Caste-based social segregation and access to public extension services in India

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Abstract:

Caste-based social segregation manifests its influence in various spheres of life and perpetuates economic inequality and oppression. The present study, analysing nationally representative data from rural India, shows that differential access to quality information on crop production technologies critically limits the income potential of farmers of socially backward castes. The inter-caste differences in crop income are found arising due to differences in both resource endowment status and access to the public extension networks. Value of public extension services was particularly low in regions where socially backward castes form a majority in the population.

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Keywords. Social segregation; Exclusion; Agricultural extension; Crop income; Information access; Impact heterogeneity

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1. Introduction

Alongside high rate of economic growth, India has witnessed a rising concentration of wealth in the last two decades (Sarkar and Mehta 2010). Exploring the economic inequality, a number of studies have indicated persisting disparity between different castes as one of the main sources (Deshpande 2000; Desai and Dubey 2012; Borooah 2005; Zacharias and Vakulabharanam 2011; Rawal and Swaminathan 2011). Caste system, an exhaustive and hereditary institution that was originally defined based on the occupation of communities (Deshpande 2000) continues to permeate Indian society, clustering its population into thousands of small endogamous groups (Fontaine and Yamada 2014; Thorat 2009; Deshpande 2000). The literature provides sufficient evidence for continued persistence of caste disparities in different dimensions of rural livelihoods in India (Borooah 2005; Zacharias and Vakulabharanam 2011; Heyer 2010). However, not many attempts have been made to identify the pathways through which caste system impedes rural development and increases economic inequality.

Farmers belonging to those castes and communities that are located at the bottom of caste hierarchy, henceforth 'socially backward castes', have only limited access to the factors of agricultural production and therefore could generate only lower crop income (Singh 2011; Iversen et al. 2010; Birthal, Roy, and Negi 2015; Anderson 2011; Kumar 2013; Birthal et al. 2015). Alongside historical disadvantages with respect to their resource endowments, farmers of socially backward castes suffer from social and physical exclusion from developmental programs (Deshpande 2011). The Government of India has recognized the need to prioritize these disadvantaged groups while framing the information dissemination strategies (Anonymous 2012b). Despite its immense consequences for economic development, inequality, poverty and inter-group conflicts in rural India, caste-based social segregation and its economic impact has not received sufficient scholarly attention, particularly in the context of agrarian change and rural development. In addition, studies that delineate the effects of caste-based social segregation from the effects of prevailing inequalities in resource endowments in the society are rare in the literature.

This paper, analyzing a nationally representative sample of about 31 thousand agricultural households in India, examines the caste-based social heterogeneity in rural India with respect to farmer's access to public extension services. Agricultural extension services have been used as one of the decisive means to enhance human capital and to improve the livelihood status of rural households of global South from the Green Revolution era (Anderson and Feder 2007; Dethier and Effenberger 2012). India has one of the heavily invested, pluralistic agricultural extension networks in the public sphere, and the Indian government has carried out a series of institutional reforms during the last few decades to improve its organizational performance (Glendenning, Babu, and Asenso-Okyere 2010; Raabe 2008). In spite of the increasing investment and conscious efforts for decentralized dissemination of information, the public extension networks in India remains to have strikingly low coverage (Anonymous 2005a, 2014). For a faster and more inclusive agricultural growth and rural development, gaining a clearer understanding on the status and process of farmer's access to the extension services and the factors influencing it would be necessary. Particularly important is to examine how certain easily identifiable, non-economic farmer attributes (like caste and gender of farmer), could potentially shape up farmer access to public extension services. The literature suggests that, apart from economic factors such as factor endowments, historically persistent social segregation could be playing a pivotal role in determining households' access to public goods in India (Balasubramaniam, Chatterjee, and Mustard 2014; Banerjee, Iyer, and Somanathan 2005). Any such discrimination with respect to information access could lead to differential access to new technologies, lower productivity, and cause far reaching distributional implications in the economy. Against this backdrop, the current paper examines the presence, prevalence, and economic effects of caste-based social segregation in accessing public agriculture extension services in rural India. We proceed by testing the following hypotheses: (i) Differential access to public extension services exists for farm households belonging to different caste groups (ii) Returns to information access vary across farm households belonging to difference castes groups, and (iii) There are quality differences in extension networks depending caste-composition in the regional population.

We analyse the differential access and economic impacts of public sector agricultural extension programmes from a nationally representative survey conducted by the National Sample Survey Office of Government of India. The characteristics of household sample and econometric methods that are used to delineate the impacts are given in the next section. In Section 3 the results of empirical estimation are provided, while the last section discusses the findings and conclusions from the study.

2. Empirical framework

2.1. Data

A nationally representative survey was conducted by the National Sample Survey Organization of Government of India in 2013 with the objective of assessing the livelihood conditions of agricultural households. This survey, called "Situation Assessment Survey of Agricultural Households" (SAS 2013 henceforth), provides the database of our empirical analyses. An agricultural household as defined in SAS 2013 may or may not possess cultivable land. Households with at least one member self-employed in agriculture and having a total value of produce more than Indian rupees 3000 (USD 54) were included as the respondents (Anonymous 2012a). A structured questionnaire was used to elicit information on socio-economic, institutional, and organizational aspects of crop production and animal husbandry.

The SAS 2013 dataset contains information from two interviews, which were conducted with an objective to collect relevant information for the two major agricultural seasons separately from the sample households. The first visit was made during January to July 2013, which covered 4,529 rural villages from 625 districts. About 8 households were selected in each sample villages, making a total sample size of 35,200 households. Of this, 34,907 were revisited and surveyed in the second round. In visit 1, information on expenses and receipts for crops and livestock were collected for the period July to December 2012 (*kharif* season), and in visit 2 for the period January to June 2013 (*rabi* season). For the present study, we excluded households having (i) no crops under cultivation in both *kharif* and *rabi* seasons, (ii) incomplete information, and (iii) extreme values in the crop income distribution (top 1% and bottom 1%). The resulting dataset contained information from 31,181 farmer households.

For the empirical analysis, sample households are categorized into five caste groups – socially forward castes, scheduled castes, scheduled tribes, other backward class (OBC) Muslim, and OBC non-Muslim. Scheduled castes and tribes were the formerly “untouchable” castes and disadvantaged tribes, for whom the Constitution of India allows for special provisions (Thorat 2009; Deshpande 2011). According to the recent census data, about 25% of Indian population belong to these two categories (Ministry of Home Affairs 2011). Among the OBC households, those belonging to the Muslim community were grouped separately, due to the relative deprivation of the community reported in many spheres of life such as education, employment, and participation in government programmes (Anonymous 2006). The population share under OBC has not been revealed in the recent census. In the SAS 2013 dataset, about 41% of the households belong to OBC non-Muslim and 4% to OBC Muslim. The caste composition shows significant inter-state differences.

2.2. Identifying the determinants of farmer access to extension networks

To test the hypothesis whether differential access to public extension services exists with respect to farmers’ caste, we estimate regression models with extension contact as the dependent variable and farmer caste dummies in the set of explanatory variables. Farmer access to formal extension services is captured in two ways in this study. First, by using a dummy variable for the households that had made contact at least once with any of the three formal extension agents (state extension, *Krishi Vigyan Kendras* or Agricultural Science Centres, and state agricultural universities) during the two cropping seasons. Second, by including the frequency of contact (that is, the number of times a household contacted the abovementioned extension agents) during this timeframe. The relationship between farmer’s caste and access to extension services is analysed using regression models as follows.

$$A_i = \alpha_0 + \sum_{1}^{k} \alpha_{1k}\, c_{i,k} + \sum_{1}^{j} \alpha_{2j}\, r_{i,j} + v_i$$

[1]

where A_i is information access variable (contact dummy or contact frequency), c_{ik} are caste dummies, r_{ij} are region dummies, and v_i is stochastic error term. However, coefficients of c_k in this specification (α_{1k}) would reflect the effects not only of social discrimination but also of the differences in resource endowments and production constraints. In order to identify whether exclusion of certain farm households occurs based on their caste, the variables representing resource status of the household are required to be controlled for, by including them in the model estimation.

$$A_i = \alpha_0 + \sum_{1}^{k} \alpha_{1k}\, c_{i,k} + \sum_{1}^{j} \alpha_{2j}\, r_{i,j} + \sum_{1}^{m} \alpha_{3m}\, h_{i,m} + v_i$$

[2]

where h_i is the set of household characteristics indicating resource ownership, education and income poverty. Negative sign of α_{1k} in Model **[2]** would denote a comparatively limited access to public extension services for households of caste k, due to social exclusion. Conventional

Probit models are adequate to estimate factors affecting information access, when the dependent variable is dichotomous.

To model the frequency of contact, count-data regression models – Poisson and negative binomial models – are used conventionally. To account for the prevalence of zero counts in the dependent variable, we attempted zero-inflated Poisson (ZIP) and zero-inflated negative binomial (ZINB) models. Selection of ZIP/ ZINB over conventional Poisson and negative binomial models is supported by a positive and significant Vuong test statistics (Vuong 1989). A comparison of ZIP and ZINB estimates carried out using Akaike's information criterion (AIC) and Bayesian information criterion (BIC) revealed a clear superiority of ZINB to explain the variation in the dependent variable. Through a splitting process that models the outcomes as zero or nonzero, the ZINB framework combines negative binomial regression model with binary model (Greene 2012). Unlike ZIP, over-dispersion is also allowed in ZINB, that is, when the conditional variance exceeds the conditional mean of the distribution. The ZINB models have been used to explain determinants of count outcomes in a number of empirical studies in different contexts (Ickowitz et al. 2014; Symes et al. 2016; Gido et al. 2015).

2.3. Modelling differential effects of public extension.

As the first step to explore the heterogeneity of effects across different caste groups, we estimate regression models on crop income (Y_i) over a set of explanatory variables as follows.

$$Y_i = \beta_0 + \beta_1 A_i + \sum_1^k \left[\beta_{2k} c_{i,k} + \beta_{3k}\left(A_i \times c_{i,k}\right)\right] + \sum_1^j \beta_{4j} r_{i,j} + \varepsilon_i$$

[3]

The statistical significance of coefficient β_{3k} would denote that the marginal value of extension contact is different for households belonging to the socially backward caste group k, compared to those from the forward castes (the reference dummy). In the extended model specification, we included additional explanatory variables so that the effect of social exclusion due to caste can be delineated from that of individual exclusion due to household-specific differences in endowments and production constraints.

$$Y_i = \beta_0 + \beta_1 A_i + \sum_1^k \left[\beta_{2k} c_{i,k} + \beta_{3k}\left(A_i \times c_{i,k}\right)\right] + \sum_1^j \beta_{4j} r_{i,j} + \sum_1^m \beta_{5m} h_{i,m} + \varepsilon_i$$

[4]

The marginal effect of extension contact ($\beta_1 + \sum \beta_{3k} . \bar{c}_{i,k}$) is not expected to be uniform across different crops, as production of certain crops could be more information intensive than others. In order to address this heterogeneity, regression model **[4]** is estimated separately for households cultivating different crop types (e.g. cereals, legumes etc.).

Several factors outside vector $h_{i,m}$ could also determine households' ability to generate income from crop production. Some of these omitted variables may be correlated with extension access, resulting in inconsistent estimates. To address this bias, we model the effects of extension access in an endogenous switching regression (ESR) framework. This forms the second step of our impact analysis. Using an instrumental variable, the ESR model accounts for observed and unobserved differences between farm households that had accessed extension and that had not. The ESR framework involves two stages. The first stage is a selection equation, based on a dichotomous choice function – access to public extension in our context. In the second stage, two regime equations are specified explaining the outcome of interest – crop income – based on the estimated selection function. Details of the ESR framework and its empirical applications are widely available in the literature (Greene 2012; Fuglie and Bosch 1995; Di Falco, Veronesi, and Yesuf 2011; Krishna et al. 2017).

For the ESR model to be correctly specified, the selection equation should contain at least one instrumental variable that is included in the selection model but is uncorrelated directly with the outcome variable. We use non-availability of extension services in the district as the instrument. The reasons for not accessing extension services were elicited in the SAS 2013 questionnaire. Non-availability is measured as the share of households that did not access information because of non-availability of extension services in their residing district. This variable is found strongly correlated with information access but not with crop income.

Using the ESR estimates, we estimate the effect of extension contact ("treatment" in the adoption-impact literature). This is done by comparing the expected crop income of households that accessed public extension services ("treated") and those who did not ("untreated"), to the expected crop income in the counterfactual hypothetical cases. The conditional expectations in these four cases are defined as follows:

$$E[Y_{1i} \mid A_i = 1] = \boldsymbol{x}_{1i}\gamma_1 + \sigma_{1\eta}\lambda_{1i} \qquad \text{(real)} \qquad \textbf{[5a]}$$

$$E[Y_{2i} \mid A_i = 0] = \boldsymbol{x}_{2i}\gamma_2 + \sigma_{2\eta}\lambda_{2i} \qquad \text{(real)} \qquad \textbf{[5b]}$$

$$E[Y_{2i} \mid A_i = 1] = \boldsymbol{x}_{1i}\gamma_2 + \sigma_{2\eta}\lambda_{1i} \qquad \text{(hypothetical)} \qquad \textbf{[5c]}$$

$$E[Y_{1i} \mid A_i = 0] = \boldsymbol{x}_{2i}\gamma_1 + \sigma_{1\eta}\lambda_{2i} \qquad \text{(hypothetical)} \qquad \textbf{[5d]}$$

where $\boldsymbol{x}_i$ are farm household characteristics (including caste dummies) affecting the outcome variable Y_i. Cases **[5a]** and **[5b]** represent expectations of the actually observed regimes for adopters and non-adopters, whereas cases **[5c]** and **[5d]** represent predicted counterfactual outcomes that adopter households had not adopted, and that non-adopter households had adopted respectively. The average effect of information access on households that accessed information ("average treatment effect on the treated" or ATT) can be estimated as the difference between **[5a]** and **[5c]**.

$$ATT = \boldsymbol{x}_{1i}(\gamma_1 - \gamma_2) + \lambda_{1i}(\sigma_{1\eta} - \sigma_{2\eta}) \qquad \textbf{[6]}$$

This equation controls for possible causes of income differences other than extension access. We eliminate the effects of unobserved factors by holding λ_{1i} constant and taking the differences in variance $(\sigma_{1\eta} - \sigma_{2\eta})$. Similarly, we calculate the average predicted effect of extension access on those who did not access extension network ("average treatment effect on the untreated" or ATU) as the difference between **[5d]** and **[5b]**.

$$ATU = \boldsymbol{x}_{2i}(\gamma_1 - \gamma_2) + \lambda_{2i}(\sigma_{1\eta} - \sigma_{2\eta}) \quad \textbf{[7]}$$

The ESR framework implies that unobserved factors have different effects depending on which regime applies. If self-selection is based on comparative advantage, access to extension services would produce bigger benefits under self-selection than under random assignment (Maddala 1986; Di Falco, Veronesi, and Yesuf 2011). If so, simple comparison of mean crop income levels between households that accessed information and those who did not would overestimate the real effect of information access.

If we do not detect significant omitted variable bias in the regression estimates, one of the possible reasons could be that the residual variation arises mainly from supply-side, that is, from the regional differences in extension infrastructure, than from demand side. The supply-side differences form an exogenous factor, the effect of which can be examined through estimating the average treatment effects from the ESR model after subgrouping the sample based on the district share of forward and backward castes. The first group includes districts where the sample contains a majority (more than 2/3rd) of socially forward caste households, while the second group is with a majority (more than 2/3rd) of socially backward caste households. Given the high regional concentration of castes in India, if quality of extension infrastructure differs according to the caste concentration in a district, we could expect significant differences in income effects of extension across these two district categories.

3. Results

Analysing the differential access to agricultural extension services, and its effects on crop income across different caste groups form the primary research objective of this study. The dataset contained 31,181 observations after excluding the missing and extreme values. We found significant differences in the socio-economic characteristics of sample households with respect to the caste they belong: socially forward castes (households that do not belong to any of the socially backward caste groups), scheduled castes, scheduled tribes, other backward class (OBC) Muslims, and OBC non-Muslims (Table 1). As anticipated, the average crop income realized by households belonging to the forward castes is significantly higher. The magnitude of the difference is highest (134%), when compared to the scheduled castes. One of the possible reasons is differential access to public extension services; only 7% of the scheduled caste farmers are found having access, compared to 13% of the forward castes.

Farmers belonging to the backward castes, especially scheduled castes and OBC Muslims, were in a disadvantaged position with respect to other production resources also. In both of these caste groups, farm households were found owning smaller farms (0.23 ha per adult equivalent) compared to their forward caste counterparts (0.43 ha per adult equivalent). In the literature, there is ample evidence for land ownership perpetually skewed against the socially backward castes (Anonymous 2012a; Desai and Dubey 2012; Anderson 2011), compromising their income generation potentials. Significant differences also exist with respect to human capital. Inter-caste differences with respect to education attainment are well-noted in the literature (Thorat 2009; Desai and Dubey 2012; Anonymous 2006), as also in the SAS 2013 dataset. Non-farm income opportunities were also lower for backward caste households.

As a cumulative effect of historic disparities with respect to ownership of production assets and social and physical isolation in the community perpetuated and reinforced by caste system, socially backward caste households are also economically poor (Thorat 2009). This fact is reflected in their increased participation in food subsidy schemes meant for households 'below poverty line' (BPL) in the SAS 2013 dataset. About 63% of scheduled caste and 72% of scheduled tribe households in the sample hold BPL cards, against only 31% in the forward castes. However, there could be multiple factors contributing to this inferior economic status of the socially backward caste farmers. In order to delineate the effect of extension access on crop income from other variables, we employ multiple regression models, the results of which are presented in the following sub-sections.

3.1. Differential access to extension networks

Determinants of farmer contact with the public extension services (dummy) and frequency of contact (number) are modelled using Probit and zero-inflated negative binomial (ZINB) models respectively. These models are estimated in two steps. Model 1 is estimated with only caste and region variables. The coefficients of caste dummies in this model represent the differential access due to both social exclusion and heterogeneity in endowments. Model 2 contains household-specific variables in addition, in order to delineate the possible effects of social exclusion on extension access. Marginal effects of caste dummies are shown in Table 2.

In Model 1, the marginal effects of caste dummies are found negative and statistically significant in both Probit and ZINB models. Compared to forward caste households, probability of access is found lower for those belonging to backward castes; the access rate was lower by 3.4 percentage points for OBC non-Muslim and by 8.0 percentage points for OBC Muslim category. The magnitude of differential access for scheduled castes and scheduled tribes falls within this range. Similar patterns are observed in the frequency of contact models. Compared to forward castes, the frequency of contact was lower by 0.29 events for OBC non-Muslims and by 0.66 events for OBC Muslims. Again, the differences in the rate of access with other groups and forward castes fall within this range.

Inclusion of the socio-economic attributes in the model estimation is found to reduce the effect of caste dummies (Model 2). Compared to forward caste households, the access rate was lower by 1.8 percentage points for OBC non-Muslims and by 5.6 percentage points for OBC Muslims, when the variables representing farmer capabilities and endowment status were included in the model estimation. The magnitude of differences falls within this range for scheduled castes and scheduled tribes. Although reduced in magnitude compared to Model 1, these differences remained statistically significant, and bear high policy significance given that the average rate of accessing public extension services is small (11%). The count data models on frequency of farmer contact with the extension agents also showed a similar pattern. Therefore, while the inferior resource endowments of socially backward castes form a major constraint in accessing extension services, we cannot reject our first hypothesis that caste-based social exclusion plays a crucial role.

3.2. Heterogeneous effects of extension access on crop income

We now analyse the income effect of farmer access to extension services with the econometric models that are described in Section 2. The key explanatory variable, extension contact, is included both in binary and in count (frequency) forms in different model specifications, and is interacted with caste variables to model crop income of farm households. Statistically significant interaction coefficients denote the presence of caste-differentiated effects in the public extension networks. The estimates of extension contact and caste variables and their interactions are shown in Table 3.

In the first step, the effect of extension access is estimated including caste, religion, and region dummies but without other farm household attributes. These estimates are shown as Model 1. As expected, the coefficients of caste dummies and their interaction with extension variables are negative. In comparison to forward caste, not only that the backward caste households generated lesser crop income, but their potential to benefit through accessing agricultural extension services was also low. Within forward caste group, farmers with extension access are found having a higher crop income by 28 thousand rupees (US$ 478) than those without any access. The marginal returns of extension contact were significantly lower for backward caste households: only 3 thousand rupees in addition for farmers belonging to OBC Muslim, 13 thousand for scheduled castes, and 16 thousand for scheduled tribe categories. Only for OBC non-Muslim category the extension interaction is statistically insignificant. In the model with frequency of extension contact, many of the interaction terms are statistically insignificant, albeit comparable in sign as well as in magnitude.

When the variables representing capabilities and endowment of farm households are included in the model estimation, most of the caste-information interaction terms became statistically insignificant (Model 2). The only exception was OBC Muslim category. These results denote that most of the socially backward households were not benefiting from their access to the public extension networks because of lower endowment status, like smaller farms and lack of formal schooling. Once these differences are accounted, farmers belonging to different castes can benefit equally from extension access. These results suggest rejection of hypothesis (ii). However, the possibility of omitted variable bias also has to be ruled out.

Adoption-impact studies using cross-sectional data often struggle with omitted variable bias, which occurs when the unobserved variables are correlated with both adoption and outcome variables. The presence and magnitude of this bias can be addressed through an endogenous switching regression model that includes an instrumental variable, non-availability of extension services in the region. Non-availability is measured as the share of farmers who did not access extension services and indicated non-availability of these services as the reason. This variable stands proxy for the low quality extension services available in the region. Access to public extension services by a farm household is treated as a regime shifter. The average treatment effects are shown in Figure 1. The "average treatment effect on the treated" denotes the returns to extension contact for those who contacted extension agents. This is the difference between expected crop income of farm households that acquired information and income from the counterfactual hypothetical case of had they not..

Similar to the ordinary least squares estimates, the farmers of forward castes benefit the most with extension access. The average effect for those who contacted extension agent was Rs. 12.2 thousand per year, and Rs. 9.8 thousand for OBC non-Muslims (Figure 1). Among scheduled caste and tribes, the incremental crop income due to accessing public extension services is significantly lower. Surprisingly, the OBC Muslim households did not benefit at all from the information accessed. These results indicate that after adjusting for omitted variable bias through switching regression, we cannot reject hypothesis (ii). Caste continue to define the economic opportunities for a vast proportion of farming population in rural India, as also shown by previous studies (Borooah 2005; Desai and Dubey 2012).

The data exhibit high regional concentration or caste homogeneity, and hence, we examined whether the quality of extension services are lower in regions where majority of the households belong to socially backward castes. We grouped the observations into (i) districts where socially backward caste households form a majority and (ii) districts where forward caste households form a majority, and compared the average treatment effect for the treated group obtained from the switching regression models across these groups. It is possible that the districts where socially backward caste households reside have poor extension infrastructure. Figure 2 shows average treatment effects for each caste group in these district groups. Irrespective of the farmer caste, marginal returns to extension contact were significantly low in districts dominated by backward caste households. In the districts where forward castes form the majority, on the other hand, returns to extension contact across the caste groups is high and consistently positive. This refines the insights we obtained from Figure 1. Extension networks are indeed weak in the regions where socially backward castes form a majority in the population. Even for forward caste farmers, who benefit the most from extension networks, magnitude of benefits from extension contact reduces by half had they been residing in backward caste dominated districts. We hence cannot reject hypothesis (iii).

3.3. Robustness checks

We examine the robustness of our estimates in two different ways. One, by using state-level fixed effects and two, by including crop types cultivated by the household as the explanatory variables. We included the dummy variables representing agro-ecological zones of India to model the effects of extension contact in Table 3. However, due to the geographical concentration of certain castes and communities (Basant 2007), controlling for the state effects in the regression models could alter the sign and magnitude of some of the estimates. An additional model including state dummies is run. (Estimates are not shown due to space limitations, but they are available upon requesting the first author). The most perceptible difference in this specification is the reduction in the magnitude of coefficient of extension dummy. The households belonging to the socially backward castes remained in the disadvantageous position to benefit from the access although the inter-caste differences remained only marginally significant due to the high standard errors associated.

Production of certain crops could be relatively more information-intensive. The possible differences in the marginal returns from extension contact across the crop types are estimated for different caste groups. (Estimates are not shown due to space limitations, and they are available upon requesting the first author). Most (93%) of sample households cultivate one or other cereal crop, and hence it is not surprising that the nature of effect of extension dummy variables of this subgroup is similar to the whole sample. Oilseeds are another crop group where the inter-caste differences in marginal effect of extension contact was significantly low for socially backward caste households. For many other crops, for example legumes, marginal effect of extension contact is statistically insignificant across different caste groups, including forward castes.

4. Discussion and Conclusion

Discrimination based on group attributes such as ethnicity and gender has long attracted the attention of economists (Alesina, Baqir, and Easterly 1999; Jurajda 2005; Banerjee et al. 2005). In the field of political economy, social divisions undermining economic progress form one of the most relevant research hypotheses (Banerjee, Iyer, and Somanathan 2005). However, there exists only limited empirical evidence on social segregation shaping agrarian change and rural development. The present study shows that caste-based social hierarchy and segregation corresponds not only to differential access to public extension services in rural India but also to heterogeneous benefits of available information. We conclude that farm households belonging to the socially backward castes are disadvantaged due to inferior resource endowment status, exclusion from public extension networks, and regional differences in quality of extension services and infrastructure.

Being heavily dependent on agricultural sector for employment and income generation, farm households of socially backward castes and communities could have benefitted significantly from quality extension services. Since the production conditions they face are inferior, an increased access to specialized information would indeed be more useful for these farmers than others. Ironically, one of the major reasons for the lower access to formal extension services is the economic backwardness of farm households itself. This forms a vicious, self-enforcing mechanism for persistence of income poverty among socially backward castes.

The second reason for lower access to public extension services and lower returns from the access for socially backward castes is the physical and social exclusion they face in the rural community. The previous estimations on higher prevalence of poverty among socially backward castes (Thorat 2009; Alkire and Seth 2015) are not very surprising against this backdrop. Making socially inclusive extension policies is therefore highly pertinent in Indian agriculture, not only to disseminate conventional production technologies but also to address the emerging challenges such as climate change and deteriorating natural resource base.

We have also observed that value of extension services is particularly low in those districts where socially backward caste households form a majority in the population. There exists empirical evidence for social heterogeneity being negatively associated with availability of public goods in India (Balasubramaniam, Chatterjee, and Mustard 2014; Anderson 2011; Banerjee, Iyer, and Somanathan 2005). Our study goes a step further showing that the mere availability of a public good does not necessarily mean equal access and equal value for households belonging to different layers of social hierarchy. Further studies are required in this direction. For example, there could be inter-caste differences on quality of production resources managed by the household, which might also be contributing to the lower marginal returns to information. The available evidence from a neighbouring country, Nepal, suggests that land productivity need not always be lower for farm households belonging to socially backward castes (Aryal 2010). However, the situation may vary from region to region.

The commonly held assumption that increasing public investment on agricultural extension programmes could inevitably ensure socially inclusive economic growth requires a revision. Ignoring the ethnic heterogeneities could pose serious challenges for inclusive growth, overcoming which requires explicit identification of socially backward communities while planning the developmental programmes. Our study has shown that economic inequalities emerge from caste inequalities in rural India. Applied research design based solely on economic stratification of society, neglecting the social dimension especially that of caste, might lead to imprecise policy recommendations that are not inclusive for rural development. Furthermore, examination of effects of caste-based stratification on developmental programmes is particularly relevant even in those regions where backward castes form a majority in the population. Explicit and focused efforts to ensure adequate participation of socially backward communities in developmental programmes are fundamental for inclusive growth. Equally important here is to recognize the information requirements and production constraints that are unique to each of the ethnic groups.

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Table 1. Descriptive statistics by caste groups

Farm household characteristics [units]	Pooled	Forward castes	Scheduled castes	Scheduled tribes	OBC Muslim	OBC non-Muslim
Crop income	36.02	47.20	20.13***	29.75***	33.55***	37.51***
[‘000 Indian rupees]	(0.66)	(1.55)	(0.98)	(1.04)	(5.66)	(1.04)
Extension contact [dummy]	0.11	0.13	0.07***	0.10***	0.08***	0.11***
Frequency of extension contact [dummy]	0.76	0.94	0.48***	0.63***	0.51***	0.74***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.02)
Landholding	0.37	0.43	0.23***	0.37***	0.23***	0.39***
[ha per adult equivalent]	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Household size	2.79	2.75	2.68***	2.76	3.05***	2.80***
[ha per adult equivalent]	(0.02)	(0.01)	(0.02)	(0.01)	(0.03)	(0.01)
Education of household head [scale]	4.58	5.72	3.99***	3.65***	3.78***	4.50***
	(0.06)	(0.04)	(0.05)	(0.04)	(0.09)	(0.03)
Main income source is non-farm [dummy]	0.04	0.05	0.04***	0.02***	0.08***	0.04***
‘Below Poverty Line’ card holder [dummy]	0.47	0.31	0.63***	0.72***	0.38***	0.44***
Number of observations	*31,181*	*8,764*	*3,675*	*6,203*	*1,225*	*11,314*

Mean values are shown with std. errors in parentheses. Sampling weights are used in the estimation. *** Difference with the mean value of forward castes is statistically significant at 0.01 level. 1US$ = Rs. 58.6 in 2013 (source: (World Bank))

Table 2. Effect of farmer caste on access to public extension in India

Caste dummies	Dependent variable: Extension contact (dummy)		Dependent variable: Frequency of extension contact (number)	
	Model 1	Model 2	Model 1	Model 2
Scheduled castes	-0.057***	-0.024**	-0.458***	-0.215**
	(0.012)	(0.012)	(0.101)	(0.099)
Scheduled tribes	-0.069***	-0.039***	-0.576***	-0.363***
	(0.012)	(0.012)	(0.087)	(0.086)
OBC Muslim	-0.080***	-0.056***	-0.660***	-0.478***
	(0.022)	(0.022)	(0.196)	(0.183)
OBC non-Muslim	-0.034***	-0.018*	-0.294***	-0.180**
	(0.010)	(0.010)	(0.071)	(0.070)
Wald χ^2	469.54***	601.28***	146.86***	199.61***
Number of observations	*31,181*	*31,153*	*31,181*	*31,153*

Marginal effects are shown with robust standard errors in parentheses. Extension contact (dummy) is modelled using Probit and frequency of contact (number) is modelled using zero-inflated negative binomial (ZINB) regression models. Model 1 includes caste and regional dummy variables only, while Model 2 includes farm household characteristics in addition. Reference category is socially forward castes. OBC stands for 'other backward communities'. See Table S1 for full models. Other model estimates are not shown here due to space limitations, and they are available upon requesting the first author.

*, **, *** : Statistically significant at 0.10, 0.05, and 0.01 levels, respectively.

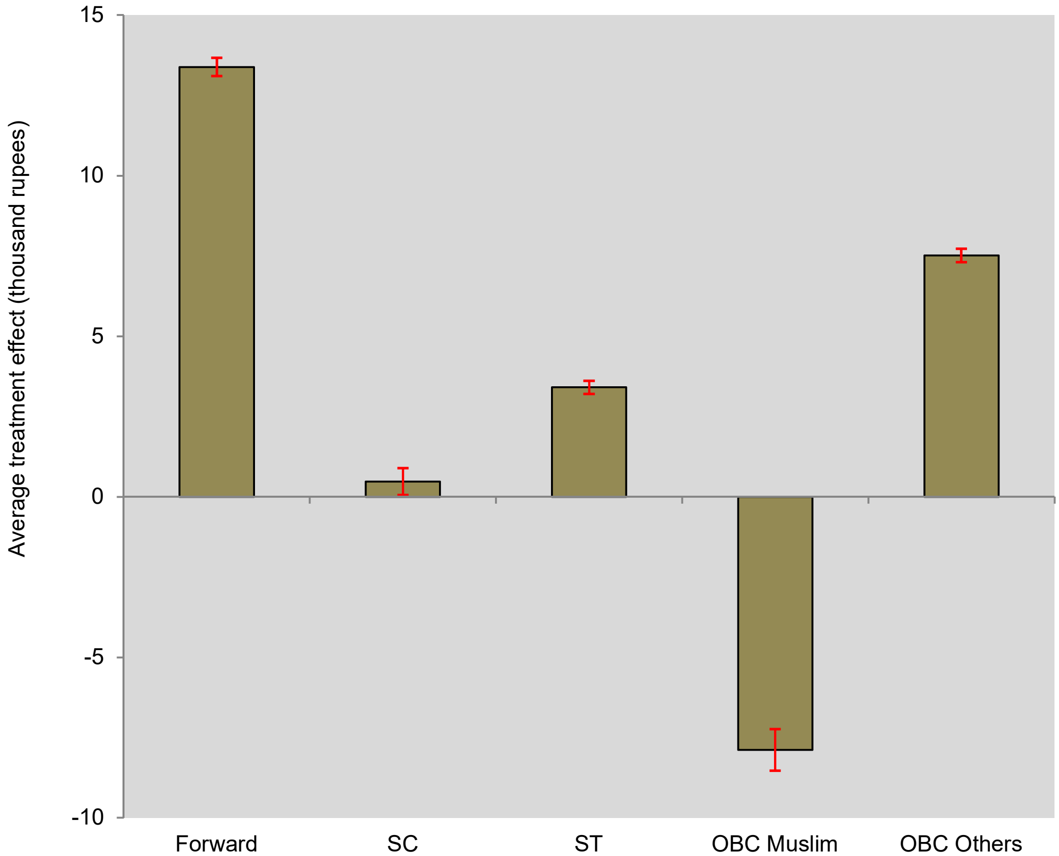
Table 3. Caste-differentiated effects of extension contact on crop income

	Extension measured as the contact dummy		Extension measured as the frequency of contact	
	Model 1	Model 2	Model 1	Model 2
Extension	28.228***	15.064***	3.648***	2.202***
	(4.934)	(4.333)	(0.652)	(0.547)
Scheduled castes	-25.195***	-9.258***	-25.462***	-9.368***
	(1.994)	(1.670)	(1.963)	(1.649)
Scheduled castes x Extension	-15.276**	-9.999*	-1.554	-1.085
	(6.493)	(6.004)	(0.962)	(0.876)
Scheduled tribes	-16.007***	-7.183***	-16.164***	-6.921***
	(2.187)	(1.849)	(2.146)	(1.811)
Scheduled tribes x Extension	-11.839**	-5.933	-1.225	-0.930
	(6.111)	(5.213)	(0.790)	(0.663)
OBC Muslim	-7.768	0.954	-8.129	0.816
	(6.141)	(5.589)	(6.082)	(5.533)
OBC Muslim x Extension	-25.120**	-22.864***	-2.466*	-2.603**
	(11.044)	(9.242)	(1.516)	(1.303)
OBC non-Muslim	-10.656***	-4.312***	-10.593***	-4.272***
	(2.060)	(1.731)	(2.020)	(1.700)
OBC non-Muslim x Extension	-8.474	-6.469	-1.150	-0.845
	(5.829)	(5.237)	(0.774)	(0.647)
Adj. R^2	0.06	0.25	0.06	0.25
Number of observations	*31,181*	*31,153*	*31,181*	*31,153*

Coefficients are shown with robust std. errors in parentheses. The dependent variable in all models is crop income (thousand Indian rupees; 1US$ = Rs. 58.6 in 2013 (source: (World Bank)). Model 1 includes caste and regional dummy variables, while Model 2 includes farm household characteristics in addition. See Table S2 for full models. Extreme values of the dependent variable are excluded from the estimation. Other model estimates are not shown here due to space limitations, and they are available upon requesting the first author.

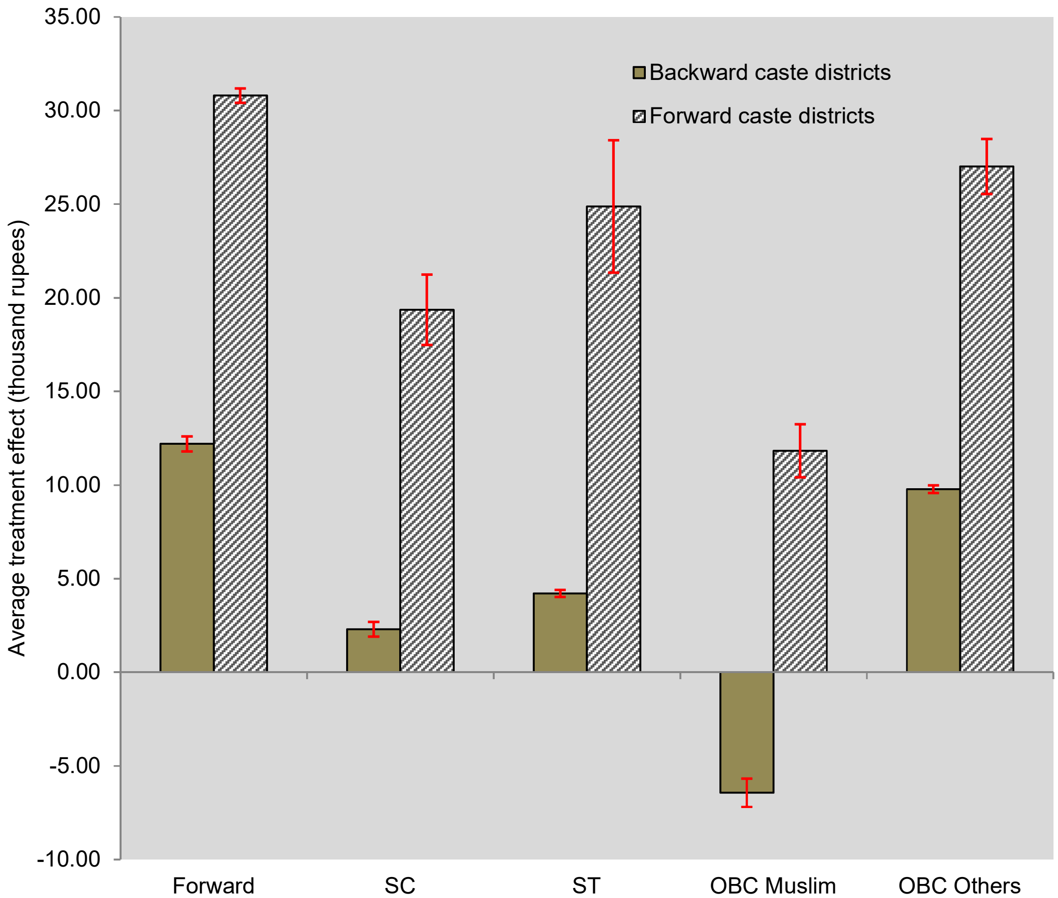
*, **, *** Statistically significant at 0.10, 0.05, and 0.01 levels, respectively.

Figure 1. Average income effect of extension access across farm households belonging to different castes



The values are derived from an endogenous switching regression model. (Estimates are not shown due to space limitations, and they are available upon requesting the first author). Extension contact is measured as dichotomous variable. Forward, SC, ST, and OBC stand for forward castes, scheduled castes, scheduled tribes, and other backward communities respectively. The crop income effect of extension access on farm households, measured in thousand Indian rupees (1US$ = Rs. 58.6 in 2013; source: (World Bank 2017)), is shown in the vertical axis. Here we report the average treatment effect on the treated, where "treated" are the households that contacted extension agents.

Figure 2: Average income effect of extension access in districts grouped with respect to share of backward caste households



The treatment effect values are derived from an endogenous switching regression model. (Estimates are not shown here due to space limitations, and they are available upon requesting the first author). We measure extension contact here as a dichotomous variable. “backward caste districts” include observations from those districts where 2/3rd of the sample belongs to socially backward castes (SC, ST and OBC categories combined). “forward caste districts” include observations from those districts where 2/3rd of the sample belongs to forward castes. Forward, SC, ST, and OBC stand for forward castes, scheduled castes, scheduled tribes, and other backward communities respectively. Values in the vertical axis show the change in the crop income, measured in thousand Indian rupees (1US$ = Rs. 58.6 in 2013; source: (World Bank)), due to extension access on “treated” group (the household that contacted extension agents during the study period).