Youth, Endogenous Discrimination, and Development Conundrum in India

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Abstract

Rising discrimination in a society - whether advanced or developing - contributes significantly to social tension and uncertain economic growth. In case of a developing society, the stake is even higher given that the society is in a transition phase to higher growth and any persistent unstable factor may reverse the process of growth and inject elements of volatility. Indian economy, unlike many other developing economies, has experienced unprecedented growth over the years, yet there has been constant debate about whether benefits of such growth vistas have been equally distributed across social strata and demography. Very importantly, the focus of the recent research in academic and policy circles has been whether persistent high growth has ameliorated the problem of discrimination or it has risen along the growth path. In this paper, we argue, despite high growth, discrimination has been on the rise. Specifically, we find that discrimination among young population across social strata and educational attainment levels is constantly rising, making the economic growth transition path more vulnerable and uncertain than is commonly assumed to be. While our overall results are consistent with much of the literature and policy findings, we demonstrate that the level of discrimination is not unique across population cohorts. Especially, it is found in our paper that young cohorts are consistently more discriminated compared to older cohorts and that the discrimination effect is rising over time. In view of growth-regenerating role of young population in any society, our findings hold enormous policy and academic implications.

Key Words: Discrimination Effect, Social position, Quantile Regression, Young Cohort, India.

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1 Introduction

Discrimination[1] - practised often endogenously in both developing and developed societies, do not beget any virtue either in the form of economic or social benefits. Indeed, discriminatory practices affect not only the current development path but also different social identities and their perspective long-term potential (Hoff and Pandey, 2006). Although imperfect competition in the product market and prevalence of greater degree of incomplete information are often attributed to the persistence of discrimination, especially in developing economies[2], a large body of literature points to its existence even in developed country settings (Holzer and Neumark, 2000). Undoubtedly, discrimination - prevalent in the form of either caste, gender, or skin-color can lead to inefficient and economically sub-optimal outcomes (Esteve-volart, 2009). Despite its strong sociological dynamics, economic study of discrimination has been motivated, first, by growth of labor supply having implications on underutilization of valuable resources (Klasen, 2002), and second, by the expected distortional incentives for investment for the next generation (Alderman and Kind, 1998). Both factors are characteristically growth-inhibiting effects and trigger a rise in inequality traps where a disadvantaged group faces a long-run opportunity set worse than that of another group even though a better set would be possible (Bourguignon et al., 2007). India is a prime case where study of discrimination possesses both social and economic values, especially in light of the recent growth spurt and upheaval social changes.

In the backdrop of this development, we focus on the study of caste[3] discrimination in India. We are especially interested in the measurement of their differential effects across social strata, human capital distribution and demographic characteristics. Practice of discrimination in India has a deep traditional root. Deininger et al. (2012) observe that 'reinforced by a social order built on endogamous castes - originally based on occupation - that are often res-identially segregated, discrimination is [particularly] pronounced in India, a country with one of the most stratified societies in the world'. Additionally, in an era of highly internationalized world economic order, while discrimination in any form is denounced on the ground of ethics and inefficient economic outcomes, its persistence in both developing and developed world are guided by some innate psychological characteristics, which as it has appeared, is independent of the economic/development status at that time.

However, presence and persistence of discrimination may have differential effect on the transitional path of an economic and social system. For instance, when an economy is at a low-level of equilibrium and is growing slower than expected, persistence of discrimination in that economy will be realized mostly in terms of sluggish growth. However, when persistence of dis-crimination appears dominant in a transition phase of the economy at a higher-level equilibrium,

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[1]Discrimination is defined as a systematic gap in rewards to key factors of production that can be attributed not to differences in relevant attributes but to easily identifiable group characteristics based on e.g., gender, skin colour or caste.

[2]In most Western countries, ethnic discrimination is largely a market phenomenon, whereas in many developing countries, it is rather government-mandated (Docquier and Rapoport, 2003).

[3]Caste, as a form of social fragmentation in India, can be traced historically in the form of ethnic divisions. To improve the living condition and decrease the social disparities between all ethnic groups, the Government of India, after independence, has constituted an anti-discrimination law for two most socially deprived social groups ST and SC. In the later years, it has extended this to the third deprived group Other Backward Class (OBC). These ethnic groups can be divided into four social groups (in ascending order) as: SC, ST, OBC and High Caste (HC).

it can make the future growth path unstable and uncertain - for economic and social reasons. Indeed, a growing body of research has documented the associations between discrimination, anger, and delinquency. Hartshornl et al. (2012), for instance, investigate whether aggressive behaviors emerge over time as a consequence of perceived discrimination and anger. They found that adolescents who engage in aggressive behavior perceive that they are being discriminated against. Perceived discrimination is but one of many strains related to unequal social position that youths of some societies may experience, and it has important implications for the proliferation of disparities in later life. Moreover, the stagnant role of caste discrimination (similar to race-relationship) in the labour market has widened the income and employment gap between deprived groups and privileged groups over time (Madheswaran and Attewell, 2007).

In view of this interesting socio-economic dynamics, in this paper we study how discrimination dynamics has evolved over time in the Indian economy and how it has affected the transitional growth dynamics over decades. We investigate, how historically deprived social groups has been treated in view of the government's 'preferential' or 'affirmative actions' policies and openness to trade since liberalization in 1991. In addition, we also seek to address how existing reservation policies for deprived groups have increased (decreased) the effect of caste discrimination over time. Has any legislative programme corresponding to most deprived groups (SCs/STs) bailed them out for the unequal treatment in society eventually after independence? Have federal reservation policies created any significant difference to reduced the effect of caste discrimination between the young generation and the old generation?

Using National Sample Survey (hereafter, NSS) data 1983-84 to 2004-05, previous research in this context found that wage inequality has risen between disadvantaged (SCs/STs) and privileged (Non-SC/ST) groups. For instance, Kijima (2006a), using employment and unemployment data for period 1983 to 1999 investigates wage inequality between these groups and finds that openness in trade policy and rapid growth during these periods have exacerbated the wage gap between SC/ST and privileged groups. Similarly, Azam (2012), adding NSS data from 2004-05 to previous study and by expanding the caste dimension in four categories (SC, ST, OBC, and General), finds a similar effect in case of the urban sector. In separate later studies Azam (2010) and Kijima (2006b) using the consumption expenditure data from rural sector, explain the dynamics of caste discrimination via distributional effect of consumption expenditure among all social groups. They demonstrate that consumption expenditure is not equally distributed across social group and a high level of social disparity exists among them. Azam's interprets his findings by suggesting that the growing consumption disparities among all social groups may be a potential source of caste discrimination.

However, it is important to note that the distribution effects between social groups is not similar to the discrimination effect. In economic sense, the distributional effect only reflects the lack of access to resources (education, health services, employment etc) between two class/groups. Therefore, it is important to understand which resources are helpful in linking the two economically deprived or socially separated societies. Furthermore, both studies include the self employed worker in their models. Such inclusion is problematic because low castes do not discriminate against themselves. They would not be exposed to employer to the discrimination. However, we can not rule out customer discrimination, which potentially has the same effect.

In this paper, thus, we attempt to cover both these issues. We use latest data set for 2010-

11 in addition to the periods 1993-94 and 2004-2005 from the NSS and examine the impact of caste discrimination among all social groups. Given that our primary interest is to demonstrate how income variation among all social groups explains the dynamics of caste discrimination in India since 1993-94, we employ quantile regression framework proposed by Koenker and Bassett (1978) and extended by Machado and Mata (2005, herafter MM) to accommodate counterfactual decompositions. The results are compared against the conventional average method as proposed by Oaxaca (1978) and Blinder (1978).

Our study finds that the observed differences between deprived groups (SC, ST, and OBC) and privileged group have increased across the entire distribution from 1993-94 to 2010-11, and more significantly at the higher quantile. This result is consistent with earlier research such as Azam (2009). The observed differences between 1993-94 and 2010-11 have been found in our study to remain constant across social groups. In addition, we also analyze, how caste discrimination has been explained in young generation who entered in the Indian labour market in the beginning of industrialization. In this context, no such studies exist to the knowledge of authors, which explains how caste discrimination persist in young generation and it has been evolving over time.

In light of the adopted 'reservation policy' aimed at protecting the SC, ST and the OBC through governments affirmative policies, we have divided our sample into two demographic components (young cohorts: population age between 15-40 years and old cohorts: population age between 41-65 years). In general, our results suggest that the effect of reservation systems has no perceived impact on young cohorts. The observed differences for the entire distribution indicate that in light of current policy framework young cohorts are facing more discrimination among all social groups and that it is steadily rising over time. Our study also suggests that the effect of discrimination experienced by most of the historically disadvantaged groups is higher due to the characteristics effect. Hence, from the policy perspective it is important that the government affirmative policies must successfully target both public and private sectors[4].

The rest of this paper follow as. Section 2 presents stylized observations and provides conceptual framework for testing various hypotheses. Section 3 provides some analytical results from a benchmark model. Section 4 discusses the methodological approach and their properties in the context of our study. Section 5 presents empirical results. Finally, Section 6 presents discussion of the main results and conclusions.

2   Stylized observations

In this section we present conceptual framework and some stylized observations that motivate our analysis and will be matched by the main results of our theoretical model and empirical investigation.

To measure discrimination, we use employment data from the National Sample Survey (NSS) in India over the period 1993-2011. Our variable of interest is the perceptible difference in variability in log wage across social strata, educational status and over time. Educational

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[4]In this view, Madheswaran and Attewell (2007) examine the importance of reservation policy for SCs/STs in different occupations. They find that the existing reservation policy is not very helpful in both the public or the private sectors and discriminates more in various in occupations.

status is proxied by educational attainment and distinguished between no education, primary, secondary, and tertiary. Similarly, demographic characteristics are taken into account by dividing the population into two cohorts, viz., young (15-40 years of age) and old (41-65 years age), whereas social stratification is captured by Scheduled Caste (SC), Scheduled Tribe (ST), Other Backward Classes (OBC) and General Category or High Caste (HC). Information in all social, economic, and demographic characteristics pertaining to wage differentials have been extracted from the NSS of various rounds beginning 1993-94.

Observation 1. *Across individuals and over time, there is divergence in the wage gap between lower and upper caste.*

By segregating the sample into low and high caste for each time period beginning 1993-94, 2003-2004, and 2010-2011, we have estimated the cross-sectional standard deviation (σ) of log wage between high and low caste. It appears that $\sigma_{1993}(= 0.21) > \sigma_{2004}(= 0.089) < \sigma_{2011}(= 0.093)$. This implies that although in the initial years of liberalization, σ declined between upper and lower caste, between 2003 and 2004 it mildly increased. It provides mixed evidence that in relation to 1993, there appears to be convergence in log-wage between upper and lower caste in 2011, but between 2003 and 2011, the difference seems to have increased. Moreover, σ for lower castes has increased between 1993 and 2004: for this group $\sigma_{1993} = 0.843 < \sigma_{2004} = 0.931$. Between 1993 and 2011, σ has increased about 4% for lower caste and 10% decline for upper caste and this trend is consistent throughout 1993, 2004, and 2011.

Observation 2. *Across cross-section of regions and social classes within a given country, discrimination effects is multi-modal.*

As reported in Fig. 1, there is strong evidence suggesting the existence of wage-discrimination trap, characterized by demographic characteristic, i.e., young and old population age groups: individuals are concentrated around at least two-levels of the log-wage. In fact Fig. 1, depicting histograms and Kernel density estimates (with optimal bandwidth), displays multi-modal distributions across all individuals. we believe that this multi-modality can be interpreted as a trap, since there is a high degree of overlap in the lower modes of the log wage distribution represented in Fig. 1. Moreover, one of the modes that represent middle of the distribution is characteristically unstable, therefore, in the presence of multiple equilibria, the economy chooses to remain in the lower-equilibria offering low-wage to discriminated cohorts in both young and old population. The higher equilibrium (that is, the third mode) is non-stationary and is not sustainable from the point of view of existing wage-distribution in the economy. This lends economic sense because the persistence of unequal earnings and labor force participation in the economy needs to be ameliorated through redistribution which is purported to benefit the disadvantaged class at the priority. As long as, convergence of disadvantaged classes does not occur with advantaged or high-class group's wage distribution, the equilibrium at the high-mode will remain non-stationary.

Along the same line, it can be argued that the distribution of log wage is also multi-modal among the social groups and that is consistent over time. In Fig. 2 we present the distribution

of log wage for four social groups beginning 1993. For this particular year there were three social groups because other backward caste (OBC) was not properly documented in NSS. For all the years, it is observed that ST and SC have higher mode than higher caste (HC) and all distributions have at least two clusters signifying the clear social division in wage earnings.

Observation 3. *In the population cohort, if discrimination is more persistent in the young than the old, the future value of economy growth is negatively affected through social tension and uncertainty.*

In the literature (e.g., Docquier and Rapoport, 2003) it has been demonstrated that when discrimination is endogenized in a political economy framework and when the economy is closed to emigration, the optimal discriminative tax is inflicted on the minority or disadvantaged class. When discrimination effect is studied within a single economy, endogenous political decisions is felt across all states and therefore emigration effect does not exist. However, in this circumstance, the effect of discrimination on the equilibrium character of the economy at low and upper segment of the distribution is noteworthy: if the economy is continuing at the low-level equilibrium with individuals concentrated mostly on the lower-tail of the distribution of log-wage, then discrimination will imply overall growth-retarding effects. However, if discrimination persists even when the economy is at the higher equilibrium growth path, feeling of social alienation among both young and old cohorts would lead to social tensions and uncertain growth. The latter would be more acute if discrimination is felt more strongly among young than old because of the growth and altruism character over generations.

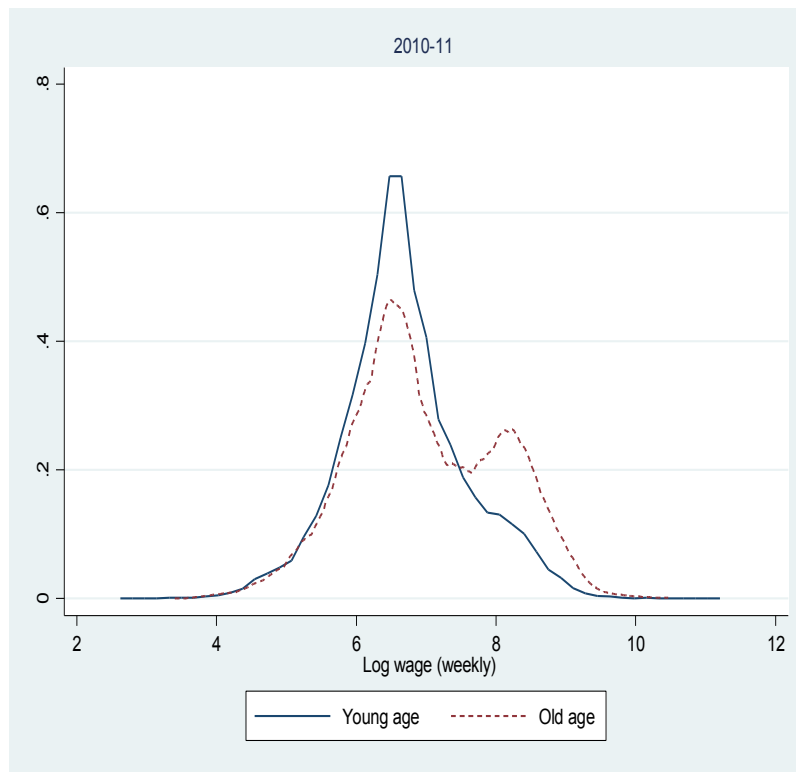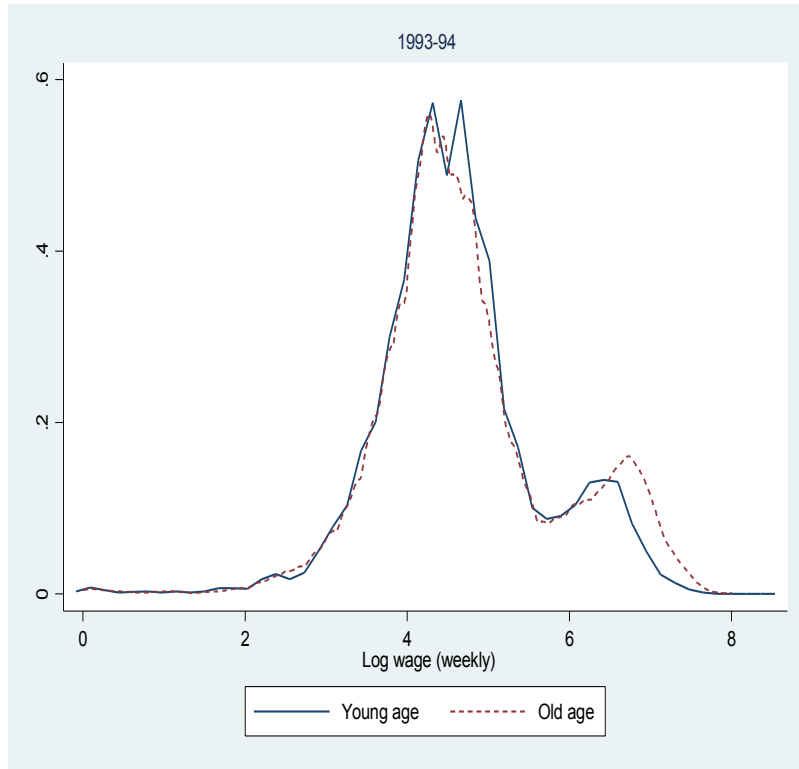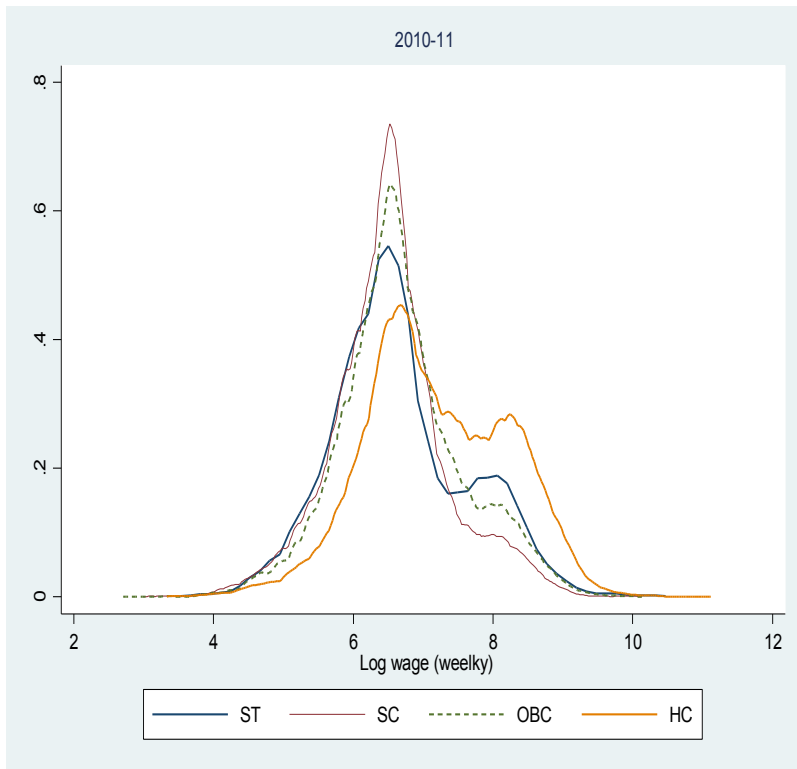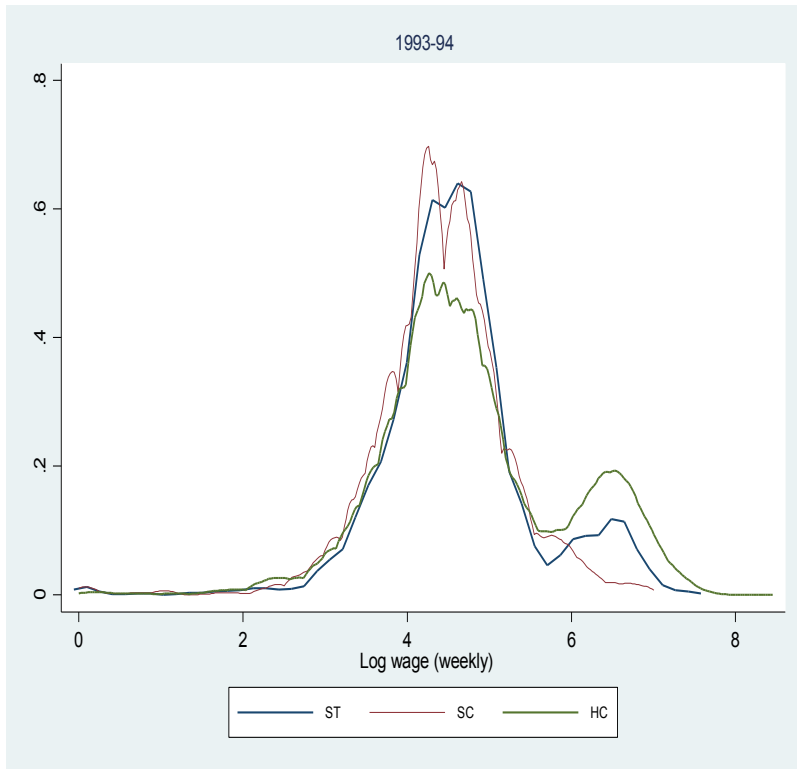Figure 1: Distribution of log wage between young and old cohorts

Figure 2: Distribution of log wage among social groups

3 The model

We consider an economy whose population is divided between upper caste (denoted by U) and lower caste (denoted by L). We hold that ethnic affiliation is an inherited trait that cannot be changed and is identifiable without any cost. Assume further that the population share of lower caste is λ, and that of upper caste is, $1 - \lambda$. The lower caste is defined by the very fact that it is discriminated against, even if it is demographically dominant. Furthermore, following Docquier and Rapoport (2003), we assume that each agent lives for two working periods and starts his life with an initial level of human capital that is identical for all agents. Even when discriminated in the social/economic growth ladder, initial human capital provides fundamental value for survivability. Convergence across social groups, $G \in (U, L)$, would occur when human capital attainment level rises and government's affirmative action policies tend to re-distribute wealth in equitable manner. For convenience, initial human capital for each agent is normalized to unity so that the period 1 initial human capital is:

$$h_{i,t}^1 = 1 \forall i. \tag{1}$$

In the first periods, each agent can allocate a time share of ζ for education. If the agent chooses not to invest in education. In case of the lower caste, this is possible due to the persisting disincentive in the policy making. Under the circumstance that no investment in education occurs, the agent's stock of human capital remains unchanged and he may not move in the social and economic ladder. Thus, for an *agent not investing in education*:

$$h_{i,t+1}^2 = 1. \tag{2}$$

Contrarily, if the agent decides to invest in education, the stock of human capital for the agent increase to the extent that depends on his ability to transform the time spent for acquiring education into valuable productive skills. We assume that individual's ability is distributed uniformly on the interval $[\bar{b}, \underline{b}]$. The ability is assumed to be distributed identically across groups/social strata. Given that the agent invests in education, then for an *investing agent i*, the individual stock of human capital at the beginning of the second period appears as:

$$h_{i,t+1}^2 = 1 + \zeta_i \tag{3}$$

In this economy the lower caste (L) is subject to a discriminative treatment. To formalize, assume that discrimination has a persistent effect on wage growth such that a shock it can be conceptualized in the form of a stochastic shock, ϵ that leaves a permanent effect on the development process. Since the effect is permanent on the transition path of the economic/social system, the representative agent, government can levy a lump-sum penalty T on each educated minority.

If the stochastic shock in the form of discrimination leaves a permanent effect on the historical trajectory of wage growth, one can then conceptualise the process as a unit root process, where for each agent i, $\epsilon_{it} = \rho_i \epsilon_{i,t-1} + v_t$, where ρ is the autoregressive coefficient that defines historical dependence. When $\rho = 1$ for each i, the shock leaves permanent effect on

log wage distribution over the life-cycle. For $\rho = 0$, shocks are temporary and leaves no long-run effect on log-wage distribution. Since, this is a one country welfare dynamics, there is no possibility emigration in view of the fact that discrimination effect is felt identically across the economy, hence by emigration to other states, individuals will not be gaining anything in terms of welfare. In the given economic system, it is possible to study the conditions under which investments are made for both upper and lower castes. Recalling that investment condition is contingent upon ability, b of the individual to transform ζ, so that for member L the condition for investment in education, b_i^L, is:

$$1 - \zeta + \frac{1 + b_i^L - T}{1 + r} > 1 + \frac{1}{1 + r} \tag{4}$$

and for b_i^U is:

$$1 - \zeta + \frac{1 + b_i^U + \theta}{1 + r} > 1 + \frac{1 + \theta}{1 + r} \tag{5}$$

In the above, r is the private rate of discount, and θ is the amount of transfer on human capital formation among individuals within the country. The elected government is exclusively concerned by the discounted sum of discriminative transfers to its ethnic constituency (that consists of current and future generations). At the steady state, maximizing the discounted sum involves maximizing the annual flow of discriminative revenues. Assuming that each member of upper caste receives an identical amount of transfer, θ, then,

$$\theta = \frac{\lambda}{1 - \lambda} T \int_{b_c^L}^{\bar{b}} U(b) db \tag{6}$$

Here c is the critical level and $U(b)$ is the utility with ability, b as argument. After developing the integral in the above and maximizing the second order polynomial with respect to T, the optimal discrimination penalty as in Docquier and Rapoport (2003) is derived as:

$$\frac{\partial \theta}{\partial T} = \frac{\lambda}{(1 - \lambda)(\bar{b} - \underline{b})} [\bar{b} - \zeta(1 + r) - 2T] = 0 \tag{7}$$

This gives the optimal penalty from the upper caste, U's, perspective in the economy which is closed to emigration. We denote this by T_{cl}^* and is given by:

$$T_{cl}^* = \frac{\bar{b} - \zeta(1 + r)}{2} \tag{8}$$

If an agent's ability is higher than a critical value, then, for the upper caste, $b_i^L > b_c^L = \zeta(1 + r)$ and for lower caste: $b_i^L > b_c^L = \zeta(1 + r)T$. Substituting T_{cl}^* in case of lower caste agent, the ability of the critical lower caste agent is given by:

$$b_{cl}^L = \frac{\bar{b} + \zeta(1 + r)}{2} \tag{9}$$

which is superior to the critical ability within the higher caste group.

The information on critical ability and its corresponding parameters will be essential in

determining the speed of convergence of log-wage distribution between upper and lower castes. Denoting the log-wage by, w and Ω is the information set the individual in both U and L groups use, the following proposition holds:

Proposition 1 *Caste groups U and L converge between dates t and $t + T$, if log-wage disparity at t is expected to decrease in value. If $w_{U,t} > w_{L,t}$, $E(w_{U,t+T} - w_{L,t+T}|\Omega) < w_{U,t} - w_{L,t}$*

Sketch of proof

The information set, Ω, contains information on past values of w as well as the state of the economic and social system. In our case, this includes government policies related to discrimination. If no affirmative action policies were undertaken to ameliorate problem of discrimination, the endogenous nature of discrimination itself will give rise to divergence in w between L and U. Since the operator $E(.)$ also reflects variances between two groups, L and U, and between time, t and $t + T$, it is expected that variance of log-wage, $\sigma_t^2 > \sigma_T^2$, where $T > t$. This is called σ convergence which is stable only if Ω contains information set which does not permanently alter distribution of w over time. However, the presence of discrimination exerts permanent effects on w and one may expect $E(w_{U,t+T} - w_{L,t+T}|\Omega) > w_{U,t} - w_{L,t}$, i.e., social convergence does not occur. Social convergence may occur between L and U, if time devoted for investment in education, ζ, rises and the ability of the individual b_i to transform ζ also increases. Together they reduce the gap between upper and lower caste's log wage.

4 Methodology

In this section, we first present the baseline conceptual framework and then provide a description of the estimation strategy.

4.1 The baseline framework

To understand the wage gap between upper and lower castes, the basic method is to decompose observed wage differentials into those attributable to productivity or *observed characteristics* and those in the return to *specific attributes*, which are interpreted as discrimination (Oaxaca, 1973; Blinder, 1973). To illustrate our point, let individual i's log wage for upper caste be denoted, as before, by w_{hc}, and that of the lower caste by w_{lc}. We thus have two sets of regressions:

$$w_{hc} = \beta_{hc} X_{hc} + \epsilon_{hc} \tag{10}$$

and

$$w_{lc} = \beta_{lc} X_{lc} + \epsilon_{lc} \tag{11}$$

where $X_i, i \in (hc, lc)$ is a vector of individual, household and community characteristics that determines $i's$ potential wage rate, β_i is a vector of parameters to be estimated, and ϵ_i is i.i.d. error term. The difference between average (daily) wage rates between upper and lower castes can be represented as

$$\overline{w}_{hc} - \overline{w}_{lc} = \hat{\beta_{hc}}(\overline{X}_{hc} - \overline{X}_{lc}) + (\hat{\beta_{lc}} - \hat{\beta_{hc}})\overline{X}_{hc} \tag{12}$$

Under the assumption that without discrimination the current upper caste wage structure will be applied to upper and lower caste wage workers, the first term on the right hand side of the above equation corresponds to the caste wage differential arising from differences in characteristics whereas the second term denotes the discrimination component that arises from wage differentials due to different returns to these characteristics. The Oaxaca-Blinder (henceforth, OB) only only measure discrimination at mean and ignores the rest of the distribution. As a result, the researchers[5] have broadened their research by extending this methodology in other forms and have applied it to the study of racial or gender differential in the labour market.

However, this methodology suffers from an index problem. For example, we can use the low caste wage structure as the above to overcome this problem. Oaxaca and Ransom (1994) suggest the cross product matrices of the sample characteristics as weights for the estimated parameters $\hat{\beta_{hc}}$ and $\hat{\beta_{lc}}$ as follows:

$$\overline{w}_{hc} - \overline{w}_{lc} = \hat{\beta}^*(\overline{X}_{hc} - \overline{X}_{lc}) + (\hat{\beta}_{lc} - \hat{\beta}^*)\overline{X}_{hc} + \overline{X}_{lc}(\hat{\beta}^* - \hat{\beta}_{lc}) \tag{13}$$

where $\hat{\beta}^*$ is the non-discriminatory coefficient structure obtained from the pooled regression of hc and lc groups and given as $\hat{\beta}^* = \omega\hat{\beta}_{hc} + (1 - \omega)\hat{\beta}_{lc}$. Oaxaca and Ransom (1994) define the weighting matrix as $\omega = (X'X)^{-1}(X'_{hc}X_{hc})$, where X and X_{hc} are the matrices of observed productivity characteristics for the pooled sample and for the high caste group.

4.2 Estimation strategy

Whilst decomposition at the mean may be informative, it potentially suffers from a fundamental weakness if wage differential across the distribution of wage of these two groups is not constant. In order to understand the complete effect across the distribution, Koenker and Bassett (1978) proposed Quantile Regression (QR) approach. With this approach one can estimate the change in parameter distribution at specific quantiles so that the response variable produced by a one unit change in the predictor variable can be gauged at both higher and lower quantile of the distribution. The superiority of this approach in relation to mean decomposition can be gauged not by is both on statistical properties as well as intuitively. If the response of wage distribution to certain endogenous shocks (in our case caste discrimination) is true for certain quantile, say at 10% and if it remains consistent throughout the entire range of quantiles, one can say that parameters estimated represent true relationship. In contrast to average method, which is based on only one point of the distribution, one cannot justify with good economic theoretic logic why and if certain changes occur with random selection of samples of a population that represent small or big numbers, if the parameter would represent true population mean and variance. Quantile regression approach solves this problem to a significant extent. The model can be specified as:

$$Q_\theta(w_i|x_i) = x_i\beta_\theta \tag{14}$$

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[5]Juhn, Murphy, and Pierce (1993), Fortin and Lemieux (1998) and Donald, Green, and Paarsch (2000) decompose any changes in distributional statistics beyond the mean.

where $Q_w(w_i|x_i)$ for $\theta \in (0,1)$ denote the θth quantile of the distribution of the log wage given the vector of x.

Koenker and Bassett (1978), use the quantile regression estimator of β_θ of equation 14 minimize the as:

$$\beta_\theta = \text{argmin}\left[\sum_{i:w \geq X,\beta} \theta |w_i - x_i\beta| + \sum_{i:w < X,\beta}(1 - \theta)|w_i - x_i\beta|\right] \quad (15)$$

To decompose the wage differential by caste, it is possible to use marginal wage distributions consistent with a conditional distribution estimated by quantile regression as well as with any hypothesized distribution of the covariates. This decomposition which is quite distinct from OB (1973), was proposed by Machado and Mata (MM, 2005). Essentially, one performs a counter-factual exercise. Using the MM (2005) procedure one can identify the sources of the increased wage inequality across different castes (in our case). On the whole, the first idea underlying MM technique is that the conditional quantiles of w can be estimated by quantile regression. If Equation 13 is correctly specified, the conditional quantile process - that is, $Q_\theta(w|x)$ as a function of $\theta \in (0,1)$ - provides a full characterization for the conditional distribution of wages given x. In more general cases, the conditional quantile model may provide a reasonable approximation to the true conditional quantile.

Assume that $w(t), x(t)$, for $t = 1993, 2011$ are log wages and k covariates in year t. In addition, letting $g(x;t)$ as the joint density of the covariates in year t, we are interested in generating sample from the wage density that would prevail for the year t if the conditional model in (13) were true and the covariates were distributed as $g(x;t)$. To get this, MM (2005) proposed that for any distribution:

Step 1: Generate a random drawn sample size m from a uniform distribution U [0,1] $u_1....,u_m$ for each period.

Step 2: Using the high caste and low caste data from each period, we store the regression coefficient for high caste and low caste individuals in sample as $\hat{\beta}_{hc}(\theta)$ and $\hat{\beta}_{lc}(\theta)$, where (θ) estimates from *1...99* quantile in each group for each period.

Step 3: For each quantile, characteristic of a randomly drawn sample of $m=1...\infty$ [in our case, we use 300 repetitions] are used to predict log wage value by using the estimated coefficient vectors of $\hat{\beta}_{hc}(\theta)$ and $\hat{\beta}_{lc}(\theta)$. This process generates sets of predicted log values for whole distribution and enables us to calculate the log wage for both high caste and low caste individuals in each period. The vectors of characteristics for high caste individuals $\bar{X}_{hc}$ and low caste individuals $\bar{X}_{lc}$ are then used to predict the log wage differential $\bar{Y}_{hc} - \bar{Y}_{lc}$. These predicated wage are equivalent to a random sample of size m drawn for marginal wage distribution for non-poor (Y_{hc}), and poor (Y_{lc}).

Step 4: The difference between the quantiles of the simulated distributions can be used to quantify wage difference across the distribution. Using the above mentioned procedure, we can estimate the coefficient and the covariates effect as;

$$Q_\theta(\hat{Y}_{hc}|\hat{\beta}_{hc} - \hat{Y}_{lc}|\hat{\beta}_{lc}) = \underbrace{Q_\theta(\hat{Y}_{hc}|\hat{\beta}_{hc}) - Q_\theta(\hat{Y}_{hc}|\hat{\beta}_{lc})}_{coffeicient} + \underbrace{Q_\theta(\hat{Y}_{hc}|\hat{\beta}_{lc}) - Q_\theta(\hat{Y}_{lc}|\hat{\beta}_{lc})}_{characteristics} + resid \quad (16)$$

In the next section, we use these both decomposition methods in context to India and

explain the convoluted picture of caste discrimination from the beginning of transition period (1993-94) through 2010-11.

5   Empirical results

5.1   Data characteristics

Earlier research on discrimination employ a variety of data, using, for example per capita consumption expenditure (PCE) data. Kijima (2006b) and Azam (2009), the two most significant studies in discrimination analysis in the case of India use log of (PCE), probably guided by their objective of comparing welfare gains and differentials across gender and social strata. However, per capita consumption expenditure data has two important limitations which can be ameliorated by employment data. Firstly, both Kijima and Azam include the self employed people from agriculture and ignore the fact that the self-employed do not potentially discriminate against themselves. Secondly, discrimination analysis by using consumption-expenditure data normally measures how expenditure is distributed among two social groups/classes. However, there may also be inter group taste differences that affects consumption patterns. This ignores the monetary values attached to expenditure that an individual receives for other economic activities, which otherwise can represent welfare gains in quantifiable terms.

For our empirical analysis, we use 1993-94 and 2010-11 National Sample Survey (NSS) data on employment and unemployment. The survey on employment and unemployment is the prime source of statistical indicators. These surveys provides individual earnings and other demographic indicators such as education, age, sex as well as occupation and industry. In order to asses the effect of discrimination among all social groups, we restrict our sample to working population aged 18-65, who actively participates in the labor market and report their regular/salried earnings per week in their usual principal activity[6]. Hence, we exclude those individuals who are self employed. Table [1] presents the descriptive statistics for those individuals for the two periods. In the first period, we can only distinguish two low caste groups, the Scheduled Caste (SC) and Scheduled Tribe (ST) and compare them to the High Caste (HC). However the second period includes an additional group Other Backward Caste (OBC).

From Table [1], we observe that the weekly log wage has significantly increased over time in both rural and urban sectors. It is evident that the growth and unprecedented trade liberalization policies of 1990 in India has significantly affected the employment structure. As a result, it has given rise to perceptible wage inequality in both rural and urban sectors. In this context, previous studies also observe that in recent years the wage inequality in India has mostly increased among social groups in urban sectors (Kijima (2006 a & b), Madheswaran and Attewell (2007)). However, most of the Indian industries depend upon agricultural output, therefore, it is worthwhile to include the rural sectors while analyzing the effect of caste discrimination. Previous studies, thus, ignore this fact that the agricultural labourers[7] in rural sector also account a positive source during analysis of caste discrimination.

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[6]The principal activity is the activity in which a person is found during a reference period.
[7]mainly employed in other household firms and received income for their economic activity

Table 1: Mean of selected characteristics of regular/casual wage earner.

	1993-94			2010-11			
	ST	SC	HC	ST	SC	OBC	HC
Log wage (per week)	4.61	4.42	4.79	6.66	6.52	6.68	7.18
Age	33.84	35.75	35.96	36.56	36.20	36.77	37.12
Individual Status							
Regular salary earner	0.79	0.76	0.78	0.58	0.50	0.53	0.74
Casual/Other labour	0.21	0.24	0.22	0.42	0.50	0.47	0.26
Education							
Illiterate	0.78	0.85	0.57	0.28	0.31	0.22	0.15
Primary	0.09	0.10	0.12	0.33	0.33	0.31	0.25
Middle	0.03	0.03	0.05	0.15	0.17	0.18	0.15
Secondary	0.07	0.02	0.11	0.15	0.14	0.18	0.23
Graduate	0.04	0.01	0.15	0.08	0.05	0.11	0.22
Marital Status							
Single	0.23	0.22	0.31	0.53	0.53	0.52	0.51
Married	0.77	0.78	0.69	0.47	0.47	0.48	0.49
Religion							
Hindu	0.81	0.96	0.82	0.65	0.89	0.85	0.72
Muslim	0.02	0.00	0.09	0.03	0.01	0.11	0.21
Christian	0.18	0.02	0.05	0.25	0.02	0.03	0.04
Other religion	0.00	0.02	0.05	0.06	0.08	0.01	0.03
Occupations							
Managers	0.00	0.00	0.01	0.01	0.01	0.02	0.06
Professional	0.05	0.02	0.15	0.04	0.02	0.04	0.10
Technicians	0.00	0.00	0.00	0.07	0.03	0.05	0.08
Clerks	0.06	0.01	0.09	0.05	0.03	0.05	0.10
Sales and Services	0.05	0.10	0.09	0.08	0.06	0.09	0.12
Agriculture, Fishing etc	0.71	0.75	0.47	0.02	0.01	0.02	0.01
Tradeworkers	0.06	0.07	0.11	0.14	0.18	0.21	0.17
Technical Operators	0.01	0.01	0.01	0.06	0.06	0.09	0.10
Labourer	0.06	0.04	0.04	0.52	0.61	0.43	0.25
Industry							
Mining	0.02	0.02	0.03	0.03	0.02	0.02	0.02
agriculture	0.70	0.74	0.47	0.30	0.27	0.22	0.11
Manufacturing							
i) Food and Beverages	0.03	0.02	0.05	0.01	0.01	0.02	0.02
ii) Textiles	0.01	0.01	0.03	0.00	0.02	0.04	0.05
iii) Wood and Paper	0.00	0.01	0.01	0.01	0.01	0.03	0.03
iv) Chemical	0.01	0.02	0.03	0.03	0.06	0.06	0.09
Utility and Constructions	0.05	0.05	0.04	0.28	0.34	0.26	0.16
Wholesale and Trade	0.01	0.01	0.02	0.03	0.04	0.08	0.10
Finance and Banking	0.00	0.00	0.02	0.01	0.01	0.01	0.04
Transport	0.00	0.00	0.01	0.06	0.06	0.08	0.09
Public Administration	0.08	0.03	0.07	0.17	0.07	0.07	0.13
Other Services	0.09	0.10	0.22	0.07	0.07	0.10	0.16
N	4272	8182	18113	3204	6489	10178	8062

Author's calculation

5.2   Results

This section explains the dynamics of caste discrimination among social groups by employing MM (2005) method. We focus on the decomposition comparisons between the MM and OB with respect to caste discrimination and argue whether it has increased (decreased) in selective social groups. We emphasize that under the compliance of the government affirmative policies, the effect of caste discrimination should be lower over time.

Previous studies in this context only measure wage inequality or distributional effect across social groups. Kijima (2006), in his extensive study, finds that the overall growth effect of wage inequality in urban India during the 1980s and 1990s between SC/ST and Non SC/ST is mainly higher due to the income difference in the upper part of the distribution while the lower half of the distribution have stayed relatively constant. Similarly, Azam (2010) uses data from 1980s through 2004 and expands social groups into SC, ST and Muslims (religion) and analyze the overall wage inequality in urban sectors. He explains that the increasing wage effect is mainly due to the increasing effect of covariates (characteristics) over time. In another study Kijima (2006b) uses consumption-expenditure data for the rural sector during the 1980s and 1990s and explains the effect of consumption disparities between SC/ST and Non-SC/ST. Additionally, Azam (2009) uses data for 2004 and explains the distributional effect of consumption and social disparities between all social groups (SC, ST, OBC and High Caste).

In order to analyze the recent trend of caste discrimination in the Indian labour market, it is also important to analyze the historical trends. It is intriguing to see how caste discrimination has moved from the beginning of the transition period until now and among all social groups. Consequently, we include all social groups and examine the possible effect of caste discrimination for period 1993-94 through 2010-11, employing mean oriented OB decomposition as well the Quantile based approach proposed by MM decomposition method.

5.2.1   Persistence of Caste Discrimination among Social groups over time - Oaxaca and Blinder Decomposition

To examine the inherent dynamics of caste discrimination over time, we first performed OB (1973) decomposition between HC and SC, ST and OBC (when available) for 1993-94 and 2010-11. As may be noted, OB decomposition method only measures the aggregate differences in coefficient effect and characteristics effect in model across the distribution and ignores the other part of the distribution. Table (2, Panel-A) depicts the increasing effect of caste discrimination among all social groups male aged 18-65 at mean.

Our result indicates that the overall observed gap between High Caste (HC) and low caste (SC, ST and OBC) has approximately increased by two fold from the period 1993-94 to 2010-11. Comparing the discrimination effect between 1993 and 2011, we find that the percentage contributed by coefficient effect, the unexplained part, has significantly increased between HC vs SC and HC vs ST. However, this effect is more visible and acute between HC and ST. Our result, therefore, indicates that this increasing effect of caste discrimination is mostly due to the effect of covariates among all social groups. This means that the deprived groups are still disconnected from the various public systems such as entering in higher government institutions or education.

In addition to our hypothesis whether existing reservation policies have increased (decreased) the effect of caste discrimination over time, we have also a concern about any legislative programmes corresponding to SC/ST, which was designed to bail them out for the unequal treatment since independence. In the next section, we claim that the presence of caste discrimination among the young cohort compared to the old cohorts in all social groups has gone up over time.

5.2.2 Persistence of Caste Discrimination among Young vs Old Cohorts over time - Oaxaca and Blinder Decomposition

This section discusses the results of persistence of caste discrimination among young workers *vis a vis* old cohorts (see Table 2, Panel-B1 and Panel-B2). As may was noted before, the policy of 'reservation systems' was introduced in 1990s to improve the participation in the labor force for deprived and privileged classes by way of reserving seats in various public places viz; in opportunity in jobs, education, and other fields of life. However, these reservation policies are not directed to different age groups. It is, therefore, interesting to study the potential effect of discrimination among the young (18-40 years) and the old (41-65 years). First, we examine the effect of caste discrimination for young cohorts followed by old cohorts for period 1993-94 through 2010-11, and then analyze which social group has more effected during these periods.

Table (2), Panel-B1 and Panel-B2 presents these results. Interestingly, our results indicate that the effect of coefficients is higher among young cohort over time. From our results one may also perceive that the relevant policy for SC/ST, which was designed to improve social connectedness with privileged class, suggests that the government intervention programmes has been less effective in the last two decades. The overall observed gap has increased between HC and all social groups. Comparing the effect of discrimination between young and old cohorts for the same social group, our result indicates that the discrimination effect are fairly acute among young population over time.

Although, the OB model suggests that the effect of caste discrimination has increased from 1993-94 through 2010-11. The reliability of OB model has been questioned in various empirical studies. Arguing that the OB model is not appropriate to measure the persistent effect of caste discrimination across the entire distribution of wage. In the next section, therefore, we examine the effect of caste discrimination across the whole distribution by using a quantile based approach and a decomposition method proposed by Machado and Mata (2005).

Table 2: Oaxaca-Blinder decomposition for 1993-94 and 2010-11

	HC vs SC			HC vs ST			HC vs OBC		
	unexplained	explained	gap	unexplained	explained	gap	unexplained	explained	gap
Panel-A					All				
1993-94	-0.052	0.421	0.369	-0.028	0.204	0.176	-	-	-
	(0.0085)	(0.0087)	(0.0121)	(0.0099)	(0.0136)	(0.0162)			
	-14%	114%		-16%	116%				
2010-11	0.128	0.533	0.661	0.126	0.395	0.521	0.119	0.376	0.496
	(0.0096)	(0.0124)	(0.0153)	(0.0114)	(0.0174)	(0.0205)	(0.0092)	(0.0113)	(0.0143)
	19%	81%		24%	76%		24%	76%	
Panel-B1					Young				
1993-94	-0.054	0.388	0.334	-0.030	0.168	0.138	-	-	-
	(0.0100)	(0.0101)	(0.0141)	(0.0113)	(0.0154)	(0.0186)			
	-16%	116%		-22%	122%				
2010-11	0.116	0.439	0.555	0.127	0.338	0.465	0.119	0.279	0.398
	(0.0111)	(0.0139)	(0.0174)	(0.0137)	(0.0194)	(0.0231)	(0.0110)	(0.0127)	(0.0166)
	021%	79%		27%	73%		30%	70%	
Panel-B2					Old				
1993-94	-0.058	0.504	0.446	-0.012	0.270	0.258	-	-	-
	(0.0157)	(0.0169)	(0.0232)	(0.0203)	(0.0279)	(0.0328)			
	-13%	113%		-05%	105%				
2010-11	0.146	0.678	0.824	0.169	0.423	0.592	0.135	0.517	0.652
	(0.0174)	(0.0237)	(0.0286)	(0.0207)	(0.0327)	(0.0385)	(0.0161)	(0.0210)	(0.0258)
	18%	82%		29%	71%		21%	79%	

Note: (i) bootstrap standard errors are in parenthesis and proportion to observed gap are mentioned under standard errors. (ii) Calculations are not possible due to unavailability of OBC data.

5.2.3 Persistence of Caste Discrimination among Social groups over time - MM (2005) Decomposition

In Table (3), we show that the effect of caste discrimination among all social groups at selected quantiles. This procedure is similar to Azam's (2010) study. We have selected three quantiles for comparisons 10th, 50th and 90th quantiles. It appears that the effect of discrimination is more acute between 50th (the median) quantile and 10th quantile for each year in our selected sample period. This reflects that the undertaken legislative laws corresponding to SC/ST or OBC were not improving the social gap between privileged classes.

Our decomposition results provides strong indication on the rising effect of caste discrimination among all social groups from 10th quantile to 70th quantile in each period and among all social groups. Figure [3] and [4] presents the distributional impact of coefficient effect at all quantiles among all social groups for periods 1993-94 and 2010-11. For instance, it is observed that the discrimination effect for HC vs. SC is increasing along the quantiles (from 10th till 80th) and this is consistent over the years. The same is true for HC vs ST for the period 1993 and 2011. The result for HC vs OBC in 2010-11 is not directly comparable to the period 1993 due to unavailability of data. If one compares discrimination effect between high caste and low caste for both periods, we observe that the discrimination is more acute between 10th quantile and median quantile. For instance, in the period 1993, the effect of discrimination among HC vs ST was 73% in the 10th quantile compared to 8% in the 90th quantile.

However, the effect of caste discrimination in the same groups for the period 2010-11 compared to 1993-94 indicates that the discrimination has gone over 20 years, exception to this result is HC vs ST. Notably, it has mostly increased at the bottom of the distribution. These findings are consistent with Azam (2010) who also find that that the inequality between HC vs SC/ST has increased at the top of the distribution. While comparing the effect of discrimination between HC vs OBC, we find that this has remained same across the whole quantile of the distribution and indicates the comparative ineffectiveness of recent reservation policies for this group. On the average, we find that caste discrimination has been increasing since 1993-94 till 2010-11, the effect is decelerating although interesting it still remains positive and significant.

Table 3: Counterfactual decomposition at selected quantiles from 1993-94 through 2010-11

			HC vs SC				HC vs ST				HC vs OBC		
		gap	explained	unexplained	residual	gap	explained	unexplained	residual	gap	explained	unexplained	residual
1993-94	10th	0.028	0.113	-0.076	-0.009	-0.105	-0.031	-0.077	0.003	†	†	†	†
			(0.0258)	(0.0253)			(0.0287)	(0.0234)					
			402%	-270%	-32%		29%	73%	-03%				
	50th	0.247	0.245	-0.038	0.039	0.049	0.108	-0.056	-0.004	†	†	†	†
			(0.0188)	(0.0160)			(0.0178)	(0.0163)					
			99%	-15%	16%		22%	-14%	-08%				
	90th	1.204	1.285	-0.115	0.034	0.560	0.644	0.047	-0.131	†	†	†	†
			(0.0314)	(0.0252)			(0.0651)	(0.0888)					
			107%	-10%	03%		115%	08%	-23%				
2010-11	10th	0.470	0.250	0.169	0.051	0.470	0.261	0.162	0.047	0.288	0.179	0.126	-0.017
			(0.0299)	(0.0274)			(0.0314)	(0.0296)			(0.0301)	(0.0280)	
			53%	36%	11%		55%	35%	10%		62%	44%	-06%
	50th	0.511	0.434	0.190	-0.113	0.511	0.408	0.163	-0.060	0.511	0.303	0.203	0.005
			(0.0231)	(0.0174)			(0.0236)	(0.0189)			(0.0239)	(0.0195)	
			85%	37%	-22%		80%	32%	-12%		59%	40%	01%
	90th	0.916	0.752	0.242	-0.078	0.444	0.482	0.026	-0.065	0.511	0.452	0.220	-0.161
			(0.0318)	(0.0373)			(0.0325)	(0.0324)			(0.0342)	(0.0398)	
			82%	26%	-08%		109%	06%	-15%		89%	43%	-32%

Note: (i) bootstrap standard errors are in parenthesis and proportion to observed gap are mentioned under standard errors. (ii) Calculations are not possible due to unavailability of OBC data.

5.2.4 Persistence of Caste Discrimination among Young vs Old Cohorts over time - MM Model

Interesting results emerge from discrimination analysis when one studies the young vs. old demographic dynamics. In Tables (4 and 5) we present discrimination effect for young vs. old across four social groups. We find that the our results follow similar trend as presented in OB decomposition. In addition, it also evinces that the young cohorts at the bottom of the distribution are more discriminated compared to the old cohorts in the same group. This has remained consistent across four social groups. The results are consistent at higher quantiles across social stratification. For instance, for young cohort at 90th quantile, the discrimination effect is -9 percent for HC vs. SC compared at 10th quantile, where it shows -294 percent in 1993. For the same social group, it is 28 percent at 90th quantile and 48 percent at 10th quantile in 2011. Similarly for old cohort, for HC vs. SC, the discrimination effect is -109 percent at 10th quantile and -11 percent at 90th quantile% in 1993, whereas it has increased to 33 percent at 10 quantile and 21 percent at 90th quantile in 2011. The overall implication is that the DE effect has increased significantly from 1993 to 2011 and discrimination is still remains positive and significant.

Table 4: Counterfactual decomposition at selected quantiles from 1993-94 through 2010-11 among young

		HC vs SC				HC vs ST				HC vs OBC			
		gap	explained	unexplained	residual	gap	explained	unexplained	residual	gap	explained	unexplained	residual
1993-94	10th	0.028	0.117	-0.083	-0.006	-0.105	-0.031	-0.071	-0.004	†	†	†	†
			(0.0303)	(0.0271)			(0.0292)	(0.0238)					
			416%	-294%	-22%		29%	67%	04%				
	50th	0.194	0.239	-0.049	0.004	0.020	0.092	-0.056	-0.016	†	†	†	†
			(0.0182)	(0.0169)			(0.0167)	(0.0158)					
			123%	-25%	02%		463%	-284%	-79%				
	90th	1.079	1.151	-0.097	0.025	0.405	0.580	-0.028	-0.146	†	†	†	†
			(0.0330)	(0.0267)			(0.0618)	(0.0946)					
			107%	-09%	02%		143%	-07%	-36%				
2010-11	10th	0.365	0.180	0.176	0.008	0.365	0.255	0.149	-0.039	0.251	0.101	0.167	-0.016
			(0.0290)	(0.0308)			(0.0300)	(0.0305)			(0.0297)	(0.0295)	
			50%	48%	02%		70%	41%	-11%		40%	66%	-06%
	50th	0.357	0.291	0.171	-0.105	0.357	0.333	0.125	-0.102	0.357	0.165	0.191	0.001
			(0.0183)	(0.0152)			(0.0183)	(0.0166)			(0.0204)	(0.0173)	
			81%	48%	-29%		93%	35%	-29%		45%	54%	01%
	90th	0.981	0.715	0.277	-0.011	0.470	0.490	0.033	-0.053	0.644	0.416	0.229	0.000
			(0.0301)	(0.0282)			(0.0384)	(0.0389)			(0.0382)	(0.0376)	
			73%	28%	-01%		104%	07%	-11%		63%	35%	01%

Note: (i) bootstrap standard errors are in parenthesis and proportion to observed gap are mentioned under standard errors. (ii) †-calculations are not possible due to unavailability of OBC data.

Table 5: Counterfactual decomposition at selected quantiles from 1993-94 through 2010-11 among old

		gap	HC vs SC explained	unexplained	residual	gap	HC vs ST explained	unexplained	residual	gap	HC vs OBC explained	unexplained	residual
1993-94	10th	0.057	0.122	-0.062	-0.003	-0.105	-0.038	-0.119	0.052	†	†	†	†
			(0.0332)	(0.0295)			(0.0322)	(0.0294)					
			213%	-109%	-05%		36%	113%	-49%				
	50th	0.272	0.273	-0.042	0.041	0.154	0.150	-0.036	0.040	†	†	†	†
			(0.0129)	(0.0165)			(0.0176)	(0.0197)					
			101%	-15%	14%		97%	-23%	26%				
	90th	1.404	1.543	-0.160	0.022	0.781	0.874	0.077	-0.170	†	†	†	†
			(0.0282)	(0.0278)			(0.0619)	(0.0828)					
			109%	-11%	02%		112%	10%	-22%				
2010-11	10th	0.606	0.377	0.201	0.029	0.546	0.250	0.257	0.038	0.383	0.342	0.070	-0.028
			(0.0343)	(0.0336)			(0.0350)	(0.0341)			(0.0340)	(0.0310)	
			62%	33%	05%		46%	47%	07%		89%	18%	-07%
	50th	1.050	0.739	0.231	0.080	0.955	0.572	0.243	0.139	0.981	0.604	0.232	0.146
			(0.0289)	(0.0197)			(0.0317)	(0.0275)			(0.0294)	(0.0252)	
			70%	22%	08%		60%	25%	15%		62%	24%	15%
	90th	0.716	0.662	0.151	-0.096	0.486	0.478	-0.015	0.023	0.530	0.466	0.139	-0.075
			(0.0294)	(0.0391)			(0.0275)	(0.0308)			(0.0291)	(0.0344)	
			92%	21%	-13%		98%	-03%	05%		88%	26%	-14%

Note: (i) bootstrap standard errors are in parenthesis and proportion to observed gap are mentioned under standard errors. (ii) † -calculations are not possible due to unavailability of OBC data.

6   Conclusions

Faster growth without social stability is not sustainable. Although India's recent growth success story has encouraged academics and policy makers alike to predict faster speed of convergence of per capita income to developed countries within a time less than about three decades, the observed and rising social and economic differential in development within this success story has been a constant worry. Under this backdrop, this paper has investigated how discrimination across demographic cohorts and socially segmented groups are responding to the growth spurts. Rising inequality between young and old cohorts and between social groups means that anger and agonies among the individuals might trigger social tension and uncertain economic growth. This is especially important if young cohorts feel the heat of rising social segmentation in terms of social and economic opportunities.

Among other important results, this paper has highlighted the role and effect of caste discrimination between demographics, viz., young and old. Both the population cohorts have their own social affiliation which has been endogenous determined within Indian context, viz., whether they belong to high or low caste. Had the effect of caste discrimination been felt equally across demographic distribution, the situation would have been different. In contrast, we have demonstrated and argued in the paper that impact of caste discrimination has been felt acutely among young then old age cohorts. This finding provides a possible direction to where our best prediction of sustainable economic growth for India could be. The restlessness among young population with heightened feeling of uncertainty and insecurity has both social and economic effects. The latter is perceived via declining the pace of innovation, corruption, and unstable labor force participation.

With respect to time, this paper finds that there is strong presence of discriminatory practice in the India from 1993-94 through 2010-11. Our results raise an important question: whether the increasing effect of caste discrimination among all social groups is due to less effectiveness of the government affirmative polices *per se* or the notable division of labour between high caste and lower caste since independence. But more importantly, our results indicate that the prevalence of caste discrimination between all social groups has remained constant compared to the transition phase. While analyzing the effect of discrimination between young and old cohorts, we find that the existence of social practises, historical juncture and socio-economics realities reinforced or reshaped the nexus of caste-class relations in India. The distributional effect of age and nexus of caste discrimination, thus, draws an attention for more qualitative studies. The effect of discrimination between young and old age reinforces policy makers to review the existing affirmative policies for lower social groups.

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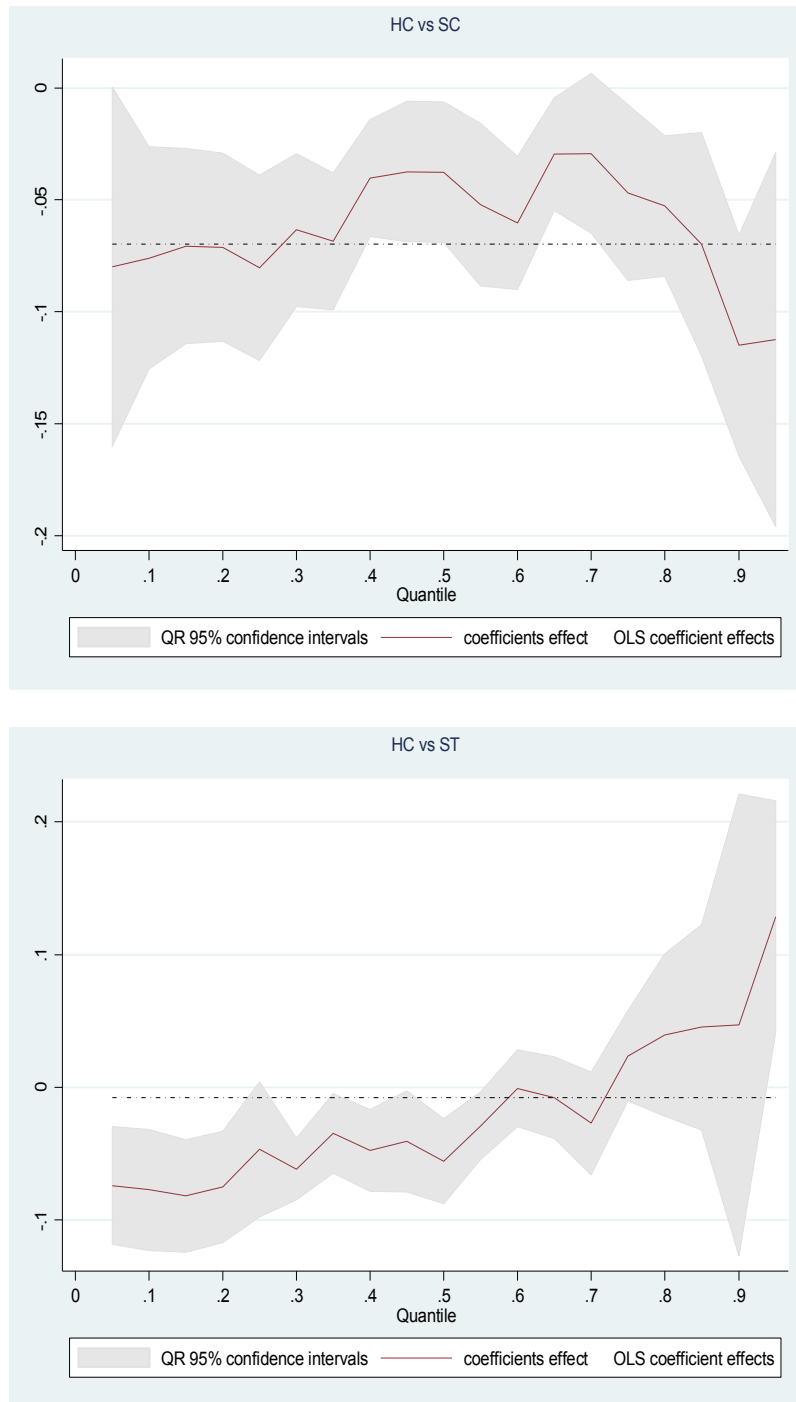Figure 3: Effect of discrimination between HC and SC/ST (1993-94)

Figure 4: Effect of discrimination between HC and SC, ST, OBC (2010-11)