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Ethnic fragmentation, public good provision, and inequality in India, 1988–2012

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Abstract: Using data from various rounds of the nationally representative NSSO survey between 1988 and 2012, we first construct national, state, and district-level figures for overall, within and between consumption inequality. We find an increase in inequality in India but only since 2004. We also document an increase in between group (or horizontal) inequality over the entire period. We then investigate the impact of ethnic fragmentation and public good provision on inequality. We hypothesize that by lowering the provision of public goods (specifically schools and health facilities), fragmentation will impact the incomes of the poorer sections more than those of the rich and thus increase inequality. Empirical results support this hypothesis. We find that the increase in overall inequality is lower in less fragmented districts, but there is no strong relationship between horizontal inequality and fragmentation or public good provision. This is because public good provision impacts within group inequality but not between group inequality.

Keywords: inequality, growth, within inequality, ethnic inequality, ethnic fragmentation, public good provision
JEL classification: I24, D63, H41, H42

Figures and tables are provided at the end of the paper and are the authors' own work.

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1 Introduction

The sustained high growth rates in India over the last quarter of a century have given rise to a voluminous literature in economics on two related questions of interest. The first question relates to the magnitude of changes in absolute levels of poverty and deprivation over the same time period while the second relates to understanding the evolution of relative economic outcomes. This paper is concerned with the second question. As in other parts of the world, there is concern about an increase in economic inequality in India as well (both vertical and horizontal). The aim of this paper can thus be delineated in to two closely related steps:

1. First, we document the evolution of overall, within and between group economic inequality (for caste and religious groups) in India from 1988–2012, as measured through consumption inequality.[1] This exercise is important to place the second part of the paper in context.

2. Second, we explore if the evolution of inequality, in part, can be traced to ethnic fragmentation. In particular we are interested in investigating the impact of ethnic fragmentation on inequality through public good provision.[2]

The importance of understanding the evolution and correlates of inequality can be traced to the vast literature relating inequality to political, social and economic outcomes. High levels of inequality may lead to conflict and crime (Murshed and Gates (2005)), inefficient redistribution and high taxation rates in democracies, and lower growth rates in general (Persson and Tabellini (1992)); high levels of inequality may not be politically acceptable in some societies leading to increased between group animosity. On the positive side inequality may be a natural outcome of the underlying growth process and societies may follow an inverted U-shaped curve of inequality as they grow (Kuznets (1955)). A much more recent literature suggests that rather than overall inequality, conflict and between group tensions are much better captured by measures of between group economic inequality (Alesina et al. (2016); Baldwin and Huber (2010)). To the best of our knowledge, this paper makes the first attempt to systematically study between group inequality at a much disaggregated level (districts) and for a much longer sample period in India.[3]

[1] The choice of the study period is guided primarily by the availability of data. More details are provided later.

[2] In this paper because of availability of data we focus on schools and health facilities.

[3] Deshpande (2000a,b) discuss measurement of inequality between castes at state level and present the numbers for Kerala.

While there is now a large body of evidence, from various contexts, that suggests that ethnic fragmentation is related to poorer provision of public goods and other economic outcomes (Alesina et al. (1999); Miguel and Gugerty (2005); Easterly and Levine (1997)), our understanding of how ethnic fragmentation impacts the evolution of distribution of economic outcomes is limited. In this paper we hypothesize that increased fragmentation results in lower public good provision. Economic outcomes of poorer sections of society may be more severely affected by lower public good provision than those of the richer sections (which may be able to acquire some publicly provided goods privately, for e.g. education). If this is indeed the case then ethnic fragmentation should have an impact on inequality through public good provision. One point to note here is that the ability to acquire private schooling is decided not just by individual income but also on the supply of private schools, which may in turn depend on the distribution of income.[4]

In this paper we aim to study the experience of India in the recent past in terms of the evolution of economic inequality and understand whether part of it can be attributed to ethnic fragmentation and the resulting lowered provision of public goods. Have more fragmented districts not only seen lower growth and poor public good provision but also seen an increased income inequality? The second part of the paper answers this question using district level data on consumption inequality and presence of public goods.

1.1 Literature and contribution

This paper relates to two different strands of literature. The first one is on the measurement and evolution of inequality in India. Inequality measurement and the relationship between growth and inequality or growth and poverty has seen several significant contributions in the past. Deaton and Dreze (2002) present a new set of integrated poverty and inequality estimates for India and Indian states for 1987-88, 1993-94 and 1999-2000. Motiram and Vakulabharanam (2012) calculate inequality in India and Indian states for the 2010 round of the National Sample Survey (NSS) as well. They also calculate between caste group inequality but only at the India level. Datt and Ravallion (2002a,b) look at the poverty reducing effect of growth in India. While the focus of the present paper is not to provide a methodological innovation in the measurement of inequality, it does

[4] This may be the case, for example, when schools have a fixed cost of operation, as this means that they need a minimum number of fee paying students to stay in operation.

complement the current literature. We provide systematic estimates of between group inequality and also discuss issues related to its measurement in India. Unlike the aforementioned papers we also present estimates of inequality in years of education. Inequality in years of education allows for a cross country comparison of inequalities.

Social scientists have long been interested in the positive and negative impacts of ethnic heterogeneity. While heterogeneity reduces public good provision by exacerbating the free rider problem it may have positive consumption externalities. Alesina and La Ferrara (2005) provide a survey of this literature. Banerjee and Somanathan (2007) show the adverse impacts of ethnic diversity in India. They show that while more diverse places have lower provision of public goods, this is not the only determinant of public good provision. Political representation of the groups matters as well. In recent papers, Alesina et al. (2016); and Baldwin and Huber (2010) show that between group inequality is a better predictor of public good provision and economic performance than other measures of social heterogeneity. This paper is different because unlike the above-mentioned papers it tries to establish a causal relationship between ethnic fragmentation, public good provision and inequality. As we discuss later in the paper the relationship between public good provision and inequality is conceptually complex.

1.2 Overview of the results

We find that between 1988 and 2012 both vertical and between group inequality in consumption expenditure has increased in India. This increase though really only happens starting in 2004. On the other hand inequality in educational attainment, both vertical and horizontal, has decreased significantly over this time. This is possibly due to a wide spread of literacy in this period. Similar trends also hold at the state level.[5] We also find that vertical inequality has increased more in faster growing states while there is a weak relationship between horizontal inequality and growth.

In the second part of the paper, using district level regressions, we find that inequality increases more in more ethnically fragmented districts. This is because more ethnically fragmented districts have fewer schools and health facilities and more schools and health facilities result in more equitable consumption outcomes.[6] However, we find that this increase in inequality primarily comes from

[5] States are the second level of administrative units in India.

[6] We only use information on schools and health facilities as these are the only public goods that were consistently reported across the three census rounds. More details are presented in a later section.

the within group inequality component rather than the between group component. These results suggest that the poor in any group do not have access to (quality) education whereas the rich in any group can afford to pay for private education if needed. Therefore the absence of schools impacts within group inequality much more than between group inequality.

The rest of the paper is organized as follows: Section 2 discusses the data sources and the construction of inequality measures while section 3 presents and discusses the inequality numbers. In section 4 we discuss the conceptual background for expecting a relationship between fragmentation, public good provision and inequality and present our empirical methodology, while section 5 presents the results and discussion. Section 6 concludes.

2 Data and construction of inequality measures

We construct various measures of inequality in consumption expenditure, and educational attainment outcomes at the state and the national level from 1988 to 2012 to study the evolution of inequality in India. For the analysis in the second part of the paper we also construct some of these inequality measures at the district level. These inequality measures are constructed using data from NSS rounds. NSS is a nationally representative household survey conducted in India, typically with a "thick" round every five years. We use five thick rounds[7] of NSS: 43rd (conducted in 1987–88), 50th (conducted in 1993–1994), 61st (conducted in 2004–05), 66th (conducted in 2009–10) and 68th (conducted in 2011–12).[8] We also use data from a thin 51st round conducted in 1994–95[9] and a thin 64th round conducted in 2007–08 because of its large sample size which is comparable to a thick round. We make an adjustment to household consumption expenditure data obtained from the NSS. The expenditure data, reported at the current prices in the NSS rounds, is adjusted for the differential price changes in rural and urban areas using Consumer Price Index (CPI) data from the Reserve Bank of India database. We do this exercise to separate the impact of differential price change in rural and urban areas from the actual change in consumption.

[7]Thick rounds are typically conducted every five years and have large sample size with the data being representative at the NSS district level. Thin rounds on the other hand have smaller sample size, with the data being representative only at the state level and are conducted in the years between two successive thick rounds.

[8]The 66th round was conducted after two successive drought years and because of this was followed by another thick round in 2011–12.

[9]The 51st round is used primarily because the 50th round does not identify households up to the district level, which makes it redundant when making district level analysis.

Using household level information on percapita consumption expenditure[10] and individual level information on education attainment from the survey rounds, we construct the following measures of overall inequality: the Gini coefficient and the Theil index. Apart from these two measures, we also compute $P\left(\frac{0.9}{0.1}\right)$ and $P\left(\frac{0.75}{0.25}\right)$ which are the ratios of y_i at the 90th and the 10th percentiles and the 75th and the 25th percentiles respectively.

The above measures capture inequality in individual/household (HH) outcomes: consumption and education attainment. However, individual agents may be associated with identifiable group markers which also have an important influence on the attainment of socio-economic outcomes. That is, the group identity of an individual may impact their socio-economic outcomes. For example studies have shown that women tend to earn less as compared to men for the same work profile (Oaxaca (1973)), individuals belonging to marginalized caste groups are often subject to discrimination (Banerjee and Knight (1985); Borooah (2005)), urban areas offer more opportunities to individuals as compared to rural areas. This motivates us to also look at inequality in consumption expenditure and education outcomes between caste groups, religious groups and gender (for gender we can only consider group inequality in educational outcomes as consumption data is only available at the household level). This can be very easily done for the case of India, as the boundaries between groups are well defined and there is very low mobility between caste and religious groups.

We again make use of NSS rounds to study inequality between groups. NSS has information on the broad caste group of the household (whether the household is Scheduled Caste (SC), Scheduled Tribe (ST), or Others[11]), gender of the members of the household and whether the household resides in rural or urban areas. Using this, as well as information on consumption expenditure and education outcomes, we construct the following measures of between group inequality: the group Gini (GGini), the group coefficient of variation (GCOV) and the group Theil (which is simply the between component of the inequality decomposition).

These three measures of between group inequality have a high correlation with each other. Apart from these three measures, we also look at a measure called crosscuttingness. This is based

[10]In India as in other developing countries measuring consumption inequality makes more sense than income inequality. People are paid in kind for a lot of the services they provide and receive transfers from friends and governments and therefore income is hard to measure for a large part of the population. Also it is not clear that income inequality is a better measure of welfare inequality than consumption welfare. In fact economic theory would suggest the opposite (see Attanasio and Pistaferri (2016).

[11]Later rounds of NSS also enumerate another group the other backward classes (OBC). We discuss more about this later in the paper.

on the idea that an individual belongs to multiple groups, rather than a single group and that there can be some overlap between the groups which can reinforce (or dampen) the advantage (or disadvantage) of a particular group. Crosscuttingness (CC) is identified when group i on cleavage x is identically distributed among groups on cleavage y with all other groups on cleavages x (Selway (2011)).

Using the above-mentioned measures, created using NSS rounds, we look at the evolution of overall inequality, inequality between caste groups, between sectors, between gender and between states at national and state level from 1988–2010. To look at the correlation of inequality (both overall and between) with economic growth, we use data on per capita state net domestic product data (NSDP) from Reserve Bank of India (RBI) and regress inequality at the state level on growth in per capita NSDP.

3 Inequality in India and Indian states

3.1 Trends in inequality at the national and state level

We begin our discussion by presenting the total inequality figures for the entire country for the period under study. The results are reported in Table 1. Columns (1) and (2) present the results for the Gini and the Theil indices. In columns (3) and (4) we present the ratio of consumption at the 90th percentile to consumption at the 10th percentile and ratio of consumption at the 75th percentile to consumption at the 25th percentile respectively. All the indicators suggest that between 1988 and 2004 inequality in India did not change much. Since 2004 inequality has risen steadily showing an upward trend between 2004 and 2012. As the table shows, inequality rises sharply in 2010 and then decreases in 2012, with 2010 being thus an outlier. As we stated previously the 2009–10 round of the NSS was conducted after two successive drought years. Therefore a possible explanation for the higher than trend inequality in 2010 could be that poorer households were more severely impacted by the drought than the richer households. Given the vast literature on the inability of the poor to smooth consumption in a developing country setting, this explanation seems very plausible. These results are in contrast to some previous papers in the literature (Motiram and Vakulabharanam (2012)) which suggest a higher level of inequality than we do in this paper. We believe that this is because of an oversight in those papers which, to the best of our knowledge, used nominal consumption data to construct inequality measures. As Figure 1 shows starting in the 2000s the urban price index in India has seen a more rapid increase than the rural price index.[12] Thus a calculation of inequality using nominal consumption is likely to overestimate overall inequality and between sector inequality.

Table 2 presents the results for horizontal or between group inequality. For comparison we present results for between state (columns (1) and (2)), between sector (rural-urban) (columns (3), (4) and (5)) and between group inequality (columns (6), (7) and (8)). The NSS collects information on religious affiliation and then for Hindus only on broad caste group affiliation (scheduled castes, scheduled tribes, other backward classes and others) and not on what is referred to by many scholars as the operative unit of caste on ground, the *jati*. Given the data we can only construct between group inequality at this level. The results present quite interesting contrasts.

The first thing to note is that in 1988 between state inequality was significantly higher than between sector or between caste group inequality, if measured using the group Gini index. However, if the Theil index is used then between sector inequality, in 1988 and later, is higher than between state inequality. Over the period of study no clear trend emerges for between state inequality. The GGini estimates suggest that it has decreased marginally over this period (2010 is an exception and this could be because of the preceding drought years), while the Theil index suggests that it has increased over this period. Given the substantial differences between Indian states in terms of endowments, institutions and governance quality, the high level of between state inequality is not surprising.

The last three columns present estimates for between caste group inequality. The numbers suggest that horizontal inequality in India has increased marginally over this period. However, the most robust increase is in the between sector inequality. Rural-urban inequality in India has not only risen steadily, it is also about three times the magnitude of between caste group inequality. For example, in 2012, between group inequality was only 5.13% of total inequality (using the Theil decomposition) while between sector inequality was nearly 19% of total inequality (the growing rural-urban inequality has been noted by earlier papers as well, see Deaton and Dreze (2002)).

There is, however, a caveat here and this relates to the categorization of caste groups in the

[12] The urban and rural price index are the consumer price index - industrial worker (CPIIW) and consumer price index - agricultural labour (CPIAL) respectively.

NSS (and Census data in India). Both the NSS and the census only obtain information on very broad group affiliations – SC, ST and others. Within themselves these groups are very disparate. In fact many scholars contend that at the ground level caste operates not at this aggregate level but at a much more disaggregated level called the *jati*. Therefore the between group component of inequality as measured by these broad caste affiliations is small. If data was available at the *jati* level it may paint a much different picture about between and within group inequality.

To see what difference disaggregation may play we can use a change in the NSS survey itself. The earlier rounds of the NSS (prior to 2000) only enumerated three caste groups,– SC, ST and others. Later rounds enumerated a fourth group, the other backward classes or OBCs. [13] This group consists of mostly landed cultivator castes. In the results presented in this paper, for later rounds, we have consolidated the OBC and others and made the data consistent across the rounds. However, if we just look at the rounds with OBCs, the between group inequality is calculated to be almost two to three times as high as that obtained when we consolidate the two groups (OBC and others).

An interesting way to look at between group inequality is to use a measure of crosscuttingness between caste and class. To illustrate the idea consider the following example: Consider a society that consists of two groups A and B and divide into two income classes, *rich* (above the median income) and *poor*, below the median income. Assume that population share A is 0.5. If there is perfect crosscuttingness between the two distributions then half of the *rich* should be from group A and half from group B. Similarly for the poor. However, if there is no overlap between the two distributions then all the *rich* could be from group A and then all the poor would be from group B. The results of doing this exercise for the 2009–10 round of the NSS are given in Table 3.[14] We find evidence of overlap between class and caste. SC and OBC groups are over-represented in the lower income quartiles. For example, OBCs and SCs should constitute 38% and 16.28% respectively of each quartile for perfect crosscuttingness. OBCs, however, constitute 41.32% of the lowest quartile and 40.88% of quartile 2. Similarly SCs constitute 23.32% of the lowest quartile. In contrast, others are over-represented in the highest consumption quartile; 48% as against 32.12% of their population share.

[13] The other backward classes (OBC) were created as a group when the affirmative action policy of reservations in public sector jobs was extended to groups other than the Scheduled Castes (SC) and Scheduled Tribes (ST).

[14] The results of the other rounds are not presented for the sake of brevity. They are obtainable from the authors.

3.1.1 Inequality analysis at the state level

The next level of administrative units in India are the states. We have already presented results of the decomposition of overall Indian inequality into those between and within states. Now, treating each state as a unit, we calculate the overall and horizontal (between caste group) inequality for each of these states and NSS rounds. The numbers are presented in Tables 4 and 5.

In Table 4 we report the Gini index of consumption expenditure in each state while in Table 5 we present the group Gini index for between caste group inequality. According to estimates in Table 4, states present a mixed picture with respect to the evolution of inequality. While some states like Andhra Pradesh have reduced inequality, others like Karnataka and Haryana have become substantially more unequal. To get a sense of change in inequality over the entire period we plot the overall inequality in the state in the last round, i.e. 2012, against inequality in the state in the first round, i.e. 1988. The result, presented in Figure 2, shows that most states have become more unequal over this period.

Between group inequality shows a similar evolution and Figure 3 plots horizontal inequality in the state in 2012 against its value in 1988. All states barring one (Tamil Nadu) have seen an increase in horizontal inequality.[15]

Thus, most states in India have become more unequal over time both in terms of overall inequality and horizontal inequality. Following Kuznets' seminal work (Kuznets (1955)) there has been substantial interest in economics in exploring the relationship between economic growth and inequality. At lower levels of economic development, economic growth may increase inequality as certain sectors innovate and expand. Then as economic development progresses growth may spillover to the whole economy and governments may have more ability to redistribute and improve welfare spending thus lowering inequality. Since the liberalization of the Indian economy many scholars have been interested in understanding the relationship between growth and poverty or inequality in India (see for example Das and Barua (1996); Datt and Ravallion (1996, 2002a,b); Deaton and Dreze (2002)).

Using growth rates in state domestic product we try to establish whether there is a relationship

[15] Tamil Nadu seems to have extraordinarily low horizontal inequality in 2008 and 2012.

between economic growth and inequality at the state level. The estimating equation is the following

$$I_{st} = \alpha_s + \beta_t + \gamma_1 ln(gsdp)_{st} + \epsilon_{st} \tag{1}$$

Here s indexes state and t the survey round. I_{st} is inequality in state s at time t and $ln(gsdp)_{st}$ is the log of the state GDP at time t. The parameter of interest is γ_1. The results are presented in Table 6 for overall inequality and Table 7 for between group inequality.

The results for overall and horizontal inequality differ significantly. As columns (1) and (3) of Table 6 show there is a positive and significant relationship between GDP growth and inequality. All specifications include state and time fixed effects. In columns (3) and (4) we lag the independent variable to partially address the issue of endogeneity (both growth and inequality are summary measures of the same distribution). The point estimates are stable and remain significant. Therefore faster growing states witness an increase in inequality. This is in contrast to the results in Table 7. There we find no relationship between horizontal inequality and growth. While the point estimates are positive the standard errors obtained are very large. This suggests that faster economic growth is increasing inequality in India by increasing inequality within groups and not between them which is an interesting observation. We will have more to say about this in later sections.

We do one final exercise in trying to understand the relationship between economic growth and inequality. This is to allow the coefficient γ_1 to vary with time. Equation 1 is modified to the following

$$I_{st} = \alpha_s + \beta_t + \gamma_1 ln(gsdp)_{st} + \gamma_2 ln(gsdp)_{st}.post_{2000} + \epsilon_{st} \tag{2}$$

Here $post_{2000}$ is a dummy which takes value one if the NSS round was conducted after year 2000 and zero otherwise. Thus γ_1 and γ_2 allow us to estimate whether growth had a differential impact on inequality in the years 1988–2000 and 2000–12. The results are presented in Tables 8 and 9. Given that inequality started increasing only in 2004 one would expect that the relationship between economic growth and inequality might be stronger in the period after 2000. That is exactly what we find. γ_2 is positive in all specifications for both overall and horizontal inequality. γ_1 is actually negative though not significant. This suggests that in the first decade after liberalization[16] growth may have been more inclusive. Also while growth and horizontal inequality do not show a significant relationship for the entire period, growth does increase inequality in the post 2000 period.

4 Ethnic fragmentation, public good provision and inequality: Concepts and methodology

This part of the paper explores the relationship between ethnic fragmentation, public good provision and inequality. The last section showed that while there is a robust relationship between economic growth and overall inequality no robust relationship between growth and horizontal inequality is observed. This negative (but expected) relationship between growth and inequality suggests that we should perhaps take a closer look at redistribution and inequality. We do this by exploring what the impact of provision of schools and health facilities in a district is on inequality.

Conceptually, we might expect that a lower provision of public goods in a district will lower the average economic outcomes in the district. But will it have distributional impacts? For some goods like education and health (perhaps less so perhaps for goods like roads) it might be possible for individual agents to pay a price and obtain these services in the private market.[17] In this case it may be possible for the relatively better off to afford the good but not for the poorer agents. This will result in an increase in subsequent inequality. So why might there be lower public good provision in some districts compared to others? Here we exploit the finding in the previous literature that ethnic diversity lowers public good provision.

The relationship between ethnic fragmentation and public good provision has been modeled extensively in the literature. However the relationship between public good provision (in the presence of private provision of the good) and inequality is not that well studied. While a full theoretical model is beyond the scope of this paper careful thought shows that impact of schools (or health facilities) on inequality will critically depend on the initial distribution, the price of schooling and the returns to schooling. In this paper we present empirical evidence for this relationship.

[16] India undertook major macroeconomic reforms starting 1991.

[17] See Banerjee et al. (2007) for a voluntary contribution game where agents can buy the public good on the market as well.

There is a sizable literature on the role of ethnic diversity and economic performance (see Alesina and La Ferrara (2005) for a survey). To the best of our knowledge, however, there is not much work on the distributional impacts of ethnic fragmentation, especially with reference to India. We postulate that ethnic heterogeneity reduces public good provision and hence results in higher inequality. One paper that comes close to the present one is Baldwin and Huber (2010). They do a cross-country analysis to show that higher between group inequality (BGI) lowers public good provision in a country and also suggest that BGI is a better predictor of poor public good provision than ethnic fragmentation. Our paper is significantly different to theirs in that we restrict attention to administrative units within a country and have a panel data set. This paper also explores the causality in the relationship between public goods and inequality in the opposite direction to the one in the previous paper. A more detailed comparison with previous work is presented in the conclusion to this paper.

In this and the next section we construct the various measures of inequality at the level of Indian districts. We do so, to run district level regressions of overall and between group inequality so as to understand the role that different factors play in the evolution of inequality. In particular, as stated above, we want to understand the role of ethnic fragmentation, through provision of public goods, in explaining overall and between group inequality. Our main estimating equations therefore are:

$$I_{dst} = \alpha_d + \beta_t + \gamma_1 PG_{dst} + \epsilon_{dst} \tag{3}$$

$$I_{dst} = \alpha_s + \beta_t + \gamma_2 EF_{dst} + \gamma_3 PG_{dst} + \epsilon_{dst} \tag{4}$$

where d indexes districts, s indexes states and t indexes NSSO round (i.e. year of data collection). I_{dst} are inequality measures (such as Gini, Theil, GGini etc.), EF_{dst} is ethnic fragmentation and PG_{dst} measures public good provision. Regression Equation 3 tests the role of public good provision in explaining inequality and Equation 4 tests whether fragmentation affects inequality though its impact on public goods provision.[18] The parameter of interests are γ_2, the coefficient of EF_{dst} and γ_1 and γ_3, coefficient of PG_{dst}, which measures public goods provision in a district. We expect $\gamma_1 < 0$ and $\gamma_3 < 0$ and $\gamma_2 > 0$.

[18]If we expect public goods to be negatively correlated to inequality and also negatively correlated to ethnic fragmentation, then γ_2 will have a positive bias if PG_{dst} is omitted from Equation 4. In the next section we will show that this is exactly what the empirical results show.

Ethnic fragmentation, as is quite standard in the literature, is measured as, $1 - \sum \beta_i^2$ where β_i is the population share of the i^{th} ethnic group. The different ethnic groups that we consider are the ones divided by caste. In India, the Hindu population (the major religious group) is divided into a number of castes with deep social cleavages due to which there is limited social and economic interaction between these caste groups. Therefore, it is reasonable to assume a caste as a separate group. To construct ethnic fragmentation, we use district level data on population shares of different groups from the Indian population census. The last census to record district level data on population shares by different castes was the population census of 1931. We use the 1931 shares and scale them by the proportion of Hindu population during the 1991, 2001 and 2011 census to arrive at fractionalization indices for 1991 and 2001 (Banerjee and Somanathan (2007)). We make this adjustment to account for the migration of Muslims to Pakistan as a result of the India-Pakistan partition in 1947. For all the newly created districts after 1931, we weight the caste figures from the original district according to the area of the new district which was taken from them, following Banerjee and Somanathan (2007).

Permanent migration is low in India and therefore previous work and this paper assumes that the caste proportions in local geographies are the same since 1931. However, to test the robustness of this assumption, in some specifications we also construct ethnic fragmentation using broad caste and religious groups using the NSSO data itself. The obvious disadvantage of this approach is that the caste data is only available at very aggregate levels. As we show later while these two constructions of fragmentation give consistent results for overall inequality the conclusions for between group inequality depend on how fragmentation is measured.

Data on public goods provision is obtained from the 1991, 2001 and 2011 census village directories. The census directories have information on the availability and the total numbers of a particular public good in a given village in a district. We aggregate this information up to the district level. The particular public goods that we focus on are the provisions of total number of schools (primary, medium and secondary) and health centers (primary health centers and maternity home centers) in a district. There are two reasons for focusing on education and health facilities. The first is that human capital investments can be made by the state as well as the individual households and therefore it is possible for households to spend on these goods themselves (unlike say roads). This allows for a richer relationship between schools (and health facilities) and inequality. The second reason is the availability of comparable public goods data across the census rounds. In all the regressions, we control for district (or state) and NSS round fixed effects. The fixed effects should capture any district or time specific effects.

5 Ethnic fragmentation, public good provision and inequality: Results

In this section we perform district level regressions of overall and between caste inequality to understand the role of concentration of caste groups in explaining inequality. Regression results are reported in Table 10. Consistent with what we expect, columns (1) and (4) indicate that, after controlling state and year fixed effects, more fragmented districts have higher overall inequality. The magnitude of the coefficient suggests that as compared to a completely homogeneous district, a perfectly fragmented district has about 0.10 higher Gini coefficient/Theil index. The result becomes stronger after controlling for district level average per capita expenditure, average literacy rates (obtained from the 1991 and 2001 population census) and state specific time trends. We argued in the earlier parts of the paper that more fragmented districts find it difficult to demand public goods which can be one of the reasons for higher inequality in those districts. To test this assertion we control for provision of public goods in a district. If our hypothesis is true, the coefficient of ethnic fragmentation should fall indicating that a part of the effect of EF is due to public goods provision. Consistent with our hypothesis, the coefficient of ethnic fragmentation falls considerably in columns (3) and (6) whereas standard errors remain the same (not reported in the table). This result indicates that ethnic fragmentation increases inequality in consumption expenditure by reducing access to public goods like schools and health centers. Since the poor rely more on public provision of schools and health centers, lower access to public goods leads to inequality. To further substantiate that higher public goods provision reduces inequality, we regress overall inequality on schools and health centers and the results are reported in Table 11. The results, indicating that higher levels of schools and health centers lead to lower inequality, confirm low public goods provision to be the channel from ethnic fragmentation to inequality.

We also test the impact of ethnic fragmentation on inequality between caste groups. Earlier in the paper we presented evidence on the overlap between caste and class. Also the Indian state targets certain public spending towards specific groups (like SCs and STs). It therefore seems reasonable to expect that public good provision and (ethnic fragmentation) could be related to between group inequality. Results reported in Table 12, however, suggest otherwise. Columns (1) and (4) show that only one of the measures of between group inequality, GCOV, is weakly positively associated with fragmentation. When we control for average district per capita expenditure, literacy rates and state level time trends, the coefficient of GCOV becomes stronger but the coefficient of Gini remains insignificant. (columns (2) and (5)). Based on this evidence, we can say that disparity in economic outcomes across caste groups cannot be attributed to ethnic fragmentation. We also control for public goods provision to see if the relationship between ethnic fragmentation and between group inequality changes after accounting for public goods. As reported in columns (3) and (5), the coefficient of both the measures of inequality (the point estimates do fall), remains insignificant suggesting that while public goods are important for welfare in general, they do not seem to benefit certain caste groups more. Separate regression of between caste inequality on public goods, reported in Table 13, confirms this claim.

Since ethnic fragmentation seems to increase overall inequality and has no (or weak) association with between group inequality, we would also like to understand how the impact of ethnic fragmentation on inequality between caste groups compares with the inequality within caste groups. To do so we regress the within and between group component of the Theil measure on ethnic fragmentation. The results are reported in Table 14. For the between group component, in the first two columns ethnic fragmentation does not seem to be associated with inequality, consistent with our previous result, whereas the coefficient for the within group component is much larger and significant. Similarly in comparing columns (3) and (6), while provision of middle schools reduces both inequality between and within caste groups, the effect is much stronger for within group inequality. This finding suggests that an increase in the number of caste groups makes the distribution of income unequal in general, irrespective of group identities. This result also indicates that whatever income divide exists between caste groups, public goods provision cannot bridge that gap. While the benefit of the public goods accrued to different caste groups is not differential, there seems to be progressive equality in the distribution of benefits within caste groups.

6 Robustness and causality

In the previous sections, our results show that ethnic fragmentation, by lowering the provision of schools and health centers, increases inequality. In this section, we address various concerns regarding the causal impact of ethnic fragmentation on inequality through public goods provision. One of the concerns could be that ethnic fragmentation in a district is endogenous, that is it is a result of the process that also impacts average income and its distribution in a district. In other words, districts which have better economic opportunities and a favorable income distribution might cause certain ethnic groups to move to these districts and thus give rise to a particular distribution of ethnic groups. To address this concern, we construct ethnic fragmentation using a lagged caste population census. We rely on the population census of 1931 to do this exercise as it was the first census to record detailed caste level data at the district level. Since it is highly unlikely that today's economic activity would have any influence on the settlement decisions of ethnic groups in 1931, we are fairly confident that ethnic fragmentation constructed with 1931 census numbers is exogenous. But one concern with using 1931 census numbers is that they might not be representative of the distribution of ethnic groups today because of population movement and dislocation after 1931. However, there is recorded evidence that permanent migration in India is too low to produce any significant change in the ethnic diversity of a district. Therefore, ethnic fragmentation using 1931 census numbers not only solves endogeneity issue but is also a good measure of ethnic fragmentation today.

The other issue that we seek to address is that time-varying omitted variables which affect both the distribution of income and ethnic fragmentation/public goods can lead to our point estimates being inconsistent. We resolve this by controlling for state level time trends and district fixed effects in our regressions. State level time trends capture the effect of policy changes, which are otherwise difficult to control for directly in the regressions that happen at the state level and affect inequality and therefore can confound the effect of ethnic fragmentation/public goods. District fixed effects control for all the district specific time-invariant omitted variables affecting both inequality and the independent variables of interest. Different specifications in Tables 10 to 14 show that our results are robust to controlling for state level time trends and district fixed effects. For any time variant omitted variable to still confound the result, it must vary at the district level, which is not very likely given that we have controlled for district level control variables, namely average per capita consumption expenditure and literacy rate, which are likely to affect both inequality and public goods.

Our channel tests show that low provision of public goods hurts the poor more and therefore increases inequality in the distribution of consumption expenditure. However, it is possible that the direction of causality is actually the other way round. That is high inequality results in low provision of public goods, rather than public goods affecting the level of inequality. For example, Baldwin and Huber (2010) show that high levels of between group inequality negatively affects the provision of public goods. We make sure that our results are not confounded by reverse causality concerns by exploiting the timing of population census, which we use to construct public goods provision in a district and NSS, which we used to construct our measures of inequality. In our main analysis, the timing of NSS and census data is as follows: for the inequality numbers obtained from the 43rd NSS round (conducted in the year 1987), we use data on schools and health centers from 1991 census data. For inequality numbers estimated for the 51st round (year 1994), we again make use of the 1991 census, inequality numbers obtained from the 61st (year 2004) and the 66th (year 2009) round are compared with public goods data from 2001 census, and we use the census 2011 public goods information for inequality numbers from the 68th round (year 2012) .

This implies that except for the year 1987, for all other years our analysis studies the effect of public goods provided much earlier in time on the distribution of income. This arrangement allows us to address the reverse causality issue. We do so by removing the year 1987 from our main regression and then study the impact of lagged public goods provision on inequality. Since it is highly unlikely for future levels of inequality to have an impact on the current provision of public goods, we expect the use of lagged public goods information will address our concerns. The results are presented in Table 15. Note that even after taking out the year 1987, lagged provision of schools and health centers decrease inequality in a district. The magnitude of the coefficients is very similar to our previous specification indicating that our main results are not confounded by reverse causality concerns.

We also do the same robustness check for our main regression where we test the impact of ethnic fragmentation through the public goods channel. Results in Table 16 show that even after excluding the year 1987, the coefficients in specifications 3 and 6, which have schools and health centers as controls, fall as compared to specifications 1 and 4. Even though the coefficients fall by much less magnitude as compared to Table 10, the qualitative result still holds. This once again confirms that low provision of public goods seems to be the channel through which ethnic fragmentation increases inequality.

7 Concluding comments

In this paper we have documented the evolution of inequality, both overall and horizontal, in India from 1988 to 2012. We find that inequality in consumption expenditure has increased especially in the period after 2004. We also find that inequality has increased more in faster growing states but find a weak relationship between horizontal inequality and economic growth. Even here the relationship between growth and inequality is much stronger after 2000.

The second objective of the paper was to investigate the relationship between ethnic fragmentation, public good provision and inequality. We find that in more fragmented districts the increase in the number of schools and health facilities is lower. More schools and health centers have an equalizing impact on income distribution and therefore more fragmented districts see sharper rises in overall inequality. We do not find a robust relationship between horizontal inequality and fragmentation. This is in contrast to Baldwin and Huber (2010) who, at a cross country level, find a strong relationship between between group inequality (BGI) and public good provision. However, one of the things that we find is that measurement of horizontal inequality in India depends critically on the data one uses. Our results on the relationship between horizontal inequality and fragmentation change significantly depending on which data is used.

We feel that there needs to be more research on understanding, that given a particular variable of interest which measure of horizontal inequality needs to be calculated and which groups then need to be enumerated. There of course is a huge dearth of data in the Indian context as well.

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Figures and Tables

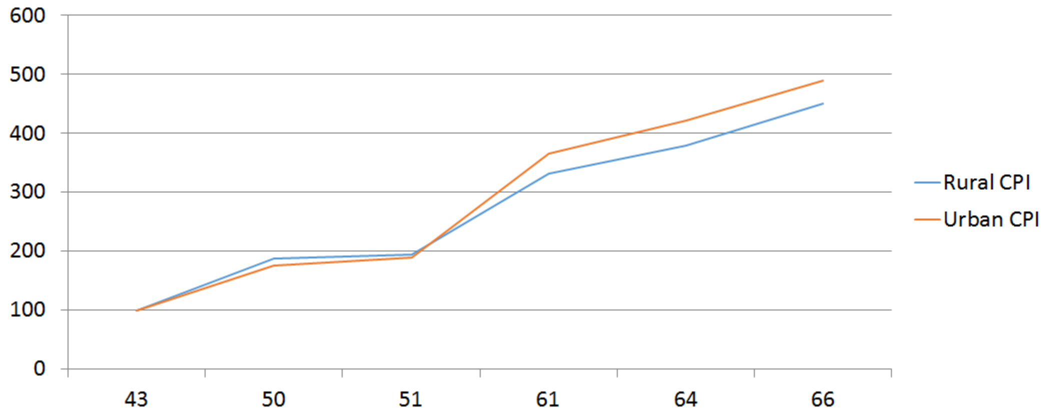

Figure 1: Rural and Urban price indices over the period of study

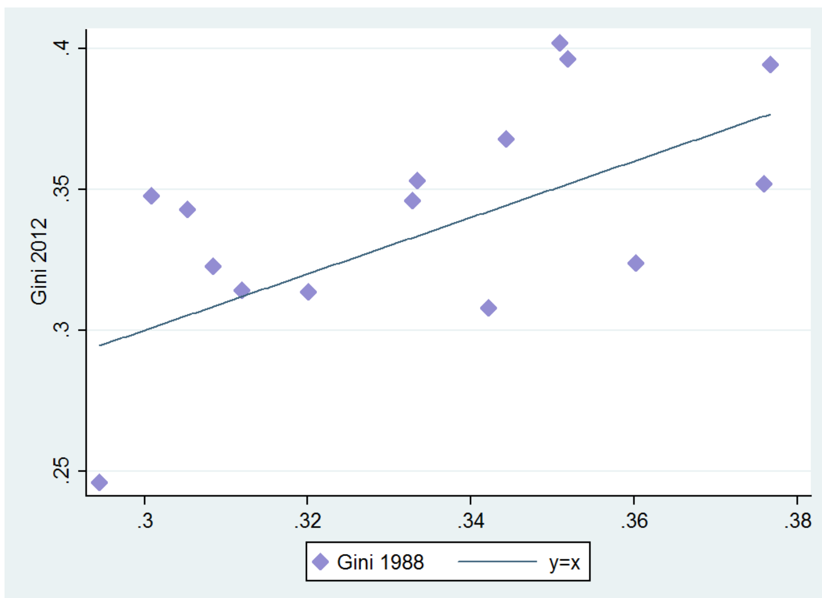

Figure 2: Evolution of inequality, 1987-2012, for Indian states

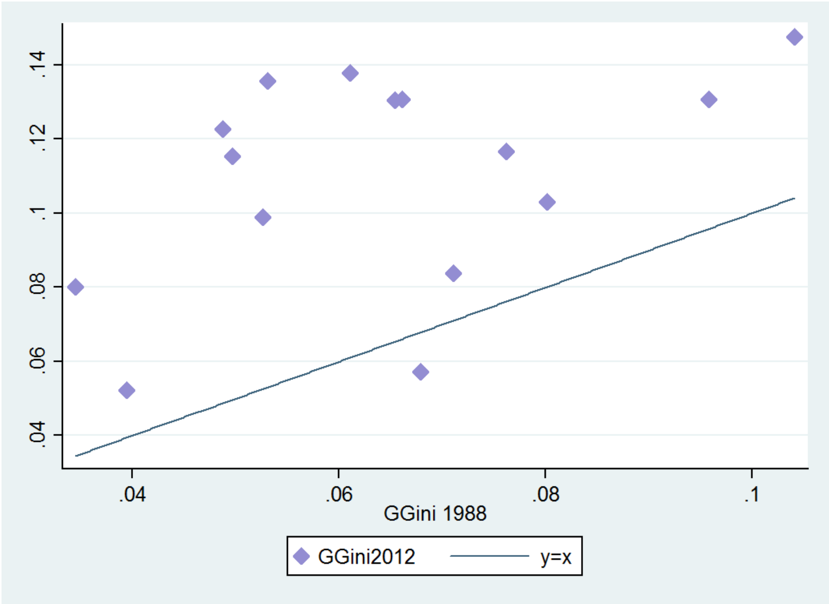

Figure 3: Evolution of group inequality, 1987-2012, for Indian states

Table 1: Overall inequality: National figures

Overall inequality: Consumption expenditure				
Year	(1) Gini	(2) Theil	(3) P(.90/.10)	(4) P(.75/.25)
1987	0.352	0.247	4.246	2.079
1994	0.350	0.248	4.147	2.053
2004	0.352	0.246	4.106	2.008
2007	0.360	0.269	4.122	2.022
2010	0.396	0.329	4.663	2.143
2012	0.375	0.277	4.603	2.188

Table 2: Horizontal inequality

Between group inequality: Consumption expenditure								
Year	GGini (states) (1)	Theil (states) (2)	GGini (sector) (3)	Theil (sector) (4)	GCOV (sector) (5)	GGini (group) (6)	Theil (group) (7)	GCOV (group) (8)
1987	0.175	0.017	0.107	0.029	0.251	0.065	0.011	0.144
1994	0.164	0.030	0.116	0.042	0.269	0.058	0.011	0.144
2004	0.167	0.027	0.104	0.038	0.243	0.065	0.014	0.143
2007	0.168	0.031	0.116	0.047	0.269	.063	0.0145	0.138
2010	0.189	0.040	0.128	0.054	0.290	0.067	0.017	0.147
2012	0.153	0.039	0.153	0.053	0.328	0.070	0.0142	0.158

Notes: Inequality measures are constructed using HH consumption expenditure data from various NSS rounds. *GGini* is the group Gini coefficient constructed by treating each group or sector or state as one unit. *GCOV* is the group coefficient of variation while Theil is the between component of the Theil decomposition. *group* here refers to the various Hindu caste groups.

Table 3: Crosscuttingness between caste and consumption quartiles

Year:2009–10					
Group	Quart 1	Quart 2	Quart 3	Quart 4	Total
ST	3.83	3.47	3.58	2.72	13.60
SC	5.83	4.61	3.50	2.34	16.28
OBC	10.33	10.22	9.51	7.94	38.00
Others	5.00	6.71	8.41	12.00	32.12
Total	24.99	25.00	25.00	25.00	100.00

Notes: The columns in this table correspond to consumption quartiles and rows to the population shares of various social (caste) groups. Thus for perfect crosscuttingness between caste and class a fourth of the total population share of each group should be in each quartile.

Table 4: Inequality in major Indian states

Overall inequality: Consumption expenditure						
Year	1988	1994	2005	2008	2010	2012
AP	0.3421	0.2922	0.3347	0.3430	0.3871	0.3078
Bihar	0.2945	0.4244	0.2438	0.2449	0.2721	0.2460
Chhattisgarh	-	-	0.3198	0.2874	0.3328	0.3511
Gujarat	0.3119	0.3042	0.3292	0.3044	0.3319	0.3141
Haryana	0.3008	0.3089	0.3630	0.2924	0.3540	0.3475
Himachal	0.3052	0.2837	0.3096	0.3611	0.3343	0.3428
Jharkhand -	-	-	0.2804	0.2844	0.3205	0.2997
Karnataka	0.3509	0.3360	0.3864	0.4416	0.4287	0.4019
Kerala	0.3518	0.3315	0.3635	0.3810	0.4078	0.3962
MP	0.3443	0.3092	0.3225	0.2896	0.3751	0.3677
Maharashtra	0.3767	0.4244	0.3893	0.3951	0.4145	0.3942
Orissa	0.3201	0.2928	0.3060	0.3508	0.3393	0.3136
Punjab	0.3084	0.2815	0.3027	0.3485	0.3488	0.3226
Rajasthan	0.3602	0.2751	0.2955	0.2878	0.3170	0.3237
Tamil Nadu	0.3759	0.3113	0.3508	0.3515	0.3647	0.3520
UP	0.3328	0.3790	0.3006	0.2935	0.3754	0.3458
Uttarakhand	-	-	0.3017	0.3136	0.5592	0.3339
West Bengal	0.3334	0.2854	0.3394	0.3661	0.3407	0.3531

Notes: The entries in each cell are the Gini coefficients of real HH consumption expenditure for that state and that round of the NSS. New states created in 2001 are missing values for the earlier rounds.

Table 5: Horizontal inequality in major Indian states

Horizontal inequality: Consumption expenditure						
Year	1988	1994	2005	2008	2010	2012
AP	0.0526	0.0409	0.0965	0.1133	0.1129	0.0989
Bihar	0.0394	0.0595	0.0590	0.0616	0.0597	0.0523
Chhattisgarh	-	-	0.1145	0.0871	0.0958	0.1205
Gujarat	0.0661	0.0611	0.1433	0.1281	0.1415	0.1308
Haryana	0.0611	0.0888	0.1418	0.1032	0.1337	0.1378
Himachal Pradesh	0.0497	0.0439	0.0611	0.0808	0.0664	0.1153
Jharkhand	-	-	0.0721	0.1052	0.1109	0.1077
Karnataka	0.0487	0.0526	0.1151	0.1045	0.1013	0.1228
Kerala	0.0345	0.0177	0.0820	0.1072	0.0917	0.0800
MP	0.1041	0.0721	0.1453	0.1140	0.1383	0.1476
Maharashtra	0.0654	0.0595	0.1252	0.1255	0.0961	0.1305
Orissa	0.0958	0.0812	0.1141	0.1417	0.1235	0.1308
Punjab	0.0801	0.0836	0.1286	0.1228	0.1314	0.1031
Rajasthan	0.0762	0.0407	0.1020	0.0932	0.0862	0.1166
Tamil Nadu	0.0679	0.0503	0.0940	0.0913	0.0804	0.0572
UP	0.0531	0.0443	0.0857	0.0697	0.1071	0.1357
Uttarakhand	-	-	0.0724	0.0473	0.1107	0.0935
West Bengal	0.0711	0.0660	0.0607	0.0723	0.0680	0.0837

Notes: The entries in each cell are the group Gini coefficients (for major Hindu caste groups) of real HH consumption expenditure for that state and that round of the NSS. New states created in 2001 are missing values for the earlier rounds.

Table 6: Relationship between economic growth and inequality

	(1)	(2)	(3)	(4)
	Gini	Gini	Theil	Theil
lnsdp	0.0999^{**}		0.1119^{+}	
	(0.020)		(0.120)	
lnsdp_l		0.0933^{**}		0.1204^{*}
		(0.020)		(0.077)
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	99	98	99	98

p-values in parentheses

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Relationship between economic growth and ethnic inequality

	(1) Gini (group)	(2) Gini (group)	(3) Theil (group)	(4) Theil (group)
lnsdp	0.0177		0.0041	
	(0.250)		(0.477)	
lnsdp_l		0.0106		0.0004
		(0.487)		(0.945)
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	117	116	117	116

p-values in parentheses

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Differential impact of economic growth on inequality

	(1) Gini	(2) Gini	(3) Theil	(4) Theil
lnsdp	-0.0149		-0.0180	
	(0.708)		(0.797)	
lnsdp_post2000	0.0645**		0.0759**	
	(0.013)		(0.045)	
lnsdp_l		-0.0142		0.0020
		(0.712)		(0.975)
lnsdp_l_post2000		0.0652**		0.0723*
		(0.014)		(0.059)
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	117	116	117	116

p-values in parentheses

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Differential impact of economic growth on ethnic inequality

	(1)	(2)	(3)	(4)
	Gini (group)	Gini (group)	Theil (group)	Theil (group)
lnsdp	-0.0139		-0.0083	
	(0.492)		(0.262)	
lnsdp_post2000	0.0219**		0.0087***	
	(0.012)		(0.007)	
lnsdp_l		-0.0187		-0.0115*
		(0.333)		(0.095)
lnsdp_l_post2000		0.0228***		0.0093***
		(0.008)		(0.003)
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Observations	117	116	117	116

p-values in parentheses

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Impact of ethnic fragmentation on overall inequality

	(1) Gini	(2) Gini	(3) Gini	(4) Theil	(5) Theil	(6) Theil
Ethnic frag	0.0968***	0.1019**	0.0628*	0.1093**	0.1144**	0.0742^{+}
	(0.005)	(0.014)	(0.076)	(0.013)	(0.024)	(0.101)
Literacy rate		-0.0079			-0.0411*	
		(0.638)			(0.091)	
lmpce_dis		0.1334***			0.1758***	
		(0.000)			(0.000)	
Secondary sch			0.0174^{+}			0.0192
			(0.147)			(0.161)
Middle sch			-0.0196***			-0.0241***
			(0.005)			(0.007)
Primary sch			0.0006			0.0020
			(0.753)			(0.417)
Prim health cntr			-0.0077			-0.0215
			(0.857)			(0.713)
Maternity homes			-0.0644*			-0.0683^{+}
			(0.065)			(0.149)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	No	No	Yes	No	No
State level time trends	No	Yes	Yes	No	Yes	Yes
Observations	1699	1698	1673	1699	1698	1673

p-values in parentheses

Standard errors are clustered at district level.

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Impact of public goods provision on overall inequality

	(1) Gini	(2) Gini	(3) Gini	(4) Gini	(5) Gini
Primary sch	-0.0005**				
	(0.011)				
Middle sch		-0.0014**			
		(0.019)			
Secondary sch			-0.0027***		
			(0.004)		
Maternity homes				-0.0581*	
				(0.052)	
Prim health cntr					-0.0237
					(0.159)
Year FE	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Observations	2064	2064	2064	2064	2064

p-values in parentheses

Standard errors are clustered at district level.

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Impact of ethnic fragmentation on horizontal inequality

	(1) Gini group	(2) Gini group	(3) Gini group	(4) GCOV	(5) GCOV	(6) GCOV
Ethnic frag	0.0430	0.0467	0.0473^{+}	0.3876^{+}	0.7042***	0.6761***
	(0.203)	(0.153)	(0.125)	(0.119)	(0.009)	(0.009)
Literacy rate		-0.0268*			-0.2319	
		(0.052)			(0.239)	
lmpce_dis		0.0249***			0.3303***	
		(0.000)			(0.000)	
Secondary sch			-0.0002			-0.1184*
			(0.985)			(0.064)
Middle sch			-0.0076			-0.0077
			(0.159)			(0.802)
Primary sch			0.0011			0.0088
			(0.412)			(0.230)
Prim health cntr			0.0265			-0.0608
			(0.260)			(0.688)
Maternity homes			-0.0077			0.0781
			(0.649)			(0.441)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	No	No	Yes	No	No
State level time trends	No	Yes	Yes	No	Yes	Yes
Observations	1698	1697	1673	1698	1697	1673

p-values in parentheses

Standard errors are clustered at district level.

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Impact of public goods provision on between group inequality

	(1)	(2)	(3)	(4)	(5)
	Gini group	Gini group	Gini group	Gini group	Gini group
Primary sch	-0.0001				
	(0.519)				
Middle sch		-0.0002			
		(0.626)			
Secondary sch			-0.0005		
			(0.631)		
Prim health cntr				-0.0132	
				(0.206)	
Maternity homes					-0.0219^{+}
					(0.140)
Year FE	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Observations	2063	2063	2063	2063	2063

p-values in parentheses

Standard errors are clustered at district level.

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Impact of ethnic fragmentation on within group inequality

	(1)	(2)	(3)	(4)	(5)	(6)
	Theil group	Theil group	Theil group	Theil_wn	Theil_wn	Theil_wn
Ethnic frag	0.0170	0.0173	0.0156	0.0920**	0.0964**	0.0586
	(0.257)	(0.236)	(0.249)	(0.024)	(0.034)	(0.167)
Literacy rate		-0.0154**			-0.0272	
		(0.019)			(0.233)	
lmpce_dis		0.0157***			0.1609***	
		(0.000)			(0.000)	
Secondary sch			-0.0014			0.0206+
			(0.757)			(0.102)
Middle sch			-0.0034*			-0.0207**
			(0.071)			(0.015)
Primary sch			0.0005			0.0015
			(0.339)			(0.518)
Prim health cntr			0.0123			-0.0338
			(0.211)			(0.536)
Maternity homes			0.0029			-0.0713+
			(0.664)			(0.120)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	No	No	Yes	No	No
State level time trends	No	Yes	Yes	No	Yes	Yes
Observations	1698	1697	1673	1698	1697	1673

p-values in parentheses

Standard errors are clustered at district level.

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Impact of public goods provision on overall inequality (without year 1987)

	(1) Gini	(2) Gini	(3) Gini	(4) Gini	(5) Gini
Primary Sch	-0.0004**				
	(0.010)				
Middle Sch		-0.0012***			
		(0.010)			
Secondary Sch			-0.0024***		
			(0.008)		
Maternity homes				-0.0580+	
				(0.102)	
Prim health cntr					-0.0180
					(0.279)
Year FE	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Observations	1713	1713	1713	1713	1713

p-values in parentheses

Standard errors are clustered at district level.

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: Impact of ethnic fragmentation on overall inequality (without year 1987)

	(1) Gini	(2) Gini	(3) Gini	(4) Theil	(5) Theil	(6) Theil
Ethnic frag	0.1364***	0.1225***	0.1007***	0.1596***	0.1385***	0.1218**
	(0.001)	(0.004)	(0.009)	(0.001)	(0.006)	(0.011)
Literacy rate		0.0281			-0.0079	
		(0.186)			(0.777)	
lmpce_dis		0.1370***			0.1784***	
		(0.000)			(0.000)	
Secondary Sch			0.0186+			0.0195
			(0.130)			(0.157)
Middle Sch			-0.0192***			-0.0224**
			(0.008)			(0.010)
Primary Sch			0.0005			0.0017
			(0.784)			(0.498)
Prim health cntr			-0.0155			-0.0267
			(0.726)			(0.657)
Maternity homes			-0.0611*			-0.0645
			(0.084)			(0.176)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	No	No	Yes	No	No
State level time trends	No	Yes	Yes	No	Yes	Yes
Observations	1373	1372	1350	1373	1372	1350

p-values in parentheses

Standard errors are clustered at district level.

$^{+}$ $p < 0.15$, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$