0.0004)	(0.000)
Religion: Muslim	0.0022*	0.0023	0.0030**	0.0029**	-0.0003	-0.0001	-0.0001	-0.0003**
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.0002)	(0.000)
Wealth recovered(%)	-0.0003	-0.0004	-0.0004	-0.0007	0.0003	0.0003	0.0001	0.0002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.0001)	(0.000)
Party ideology	-0.0028	-0.0048	-0.0050	-0.0014	0.0038	0.0004	-0.0001	0.0005
	(0.006)	(0.010)	(0.008)	(0.007)	(0.008)	(0.002)	(0.001)	(0.001)
Centre/State party	0.0215	0.0131	0.0112	0.0128	-0.0113	-0.0038	-0.0019	-0.0018
	(0.020)	(0.025)	(0.020)	(0.018)	(0.018)	(0.005)	(0.002)	(0.002)
Urbanization	0.172	0.186	0.096	0.0941	-0.101	0.0305	0.00494	-0.0148
	(0.314)	(0.391)	(0.358)	(0.347)	(0.401)	(0.096)	(0.046)	(0.043)
Gender ratio	0.314	0.328	0.300	0.355	0.0159	0.0398	0.0005	0.0003
	(0.360)	(0.485)	(0.396)	(0.344)	(0.471)	(0.129)	(0.055)	(0.053)
$GENEDU_{it}$ dummy	6.254	8.376	9.621	11.630	-8.736	-0.988	-0.400	-0.693
	(7.898)	(7.609)	(6.617)	(7.810)	(7.805)	(3.555)	(1.605)	(0.865)
Year 1999	0.151***	0.198***	0.168***	0.166***	-0.0746**	-0.0344***	-0.0147***	-0.0168***
	(0.022)	(0.031)	(0.026)	(0.024)	(0.028)	(0.008)	(0.004)	(0.004)
Constant	13.51*	23.73***	22.23***	20.29**	-12.35	-1.296	-0.102	0.774
	(7.317)	(7.819)	(7.067)	(7.631)	(8.960)	(2.944)	(1.327)	(0.769)
Observations	102	102	102	102	102	102	102	102
R-squared	0.89	0.89	0.90	0.91	0.90	0.91	0.89	0.79
Number of State	17	17	17	17	17	17	17	17
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State specific trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
*p-value:*Ln$PCSSE_{t-1}$*I($GENEDU_{it} > \hat{\lambda}_{GENEDU}$)=Ln$NSDP_{t-1}$	0.000	0.000	0.000	0.000	0.012	0.193	0.45	0.924
p-value: joint F test of difference	0.103	0.012	0.002	0.001	0.156	-	-	-

Table A16: Estimation results of threshold panel model with endogenous threshold variables

Variables	(1) RPPG	(2) $PEGR_{\alpha=0}$	(3) $PEGR_{\alpha=1}$	(4) $PEGR_{\alpha=2}$	(5) HCR	(6) PGR	(7) Gini
Panel A: Threshold variable - Literacy (LIT)							
Threshold value ($\hat{\lambda}_{LIT}$)	47.59	44.56	55.66	46.58	55.39	68.03	53.29
Ln$PCSSE_{t-1}$ * I($LIT_{it} > \hat{\lambda}_{LIT}$)	2.690*	3.959**	1.525	3.885**	1.104	1.009	0.616
	(1.4305)	(1.7075)	(3.2514)	(1.6674)	(5.2510)	(2.4700)	(1.5280)
Ln$PCSSE_{t-1}$ * I($LIT_{it} < \hat{\lambda}_{LIT}$)	-5.627	-2.099	-9.226	-7.369	12.16	-0.754*	1.906
	(9.1668)	(7.8666)	(11.4904)	(12.3050)	(24.8015)	(0.4070)	(5.0250)
Ln$PCSSE_{t-1}^2$* I($LIT_{it} > \hat{\lambda}_{LIT}$)	0.127*	0.187**	0.0629	0.183**	0.0642	0.0513	0.0298
	(0.0681)	(0.0822)	(0.1627)	(0.0795)	(0.2655)	(0.1246)	(0.0779)
Ln$PCSSE_{t-1}^2$* I($LIT_{it} < \hat{\lambda}_{LIT}$)	-0.262	-0.0921	-0.423	-0.337	0.559	-0.0360*	0.0898
	(0.4272)	(0.3639)	(0.5313)	(0.5693)	(1.1451)	(0.0199)	(0.2337)
Panel B: 8 years of schooling (YS)							
Threshold value ($\hat{\lambda}_{YS}$)	10.43	8.34	7.94	7.94	19.13	10.02	12.50
Ln$PCSSE_{t-1}$ * I($YS_{it} > \hat{\lambda}_{YS}$)	2.536**	4.234***	4.423***	4.562***	5.858	-0.269	1.106
	(1.0398)	(1.3644)	(1.0227)	(1.0724)	(6.7232)	(0.3094)	(3.7224)
Ln$PCSSE_{t-1}$ * I($YS_{it} < \hat{\lambda}_{YS}$)	-2.077	-21.04**	-16.29*	-14.51	-1.210	0.138	0.564
	(2.0106)	(9.7697)	(9.2747)	(10.3877)	(0.9796)	(0.9560)	(1.5977)
Ln$PCSSE_{t-1}^2$* I($YS_{it} > \hat{\lambda}_{YS}$)	0.122**	0.205***	0.215***	0.221***	0.287	-0.0134	0.0571
	(0.0502)	(0.0664)	(0.0486)	(0.0505)	(0.3287)	(0.0151)	(0.1948)
Ln$PCSSE_{t-1}^2$* I($YS_{it} < \hat{\lambda}_{YS}$)	-0.0897	-0.950**	-0.733*	-0.654	-0.0556	0.00506	0.0289
	(0.0944)	(0.4414)	(0.4179)	(0.4681)	(0.0478)	(0.0436)	(0.0890)
Panel C: Mean years of schooling (MYS)							
Threshold value ($\hat{\lambda}_{MYS}$)	5.34	9.41	9.41	5.71	12.73	12	11.63
Ln$PCSSE_{t-1}$ * I($MYS_{it} > \hat{\lambda}_{MYS}$)	2.481*	1.173	3.045	2.390	-6.963	1.078	-0.705
	(1.4479)	(3.9135)	(2.5481)	(12.5474)	(28.5225)	(1.8936)	(2.0741)
Ln$PCSSE_{t-1}$ * I($MYS_{it} < \hat{\lambda}_{MYS}$)	2.437*	-5.004	-3.639	8.587	3.393	0.786	1.703
	(1.3645)	(5.6507)	(3.9220)	(47.4723)	(14.1864)	(1.9806)	(2.1506)
Ln$PCSSE_{t-1}^2$* I($MYS_{it} > \hat{\lambda}_{MYS}$)	0.120	0.0548	0.148	0.146	-0.356	0.0525	-0.0382
	(0.0730)	(0.1991)	(0.1307)	(0.5338)	(1.4515)	(0.0957)	(0.1061)
Ln$PCSSE_{t-1}^2$* I($MYS_{it} < \hat{\lambda}_{MYS}$)	0.115*	-0.233	-0.168	0.384	0.162	0.0363	0.0807
	(0.0653)	(0.2684)	(0.1863)	(2.1380)	(0.6780)	(0.0937)	(0.1024)

Note: Heteroscedasticity corrected standard errors clustered at state level are provided in parentheses. Regression tables with all controls can always be provided on request. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 17: Restricted model with clustered standard errors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	RPPG	PEGR$_{\alpha=0}$	PEGR$_{\alpha=1}$	PEGR$_{\alpha=2}$	HCR	PGR	SPGR	Gini
LnPCSSE$_{t-1}$	4.043***	5.615***	5.363***	5.356***	-3.765***	-0.454**	-0.123	-0.0622
	(0.5754)	(0.9279)	(0.8474)	(0.8089)	(0.7965)	(0.1834)	(0.0788)	(0.1068)
LnPCSSE$_{t-1}^2$	0.185***	0.254***	0.244***	0.244***	-0.172***	-0.0190**	-0.0048	-0.00302
	(0.0269)	(0.0433)	(0.0400)	(0.0383)	(0.0377)	(0.0087)	(0.0037)	(0.0050)
LnMPCE$_{t-1}$	-0.707***	-1.047***	-0.885***	-0.859***	0.0693	-0.0115	-0.0067	-0.0316**
	(0.1215)	(0.1650)	(0.1529)	(0.1573)	(0.0889)	(0.0318)	(0.0165)	(0.0135)
LnNSDP$_{t-1}$	0.0277**	0.0281*	0.0326***	0.0385***	0.0164	-0.0004	-0.0001	-0.00426**
	(0.0107)	(0.0137)	(0.0108)	(0.0095)	(0.0142)	(0.0030)	(0.0013)	(0.0015)
Year 1999	0.0962***	0.130***	0.115***	0.115***	-0.0550**	-0.0288***	-0.0123***	-0.0180***
	(0.0221)	(0.0271)	(0.0235)	(0.0226)	(0.0243)	(0.0061)	(0.0027)	(0.0021)
Constant	22.20***	31.24***	29.60***	29.51***	-20.28***	-2.573**	-0.727*	-0.0213
	(3.0705)	(4.9803)	(4.4859)	(4.2664)	(4.2166)	(0.9681)	(0.4147)	(0.5736)
Observations	102	102	102	102	102	102	102	102
R-squared	0.508	0.51	0.517	0.528	0.766	0.765	0.728	0.455
Number of id	17	17	17	17	17	17	17	17
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State specific trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A18: Restricted model with bootstrapped standard errors

VARIABLES	(1) RPPG	(2) $PEGR_{\alpha=0}$	(3) $PEGR_{\alpha=1}$	(4) $PEGR_{\alpha=2}$	(5) HCR	(6) PGR	(7) SPGR	(8) Gini
$LnPCSSE_{t-1}$	4.043***	5.615***	5.363***	5.356***	-3.765***	-0.454***	-0.123*	-0.0622
	(0.5749)	(0.8850)	(0.8191)	(0.7884)	(0.6800)	(0.1543)	(0.0678)	(0.0941)
$LnPCSSE_{t-1}^2$	0.185***	0.254***	0.244***	0.244***	-0.172***	-0.0190**	-0.0048	-0.00302
	(0.0283)	(0.0435)	(0.0404)	(0.0390)	(0.0331)	(0.0076)	(0.0033)	(0.0046)
$LnMPCE_{t-1}$	-0.707***	-1.047***	-0.885***	-0.859***	0.0693	-0.0115	-0.0067	-0.0316***
	(0.0943)	(0.1236)	(0.1207)	(0.1256)	(0.0699)	(0.0270)	(0.0144)	(0.0102)
$LnNSDP_{t-1}$	0.0277***	0.0281***	0.0326***	0.0385***	0.0164*	-0.0004	-0.0001	-0.00426**
	(0.0071)	(0.0085)	(0.0063)	(0.0062)	(0.0098)	(0.0023)	(0.0011)	(0.0017)
Year 1999	0.0962***	0.130***	0.115***	0.115***	-0.0550***	-0.0288***	- 0.0123***	-0.0180***
	(0.0146)	(0.0182)	(0.0154)	(0.0156)	(0.0177)	(0.0044)	(0.0019)	(0.0017)
Constant	22.20***	31.24***	29.60***	29.51***	-20.28***	-2.573***	-0.727**	-0.0213
	(2.8848)	(4.4591)	(4.1032)	(3.9330)	(3.4697)	(0.7780)	(0.3417)	(0.4919)
Observations	102	102	102	102	102	102	102	102
R-squared	0.508	0.51	0.517	0.528	0.766	0.765	0.728	0.455
Number of id	17	17	17	17	17	17	17	17
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State specific trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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