Wage differential between caste groups: Are younger and older cohorts different?

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Abstract

Recent literature has provided evidence that a gender and caste-based wage discrimination can exert negative economic impact on a country's development process. Given the enormous contribution of a young population to India's workforce, we examine whether there is any caste-based discrimination considering demographic distinction. Using employment and unemployment National Sample Survey data from India for two rounds during the last two decades (1993 and 2010), we find rising wage gap between privileged and marginalized groups within younger and older cohorts across the distribution and over time. Furthermore, we decompose the wage gap using the counterfactual decomposition into endowment effect (explained by differences in characteristics) and a discrimination effect (attributable to unequal returns to covariates). We find that the discrimination effect against marginalized castes (in both cohorts) decreases, implying an increasing endowment effect across the distribution of the wage gap. This discrimination effect is more pronounced among younger compared to older cohorts.

Key Words: Caste discrimination; Demographic dividend; Social position, Young-old discrimination; Quantile Regression; India.

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'*Indian society has an enduring exclusion that is based, among other things, on caste identities. This bias can impede shared prosperity, serving as a basis for discrimination in many spheres, including in employment and other markets, as well as in public services"*, Jim Yong Kim, president of the World Bank, 11th Jan., 2015 (Times of India).

1 Introduction

Discrimination[1] - practised often endogenously in both developing and developed societies, is not known to beget any virtue either in the form of economic or social benefits. The economic study of discrimination has been motivated, first, by the growth of labour 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 King, 1998). Both factors have 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). Undoubtedly, discrimination, prevalent in the form of either caste, gender, or skin colour can lead to inefficient sub-optimal outcomes (Esteve-Volart, 2009); increases social inequality which in effect can also lead to social alienation in the society (Gupta et al., 2018).

In the context of a developing country such as India, its occurrence is mostly observed on the basis of caste[2]. It is found, using both field and survey data, that it is not only affecting current development path but it also negatively impacts on the labour market (Kijima 2006a, Thorat and Attewell 2007, and Azam 2012). These latter findings suggest that caste system in India has a strong impediment in the labour market and thus can create distortions in incentives for next generation. More importantly, the continuous practiceing of discrimination can offset the gains from the demographic dividend, i.e., the contribution of a specific population cohort, such as young population over old. In this spirit, Jaimovich and Siu (2009), for example, using the U.S data have established that different age composition of the labour force has a large and statistically significant volatility effect on the business cycle.

Taken together, this research focuses on caste-based discrimination on young and old cohorts. A primary motivation of this choice is based on a number of important research in demography (Bloom et al., 2003; Lindh and Malmberg, 2007; Crespo-Cuaresma and Mishra, 2011, Parhi et al. 2013) which has established that a (developing) country seeking to maintain a high growth momentum needs to endogenise fully the positive externalities of demographic

[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 India, caste is broadly classified into four groups, namely Schedule Caste (SC), Scheduled Tribe (ST), Other Backward Classes (OBC) and High Caste (HC). The first three groups are classified as underprivileged/marginalized groups or low caste whereas the last group is classified as the privileged group or high caste. Historically, the Scheduled Caste are the untouchable group and have socially been placed outside of the society for centuries. The second group, Schedule Tribe, are a group whose distinction is made on the basis of language and cultural activities from rest of the Indian society. These two groups were often not allowed to participate in most of the economic decision-making process in India. The Other Backward Classes were classified as those who were not the part of the former two groups and neither were part of the upper caste. This group is also deprived, both socially and economically. These four groups represent approximately 20%, 8%, 42% and 30% of the population of India respectively.

dividend. Aiyar and Mody (2013) offered support to this broad proposition and demonstrated that a substantial portion of the growth experienced by India since the 1980s is attributable to the countrys changing age composition. In view of these findings, when a country like India experiences rare dividend from age-composition, a continuous discriminatory practice among them is likely to create social tensions and contribute to social conflict in the society.

This paper aims to contribute to the existing literature in the three distinct ways. First, we investigate whether the continuous practice of caste based discrimination in the Indian labour market, after the thirty years of the reform, has ameliorated the problem of discrimination in the case of different demographic groups such as young and old cohorts. To the best of the authors knowledge no such study exists which describes the heated debate of caste discrimination for these two demographic units.

Second, the existing literature primarily concentrates on the average, with the exception of Azam (2012) who had studied wage inequality for the entire distribution using the consumption expenditure data. However, the shortcoming of this recent literature is that it has only examined for urban area and neglected rural in the analysis. We fill this gap by including the rural sample and examine caste based discrimination for the most recent period i.e., 2010-11. To better understand the discriminatory practice we look at the entire wage distribution between two groups, using the counterfactual decomposition method proposed by Machado and Mata (2005) underpinning of quantile regression framework by asking a question what would be happen if lower caste is the given the same wage structure as the high caste.

Third, as a robustness exercise, we use the matching procedure and re-estimate the result obtained from the counterfactual approach and correct for potential specification bias in unmatched samples with individuals of different characteristics. In this case, we use the decomposition only on the matched sample, enabling us to compare the matched results against the unmatched one using the same counterfactual decomposition method. We use the employment and unemployment data from National Sample Survey (NSS) for two different survey periods. The first sample period is 1993-94, which provides information on to the presence of discrimination before or at the beginning of reform period. The second sample period is 2010-11, which is used to examine the effect of discriminatory practices after the thirty years of the reform.

Our findings can be summarised as follows: firstly, the observed differences between deprived groups and the privileged group have increased across the entire distribution from 1993-94 to 2010-11, and more significantly at the higher quantiles of the wage distribution. This result is consistent with earlier research such as Azam (2012). The observed differences between 1993-94 and 2010-11 have been found to remain constant across social groups. In addition and in the light of adopted reservation policy, which was placed after independence to protect the marginalized groups from discrimination practice, the results suggest that the effect of reservation systems has not had its expected impact on reducing wage discrimination against low castes, and in particular against low caste young cohorts.

The rest of this paper follow as. In Section 2, we present related literature to our research work and why this study is relevant to India. Section 3 describes our methodological approaches. In Section 4, we describe the data and presents the stylized observation. Section 5 provides the empirical findings and discuses the robustness of the result. Finally, Section 6 presents the discussion of the main results and conclusions.

2 Related literature and context

In this section, we consider only those literature that is more relevant to Indian labour market and based on caste discrimination. Following this we also explain why the study of wage-gap differential among young-old based on social identities (such as caste) is so important in the Indian context.

2.1 Literature survey

The literature on discrimination has a deep facilitator in labour economics. Country specific empirical studies have added various dimensions by identifying distinct social, economic and demographic characteristics. From policy point of view, the most important reason for persistence of discrimination is attributed to policy ineffectiveness. For instance, in the case of India, the effort made by federal and state government to minimise the impact of caste based discrimination has appeared to be insufficient because in recent times the problem of discrimination has moved from being a thoughtful social issue to becoming a nagging human rights issue (Borooah et al. 2007). Research has shown that its occurrence is more visible in rural compared to urban areas.

Caste discrimination in India is not new. This phenomenon has been seriously debated in many international forms (European Commission, 2009). It is a cultural and social phenomenon that has been a part of the traditions of the Indian society for thousands of years, dividing people into castes in a hierarchical order based on their descent. Indeed, caste-based discrimination can influence all spheres of life and can violate many basic human rights including civil, political, social, economic and cultural rights. It is also a major obstacle to achieving development goals because affected populations are often excluded from the development process. Discrimination is practiced in many areas, such as housing, marriage, and general social interaction that are reinforced through the practice and threat of social exclusion, economic boycotts, and even physical violence.

Being based on deeply ingrained social structures, caste based discrimination is currently part of day-to-day life in India. The effort made in recent years to reduce the impact of caste-based discrimination by federal and state governments, such as legislation changes, seems to have been proven insufficient and has moved from social issue to becoming a human rights issue. Research has shown that occurrence of discriminatory practices, however, are more visible in rural compared to urban areas. For instance, Kijima (2006a) using NSS data for the periods 1983-1999, has reported that the disparities of living standards among SC/ST (marginalized groups) compared to non-SC/ST (privileged group) still remain very high.

Affirmative policies[3] have been placed immediately after independence in India to increase access to education and employment for marginalized groups (SC/ST) and more recently these affirmative policies have extended for another deprived group OBC. However, research on caste

[3] To reduce the social disparity and to improve the social and economic standards of the first three groups- SCs, STs and OBCs, the Indian governments have created a specialized system called reservation policy or reservation system. The role of reservation system was created to empower the social position of members of these groups by providing some reserved seats in the administration, higher education, and elected bodies for their upliftment. Under the provision of the reservation system, each state in India provides equality of opportunities in matters of employment and education.

discrimination has observed a failure of affirmative policies on many grounds. For instance, Bhaumik and Chakrabarty (2006), using NSS employment-unemployment data for the urban sector for the years 1987 and 1999, observed that privileged group (HC) has enjoyed most of the development compared to their counterpart (SC/ST) between 987 and 1999. Using the OB decomposition method, they also observed that differences in earning between these two groups were mainly due to differences in returns to education characteristics . In other words, they identified that marginalized groups possess low or medium educational attainment levels and return to education for these two groups is low, which in part, contribute towards the wage gap between these groups.

Serious concerns have begun to emerge regarding the effect of discrimination on the return to education and rising income inequality, especially after the beginning of the reform period. Research has identified that urban areas have experienced rising income inequality. For instance, Kijima (2006b), using four rounds of the NSS data conducted in 1983, 1987, 1993, and 1999 on employment and unemployment, has observed that both urban wage and wage inequality between the advantaged group and the deprived groups has widened. However his study does not look at the entire wage distribution. Azam (2012) uses data from the 1980s through to 2004 and expands social groups into SC, ST and Muslims (religion) and analyse the overall wage inequality in urban sectors. He argues that the increasing wage effect is mainly due to the increasing effect of covariates (characteristics) over time. In similar vein, Hnatkovskaet. et al (2012) have observed that the educational attainment levels, occupation choices, wages and consumption levels among marginalizedgroup have started converging compared to privilege group. However, the majority of the observed difference in wages between the two groups is attributed to the difference in covariate effects.

The existing literature have successfully that marginalized groups are rewarded less compared to the privileged group and they also posses inferior productivity augmenting characteristics. However, these research have important limitations; (i) the inclusion of self-employed in the analysis, (ii) restricted sample for either urban or rural area examined usually at the mean, such as OB, (iii) the application of quantile regression approach with counterfactual decomposition to untreated samples, (iv) and little insights on the persistence of discrimination in the treated samples. These limitations from the literature form the basis of investigation in the present work.

Following this literature survey on caste based discrimination related to India, we next explain why it is important from different demographic perspective such as young and old in our case.

2.2 Why young and old demographics

The practice of discrimination in India, as explained in the previous section, has a deep traditional/historical root. Although identifying people with respect to castes (in a hierarchical order) based on their descent has been a part of the cultural and social phenomenon of the Indian society for thousands of years, it has experienced a strong emergence in the post-colonial period. There are at least two leading reasons why the study of wage-gap differential among young-old and social identities (such as caste) is so important in the Indian context.

1. Social identities

   In an interesting research with respect to household consumption behaviour, Khamis et al. (2012) demonstrated that consumption pattern in India is significantly determined by caste and religious affiliations. As such, (prevalence of) discrimination not only affects individuals social identities but also may germinate social tensions (leading to social alienation) in the long-run. In a number of studies, both in sociology and economics, it has been repeatedly claimed that rising social tensions in India in recent years is an outcome of continuous discrimination in wage-reward (for instance, Deininger et al., 2012). In a related research, Hnatkovska et al. (2012) also documented the associations between discrimination, anger, and delinquency; investigating whether aggressive behaviors emerge over time as a consequence of perceived discrimination and anger. The authors 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 the 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 Indian labour market has also widened the income and employment gap between deprived groups and privileged groups over time (Madheswaran and Attewell, 2007).

2. Growth effect via demographic pressure

   Additionally, the prevalence of discrimination may exert significant negative effects on economic growth especially when the economy is in a transitional path. At a time when an economy is poised to experience high growth momentum, persistent of discrimination can translate into unstable and uncertain economic growth (see Deshpande, 2007 for analysis during the liberalization period). This is nowhere more true than in the case of India where demographers have been advising that the positive externalities from demographic dividend need to be tapped to translate the growth of young population into a sustainable long-run stable economic growth. Indeed, a recent UN report on Population Fund (UNPFA) shows that currently there are 356 million 10-24 year-olds in India, which is about 28% of Indias total population. While a monotonic growth of young population is necessary to continually push Indias growth trajectory continuous discrimination among young population can have the distortionary effect on economic growth via productivity dynamics where the latter is influenced by rising social tension.

3 Methodology: Counetrfactual decomposition with distributional heterogeneity

In this section, we summarize the main methodological tool leading to our empirical investigation. To understand the wage differential between privileged and marginalized groups, the basic method is to decompose the observed wage differentials into those attributable to productivity or observed characteristics and those in the return to specific attributes, which are interpreted as endowment and discrimination effect respectively (Oaxaca, 1973; Blinder, 1973 henceforth, OB)). To illustrate our point, let individual wage (log) for upper caste be w_{hc}, and that of the lower caste w_{lc}. We thus have wage equation for each group as follow:

$$w_{hc} = \beta_{hc} x_{hc} + \epsilon_{hc} \tag{1}$$

and

$$w_{lc} = \beta_{lc} x_{lc} + \epsilon_{lc} \tag{2}$$

where x is a vector of individual characteristics that determines potential wage in each group and ϵ is *iid* error term for each group. The vector of explanatory variables controls for human capital, demographic and various other observed individual characteristics. Due to the assumption of *iid* error, the covariates x in each group hc and lc can be consistently estimated using OLS. The average wage difference between hc and lc can be calculated as

$$\overline{w}_{hc} - \overline{w}_{lc} = \hat{\beta_{hc}}(\overline{x}_{hc} - \overline{x}_{lc}) + (\hat{\beta_{lc}} - \hat{\beta_{hc}})\overline{x}_{hc} \tag{3}$$

Under the assumption of no discrimination, if lower caste is the awarded the same wage as the high caste, then their average wage would be:

$$w^*_{lc} = \beta_{hc}\overline{x}_{lc}$$

Using the properties of counterfactual distribution, the overall wage gap between high caste and low caste (i.e., equation 2) can be written as

$$\begin{aligned} w_{hc} - w_{lc} &= \beta_{hc}\overline{x}_{hc} - w^*_{lc} + w^*_{lc} - \beta_{hc}\overline{x}_{lc} \\ &= \beta_{hc}\overline{x}_{hc} - \beta_{hc}\overline{x}_{lc} + \beta_{hc}\overline{x}_{lc} - \beta_{lc}\overline{x}_{lc} \\ &= \beta_{hc}(\overline{x}_{hc} - \overline{x}_{lc}) + (\beta_{hc} - \beta_{lc})\overline{x}_{lc} \end{aligned} \tag{4}$$

The first term on the right-hand side of the above equation corresponds to the caste wage differential arising from differences in characteristics normally representing the endowment effect. The second term denotes the discrimination component that arises from wage differentials due to different returns to these characteristics. Using equation 4, we observe the wage gap between high caste and low caste for each period and each cohort (i.e., young and old).

The OB approach measures only the discrimination at the mean and thus ignores the information content in the rest of the distribution. Machado and Mata (2005) extended OB decomposition to account for distributional heterogeneity and thus extended the estimation of discrimination effects at various quantiles of the wage distribution. Under this decomposition approach, conditional quantile regression for each group has been separately performed as:

$$Q_\theta(w|x) = x'\beta_\tau(\theta) \tag{5}$$

where τ= *hc, lc* and $\beta_\tau(\theta)$ is a vector of the quantile regression coefficient for social group τ. Under the probability integral transformation theorem, the estimated parameter can be used to simulate the conditional distribution of w given x for each social group. If θ is a uniform random variable on [0,1], then $F^{-1}(\theta)$ has the distribution F. Thus, if $\theta_1, \theta_2, \theta_3 \ldots \theta_m$, the corresponding m are drawn from a uniform (0,1) distribution, the corresponding m estimates of the conditional quantiles of wage distribution w at x_i, $\hat{w} = x_i'\beta(\theta)_{i=1}^m$, constitute a random sample from the (estimated) conditional distribution of wage at given x. To integrate x out and get a sample from the marginal distribution, instead of keeping x fixed at a given value, random sample can be drawn from appropriate distribution. Using the above counterfactual approach (equation 4) the MM decomposition can be written as follow (The detailed counterfactual steps are summarized in the Appendix):

$$\begin{aligned} f(w_{hc}) - f(w_{lc}) &= f^*(w_{hc}) - f^*(w_{lc}) + residual \\ &= \underbrace{[f^*(w_{hc}) + f^*(w_{hc}; x_{lc})]}_{covariateeffect} - \underbrace{[f^*(w_{hc}; x_{lc}) - f^*(w_{lc})]}_{coefficienteffect} + residual \end{aligned} \tag{6}$$

The counterfactual decomposition as described above explains how one can compute the wage gap between two groups across the distribution. However, one of the potential problem with the underlying model is that it does not account for misspecification due to differences in support of the empirical distribution of individual characteristics between two groups. In order to mitigate this problem, we use Ñopo (2008) proposed matching algorithm over the traditional propensity score matching. The reason for using the Ñopo's matching approach rather than propensity matching scores is that this approach allows for the counterfactual mean wage to be simulated for the common support, thus implying that no assumption on the out-of-support is required. Another reason for using this matching approach is that Ñopo matching provides matched sample with "similar" observable characteristics (or a linear combination of them) in a non-parametric setting, i.e., the conditional probability of receiving the treatment given the covariates, rather than directly for the covariates. Under this assumption, this reduces the problem of 'curse of dimensionality' that often arises when controlling for multidimensional covariates in propensity matching. More importantly, Ñopo matching in contrast to propensity score often approximates random matching but in the Ñopo matching this is not the case (see Frolich et al 2015, Fan et. al 2016, Bhaltra et. al 2016 for more discussion). The details steps for the Ñopo matching approach is presented in the Appendix.

We apply this matching approach for both young and old groups separately to remove the misspecification due to differences in support of the empirical distribution individual characteristics between two groups and re-run the counterfactual decomposition approach as a robustness test of our counterfactual results. The descriptive statistics of the covariate after matching is presented in Section 5.1.

4 Data characteristics

To analyse the discriminatory practices in Indian labour market we use employment unemployment data from the National Sample Survey (NSS) for the periods 1993-94 and 2010-11. The survey on employment and unemployment[4] is the prime source of statistical indicators in India. These surveys provide individual earnings and other demographic indicators such as education, age, sex as well as occupation and industry. Our variable of interest is the perceptible difference in variability in log wage[5] (in real terms) across social strata, educational status and over time. Educational status is proxied by educational attainment and represented by dummy variables no education, primary, secondary, and tertiary. Other control variables include age, sex, marital status and regions. In order to assess more in depth and 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 thus report their earnings per week from their usual principal activity[6].

In Table [1] we present the descriptive statistics for these two selected periods. In the period 1993, we can distinguish two low caste groups SC and ST and compared them to their counterpart HC. However the second period i.e., 2010-11 includes an additional marginalized group Other Backward Class [7] (OBC) in the analysis.

From the Table [1], we observe that the weekly log wage has significantly increased over time among all social groups. It seems that the growth and unprecedented trade liberalization policies of the 1990s in India have significantly affected the employment structure. As a result, it has given rise to perceptible wage inequality among the privileged group and socially deprived groups. 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)). The other obvious change has noted is the reduction in lower levels of educational attainment for all castes and increasing proportion in secondary and university level (graduate) education attainment. This is probably associated with return to education, in favour of high-level occupations observed in the case of managerial occupation.

In Figure 1, we also plot the wage distribution for different groups to show the variability in their wage profiles, whereas in Figure 2 we plot the wage distribution with respect to demographic distinction, viz., young and old in their respective groups and over time. We believe that the density plot can be interpreted as a wage trap since there is a high degree of overlap in the lower modes of the wage distribution. This suggests the presence of multiple equilibria where the economy chooses to remain in the lower-equilibria offering low-wage structure to low caste and to both cohorts. 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, the convergence of

[4]Previous research on discrimination employ a variety of data (Kijima (2006b) and Azam (2012)) using, for example, per capita consumption expenditure (PCE) probably guided by their objective examined welfare gains and differentials across gender and social strata. However, per capita, consumption expenditure data has an important limitation which can be ameliorated by using employment data. Consumption expenditure data normally measures how expenditure is distributed among two social groups/classes, however, there may also be inter-group taste differences that affect 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.

[5]In order to adjust the effect of inflation over time, we have used Maharastra poverty line as a benchmark to convert wage earning in real terms (see Hnatovska et al. (2012)

[6]The principal activity is the activity in which a person is found during a reference period.

[7]The Other Backwards Class were classified as those who were not the part of the former two groups and neither part of the other caste, but they were deprived both socially and economically. This group came into the system after the Mandal Commission submitted a report to the government in 1999. Prior to 1999, this group was merged with High Caste or Privilege group.

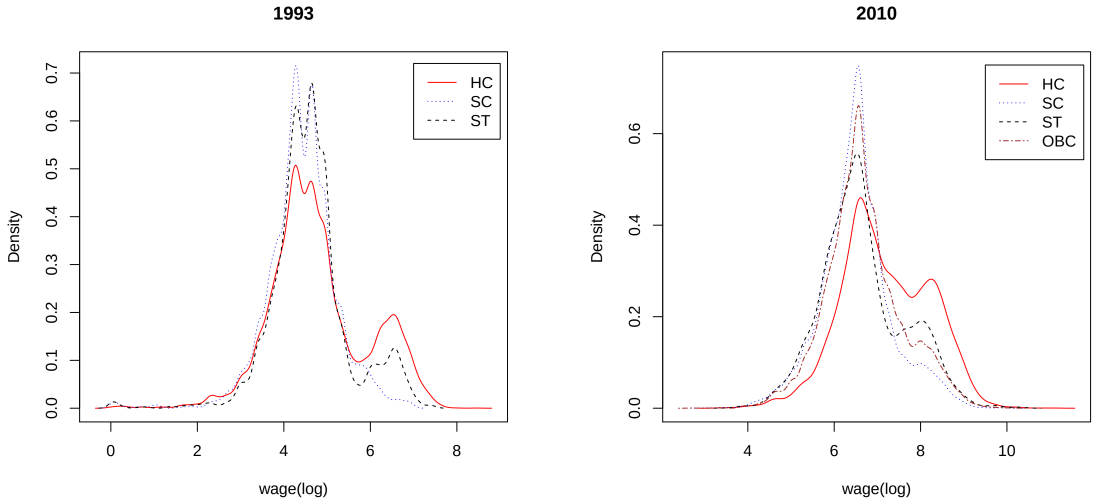
disadvantaged classes does not occur with advantaged or high-class group's wage distribution, the equilibrium at the high-mode will remain non-stationary.

Table 1: Data description of pervilaged and marginalized groups before matching

	1993-94			2010-11				1993-94		2010-11		
	ST	SC	HC	ST	SC	OBC	HC	HC vs ST	HC vs SC	HC vs ST	HC vs SC	HC vs OBC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log wage (per week)	4.61	4.42	4.79	6.66	6.52	6.68	7.18	23.14	45.14	17.49	21.35	21.16
	(0.890)	(0.914)	(0.923)	(0.785)	(0.806)	(0.900)	(0.958)					
Age	33.84	35.75	35.96	36.56	36.2	36.77	37.12	6.93	6.50	2.84	3.31	0.02
	(10.113)	(11.872)	(10.347)	(10.105)	(10.786)	(10.303)	(10.980)					
Education												
Illiterate	0.78	0.85	0.57	0.28	0.31	0.22	0.15	-23.26	-55.53	-9.84	-11.87	-6.26
	(0.476)	(0.507)	(0.503)	(0.441)	(0.431)	(0.395)	(0.364)					
Primary	0.09	0.10	0.12	0.33	0.33	0.31	0.25	2.22	5.72	-0.10	-2.45	-3.46
	(0.416)	(0.448)	(0.453)	(0.477)	(0.463)	(0.460)	(0.454)					
Middle	0.03	0.03	0.05	0.15	0.17	0.18	0.15	5.76	12.16	2.58	1.47	2.51
	(0.273)	(0.313)	(0.357)	(0.339)	(0.350)	(0.347)	(0.340)					
Secondary	0.07	0.02	0.11	0.15	0.14	0.18	0.23	15.12	35.87	6.50	9.15	5.63
	(0.288)	(0.273)	(0.395)	(0.330)	(0.351)	(0.358)	(0.425)					
Graduate	0.04	0.01	0.15	0.08	0.05	0.11	0.22	16.55	35.52	3.09	10.24	9.78
	(0.181)	(0.156)	(0.312)	(0.195)	(0.198)	(0.286)	(0.308)					
Marital status												
Single	0.23	0.22	0.31	0.53	0.53	0.52	0.51	-5.06	-5.26	0.11	-2.16	-0.09
	(0.393)	(0.397)	(0.378)	(0.495)	(0.508)	(0.509)	(0.520)					
Religion												
Hindu	0.81	0.96	0.82	0.65	0.89	0.85	0.72	5.17	12.89	-2.76	-56.88	-11.74
	(0.243)	(0.214)	(0.160)	(0.168)	(0.164)	(0.318)	(0.256)					
Muslim	0.02	0.00	0.09	0.03	0.01	0.11	0.21	-0.93	8.46	2.90	7.10	10.72
	(0.191)	(0.069)	(0.100)	(0.121)	(0.080)	(0.300)	(0.193)					
Christian	0.18	0.02	0.05	0.25	0.02	0.03	0.04	-12.30	0.29	-0.56	1.79	0.82
	(0.160)	(0.098)	(0.099)	(0.087)	(0.085)	(0.115)	(0.106)					
Other religion	0.00	0.02	0.05	0.06	0.08	0.01	0.03	0.29	0.23	-0.08	0.10	2.79
Occupations												
Managers	0.00	0.00	0.01	0.01	0.01	0.02	0.06	-3.11	-6.23	1.00	2.90	4.15
	(0.175)	(0.198)	(0.193)	(0.072)	(0.065)	(0.110)	(0.097)					
Professional	0.05	0.02	0.15	0.04	0.02	0.04	0.10	-0.81	11.83	1.58	8.54	7.20
	(0.264)	(0.250)	(0.254)	(0.093)	(0.115)	(0.177)	(0.198)					
Technicians	0.00	0.00	0.00	0.07	0.03	0.05	0.08	2.02	9.18	1.83	7.86	5.36
	(0.214)	(0.234)	(0.267)	(0.118)	(0.116)	(0.161)	(0.186)					
Clerks	0.06	0.01	0.09	0.05	0.03	0.05	0.10	-2.87	-2.16	2.41	7.49	9.09
	(0.071)	(0.078)	(0.069)	(0.131)	(0.150)	(0.151)	(0.235)					
Sales and Services	0.05	0.10	0.09	0.08	0.06	0.09	0.12	-9.73	-9.84	2.22	8.16	8.51
	(0.296)	(0.282)	(0.264)	(0.199)	(0.190)	(0.232)	(0.252)					
Agriculture,	0.71	0.75	0.49	0.02	0.01	0.02	0.01	-12.02	-44.79	-0.08	0.89	0.83
Fishing etc	(0.513)	(0.523)	(0.494)	(0.027)	(0.044)	(0.027)	(0.041)					
Labourer	0.06	0.04	0.04	0.52	0.61	0.43	0.25	17.84	44.77	-4.78	-11.15	-11.70
	(0.392)	(0.408)	(0.495)	(0.288)	(0.271)	(0.396)	(0.377)					
N	9831	21782	68512	3381	7123	10792	8673					

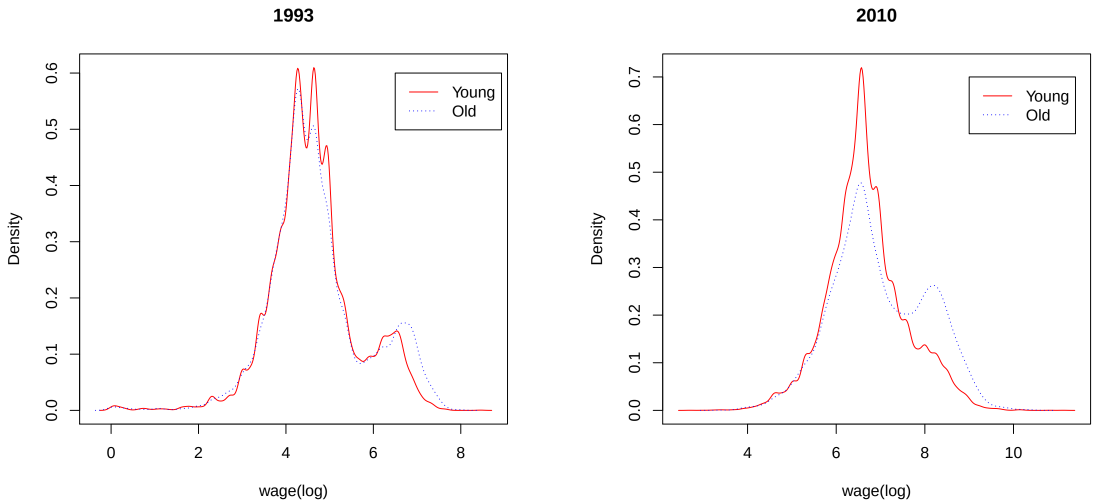
Author's calculation. Standard deviations are reported in bracket. Mean test between groups are reported in cols. 8-12

Figure 1: Wage distribution among all social groups



The visual inspection reveals the following: the wage distribution depicts higher variability at the tail of the distribution. It does not confirm that wage distribution in one group compares to another group in terms of some measure of location intended to reflect the wage gap. To confirm this, we also perform the significant test across the distribution, as proposed by Wilcox and Hurn (2012), between high castes (HC) and low castes (SC, ST and OBC). We found a significant[8] wage differential across the distribution between groups and over time.

Figure 2: Wage distribution among Young and Old cohorts



[8]The result for theses test is available on the request from the corresponding author.

5 Empirical results

In this section, we analyse the trend of caste discrimination across the wage distribution and show why mean-based approach and unmatched sample are not the best to understand differences between two groups. From Indian labour perspective, we emphasise that under the compliance of the government affirmative policies, the effect of caste discrimination, if it exists, should fall over time. Specifically, we are most interested in analysing how caste discrimination has moved from the beginning of the reform period and has shaped the discriminatory practice until now. We further extend this analysis for young and old cohorts separately and look at the discriminatory effect between privileged and marginalized groups. For robustness, we use matching approach and re-run the counterfactual decomposition approach.

In order to examine our contention and as a starting point, we first estimate the presence of discrimination using OB method as a baseline model to show the average change in discrimination between groups and among young and old cohorts over time.

5.0.1 Caste based discrimination over time - OB Decomposition

Table (2) depicts the results obtained from OB decomposition method among all social groups male aged 18-65 and between young and old cohorts.

We first examine the average wage gap between privileged and marginalized groups (Panel-A) and among young and old cohorts (Panel B) over time. We observe that the overall wage gap between privileged and marginalized groups has increased in the period 2011 compared to 2011. A similar trend is also observed for young and old cohorts. In terms of percentage change in wage gap, we find that this has been widened from the period 1993 to 2011 by 22% and by 41% between HC vs SC and HC vs ST respectively. We find a similar trend in the wage gap among young and old cohorts. Interestingly, our results show that young cohorts in both groups (SC and ST) are rewarded less in the labour market (see the explained column of Table 2, and therefore experiencing higher wage gap compared to old cohorts. For example, young cohorts (HC vs SC) characteristics effect in the period 1993 accounts for three-quarter of the total wage gap, whereas in the period it has declined from 72% to 56% of total wage and therefore experiencing higher discrimination effect. A similar effect has been noticed between HC and another group ST.

Although, we marked a sharp increase in the wage gap between privileged and marginalized groups using the OB method, however, decomposing the overall wage gap between covariate (explained part) and return to labour market characteristics (unexplained part) does not provide an evidence of increasing discriminatory practises between these two groups. In fact, we find a rise in discrimination effect among young and old cohorts. Bhaumik and Chakrabarty (2006), using NSS data for the urban sector and for the period 1987 and 1999 have not also identified any discrimination along caste arguments.

Our results, at this stage, shows that the average wage gap between privileged and marginalized groups has not only widened, but it has also provided a strong evidence of discriminatory practices among young cohorts compared to old, and over time. Understanding the rise in the wage gap between privileged and marginalized groups and to what extent rise in the wage gap characterise the discriminatory practices in the labour market, remains a critical policy concern in India, especially after the implementation of reservation policy. Various studies have focused on this aspect, however, these studies have examined the wage gap at mean level (Kijima, 2006 a and b). Only a few have examined this issue by using QR approach under counterfactual distribution approach (Azam, 2012 and Hnatkovska et. al, 2012).

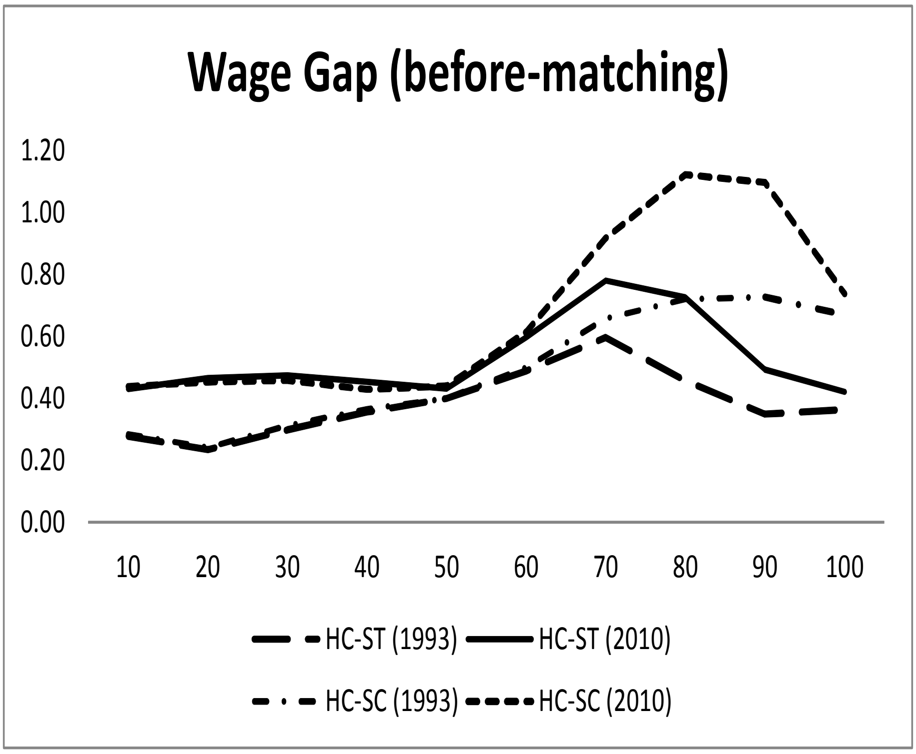
The previous studies, however, have neglected two issues. First, the mean-based approach, such as the OB decomposition method, is only examined at the mean and thus does not cover the entire distribution conditional on individual characteristics. Therefore, it does not help us to obtain a complete picture of the discrimination affecting the labor market such as one can observe using the QR method. Second, it is often the case that the individual lies on the both end of wage distribution may have different taste and preferences and thus possible that they experience the different level of discrimination. It is, therefore, important that one should use the complete distribution and match the sample according to individual characteristics. In this view, we next use the matching approach, as suggested by $\tilde{N}$opo (2008), and use the counterfactual decomposition method across the distribution as proposed by MM (2005) and investigate the overall wage gap and contribution towards discrimination between privileged and marginalized groups and for both cohorts for the entire distribution.

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

	HC vs SC			HC vs ST			HC vs OBC		
	gap	explained	unexplained	gap	explained	unexplained	gap	explained	unexplained
Panel-A					All				
1993-94	0.528	0.405	0.123	0.391	0.272	0.120	-	-	-
		(0.0051)	(0.0070)		(0.0082)	(0.0095)			
		76.72	23.28		69.46	30.54			
2010-11	0.641	0.503	0.138	0.551	0.405	0.146	0.496	0.376	0.119
		(0.0124)	(0.0096)		(0.0174)	(0.0114)		(0.0113)	(0.0092)
		78.51	21.49		73.53	26.47		75.93	24.07
Panel-B1					Young				
1993-94	0.433	0.314	0.120	0.287	0.187	0.101	-	-	-
		(0.0055)	(0.0080)		(0.0089)	(0.0106)			
		72.35	27.64		64.99	35.01			
2010-11	0.567	0.318	0.250	0.485	0.194	0.291	0.396	0.200	0.196
		(0.0140)	(0.0180)		(0.0192)	(0.0229)		(0.0120)	(0.0154)
		55.99	44.01		40.05	59.95		51.52	49.48
Panel-B2					Old				
1993-94	0.700	0.618	0.082	0.604	0.435	0.169	-	-	-
		(0.0107)	(0.0128)		(0.0173)	(0.0200)			
		88.31	11.69		69.82	30.18			
2010-11	0.823	0.498	0.326	0.577	0.246	0.312	0.635	0.410	0.224
		(0.0226)	(0.0284)		(0.0331)	(0.0369)		(0.0193)	(0.0232)
		60.46	39.54		44.04	55.96		64.67	35.33

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.

Figure 3:


Wage Gap (before-matching)
1.20
1.00
0.80
0.60
0.40
0.20
0.00
10
20
30
40
50
60
70
80
90
100
HC-ST (1993)
HC-ST (2010)
HC-SC (1993)
HC-SC (2010)

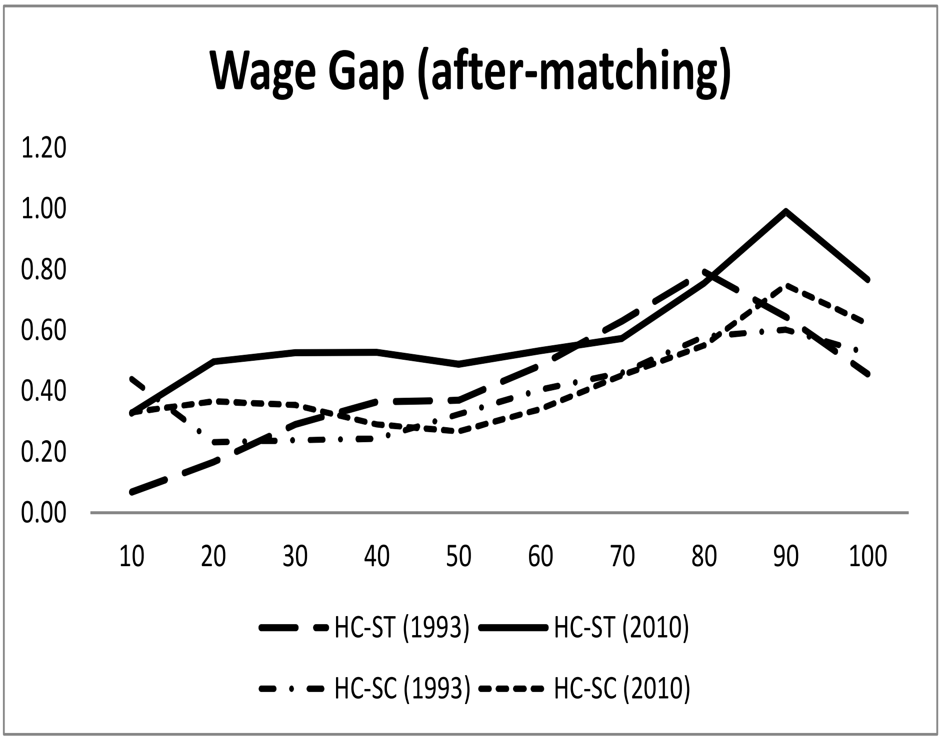

Wage Gap (after-matching)
1.20
1.00
0.80
0.60
0.40
0.20
0.00
10
20
30
40
50
60
70
80
90
100
HC-ST (1993)
HC-ST (2010)
HC-SC (1993)
HC-SC (2010)

Table 3: Data description of pervilaged and marginalized groups after matching

	1993-94			2010-11				1993-94		2010-11		
	ST	SC	HC	ST	SC	OBC	HC	HC vs ST	HC vs SC	HC vs ST	HC vs SC	HC vs OBC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log wage (per week)	4.91	4.96	5.22	6.28	6.45	6.58	6.78	22.09	44.03	16.56	20.60	19.90
	(0.901)	(0.954)	(1.034)	(0.775)	(0.786)	(0.840)	(0.908)					
Age	33.73	34.69	34.66	34.03	34.82	35.47	34.74	6.14	5.75	1.90	2.36	0.01
	(11.113)	(11.687)	(10.847)	(10.471)	(10.679)	(10.570)	(10.680)					
Illiterate	0.56	0.55	0.41	0.33	0.31	0.22	0.21	-21.50	-54.93	-7.86	-11.87	-5.72
	(0.496)	(0.497)	(0.493)	(0.471)	(0.461)	(0.415)	(0.384)					
Primary	0.25	0.25	0.27	0.39	0.37	0.36	0.39	1.80	4.28	-0.08	-2.45	-3.37
	(0.436)	(0.434)	(0.443)	(0.488)	(0.483)	(0.480)	(0.474)					
Middle	0.07	0.10	0.09	0.13	0.16	0.17	0.17	4.79	11.11	2.77	1.47	-1.51
	(0.263)	(0.302)	(0.341)	(0.342)	(0.367)	(0.377)	(0.379)					
Secondary	0.08	0.07	0.14	0.11	0.13	0.16	0.18	13.66	33.85	5.47	9.15	4.80
	(0.268)	(0.263)	(0.385)	(0.310)	(0.331)	(0.368)	(0.405)					
Graduate	0.03	0.02	0.09	0.04	0.04	0.08	0.06	15.26	34.57	2.74	10.24	8.56
	(0.171)	(0.146)	(0.303)	(0.185)	(0.192)	(0.278)	(0.298)					
Single	0.53	0.53	0.54	0.54	0.54	0.53	0.52	-4.18	-4.77	0.09	-2.12	-0.94
	(0.389)	(0.391)	(0.377)	(0.499)	(0.498)	(0.499)	(0.500)					
Hindu	0.942	0.956	0.962	0.974	0.972	0.894	0.960	7.17	11.83	-2.16	-6.46	-10.75
	(0.233)	(0.204)	(0.156)	(0.158)	(0.164)	(0.308)	(0.236)					
Muslim	0.034	0.003	0.032	0.016	0.008	0.093	0.031	-0.91	6.41	2.67	8.01	10.57
	(0.181)	(0.059)	(0.090)	(0.125)	(0.090)	(0.290)	(0.183)					
Christian	0.022	0.008	0.004	0.008	0.006	0.011	0.006	-14.64	0.27	-0.63	1.77	0.72
	(0.146)	(0.088)	(0.089)	(0.087)	(0.075)	(0.105)	(0.096)					
Other Religion	0.002	0.032	0.002	0.002	0.014	0.002	0.002	0.30	-20.06	-0.10	0.09	2.39
	(0.046)	(0.177)	(0.094)	(0.046)	(0.118)	(0.047)	(0.119)					
Managers	0.036	0.037	0.030	0.005	0.003	0.009	0.008	-2.30	-1.23	0.98	2.59	3.13
	(0.185)	(0.188)	(0.183)	(0.069)	(0.055)	(0.095)	(0.086)					
Professional	0.061	0.046	0.058	0.009	0.013	0.033	0.015	-0.95	10.10	1.58	6.52	6.32
	(0.240)	(0.210)	(0.252)	(0.094)	(0.114)	(0.179)	(0.188)					
Technicians	0.043	0.048	0.054	0.012	0.014	0.027	0.020	3.50	8.13	1.88	5.24	4.32
	(0.203)	(0.214)	(0.247)	(0.108)	(0.117)	(0.161)	(0.177)					
Clerks	0.005	0.006	0.002	0.012	0.017	0.026	0.019	-3.68	-3.17	1.47	6.50	7.09
	(0.072)	(0.079)	(0.065)	(0.111)	(0.130)	(0.159)	(0.203)					
Sales and Service	0.090	0.085	0.055	0.040	0.030	0.047	0.057	-10.28	-8.96	2.13	6.19	6.51
	(0.286)	(0.278)	(0.244)	(0.196)	(0.170)	(0.212)	(0.238)					
Agriculture, Fishing etc	0.582	0.581	0.506	0.001	0.001	0.001	0.001	-11.01	-43.25	-0.06	0.35	0.73
	(0.493)	(0.493)	(0.488)	(0.026)	(0.034)	(0.025)	(0.039)					
Labourer	0.182	0.197	0.295	0.921	0.922	0.857	0.880	18.26	43.11	-3.78	-13.13	-13.70
	(0.386)	(0.398)	(0.484)	(0.270)	(0.268)	(0.350)	(0.386)					
N	8212	19089	61217	2967	6593	9681	7893					

Author's calculation. Standard deviations are reported in bracket. Mean test between groups are reported in cols. 8-12

Before proceeding to explore QR results, in Figure 3 we present the unconditional wage distribution between both groups in matched and unmatched sample, and the matched covariates in Table 3. Despite the sharp rise in wage across groups and increasing participation rate in all occupational categories, as we observed in Table 1), the patterns for both matched and unmatched samples at different quantiles suggest that the differences between two groups have widened over time. In other words, the widened gap between both groups give an indication of less success of reservation policies and thus give an indication that both marginalized groups (SC and ST) are still facing discriminatory practice in the labour market.

5.0.2 Caste based discrimination over time - the MM decomposition

Although, the graphical pattern in Figure 3 has revealed higher wage differential between groups at different quantiles, we have not yet examined what proportion of this wage gap is explained by individual characteristics and unexplained by the same across th wage distribution. We therefore use the QR approach to study them rigorously along the overall wage gap for the entire distribution and contrast our results in both matched and unmatched samples.

The motivation to use the QR under MM decomposition has been discussed in detail in our methodology section. Using this method, we are able to assess the complete wage gap across the distribution, and the extent the overall wage gap is contributed by covariate and coefficient effect in the labour market. As argued above, there is a possibility that combination of individual and characteristics for which it is possible to find the same members in the labour force compared to their counterpart. Neglecting this issue in the estimation may result in serious over (under) estimate the effects or even fail to identify effects at all. In this view, we therefore next presention of our results. We start to examine first for complete sample and then separately examine the young and old cohorts.

In Table 4, we present the results of counterfactual distribution obtained by MM decomposition for both matched and unmatched sample. We do this by estimating a series of quantile, however, to save the space, we only report lower (10th), middle (50th), and higher (90th) quantile results. In comparison to OB results (see, Table 2), these results show vast differences in the wage gap between privileged and marginalized groups across the distribution. We observe that in both samples (unmatched and matched) the wage gap has not only widened from lower to higher quantile but also shows a strong evidence of discrimination (unexplained part) at the median quantile compared to both lower and higher quantiles. Additionally, the overall wage gap and discrimination effect between both privileged and marginalized groups are observed larger in the period 2011 compared to the period 1993. For instance, comparing the unexplained part between HC and SC, in the period 1993 and in the unmatched sample, we observe only 16% increase in discrimination at 90th quantile, whereas in the period 2011, we observe that it has increased by approximately threefold (45%) from the period 1993. A similar trend has been observed when the sample is matched and for all groups.

Table 4: 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
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Unmatched													
1993-94	*10th*	0.223	0.232	0.022	-0.031	0.223	0.165	0.073	-0.015	-	-	-	-
			(0.0426)	(0.0384)			(0.0460)	(0.0445)					
			104	10	-14		74	33	-7				
	50th	0.470	0.423	0.098	-0.052	0.470	0.298	0.189	-0.017	-	-	-	-
			(0.0326)	(0.0274)			(0.0336)	(0.0327)					
			90	21	-11		63	40	-4				
	90th	0.734	0.612	0.119	0.003	0.377	0.305	0.063	0.009	-	-	-	-
			(0.0342)	(0.0422)			(0.0384)	(0.0403)					
			83	16	0		81	17	2				
2010-11	*10th*	0.470	0.177	0.248	0.044	0.511	0.145	0.324	0.042	0.357	0.147	0.156	0.053
			(0.0404)	(0.0414)			(0.0449)	(0.0451)			(0.0455)	(0.0443)	
			38	53	9		28	64	8		41	44	15
	50th	0.501	0.341	0.273	-0.114	0.501	0.263	0.302	-0.064	0.501	0.260	0.238	0.003
			(0.0309)	(0.0243)			(0.0324)	(0.0287)			(0.0347)	(0.0301)	
			68	55	-23		52	60	-13		52	48	1
	90th	0.916	0.582	0.411	-0.077	0.444	0.303	0.202	-0.060	0.545	0.373	0.292	-0.120
			(0.0435)	(0.0452)			(0.0539)	(0.0500)			(0.0473)	(0.0523)	
			64	45	-8		68	45	-14		68	54	-22
Matched													
1993-94	*10th*	0.196	0.147	0.039	0.01042	0.069	0.069	0.036	-0.037	-	-	-	-
			(0.047)	(0.045)			(0.0370)	(0.0330)					
			75	20	5		101	52	-53				
	50th	0.405	0.294	0.077	0.034634	0.223	0.145	0.139	-0.061	-	-	-	-
			(0.031)	(0.026)			(0.0282)	(0.0226)					
			73	19	9		65	62	-27				
	90th	0.580	0.496	0.124	-0.03973	0.442	0.337	0.141	-0.035				
			(0.041)	(0.042)			(0.0373)	(0.0461)		-	-	-	-
			85	21	-7		76	32	-8				
2010-11	*10th*	0.377	0.074	0.267	0.036	0.511	0.057	0.409	0.045	0.223	0.069	0.167	-0.013
			(0.046)	(0.045)			(0.039)	(0.036)			(0.045)	(0.043)	
			20	71	10		11	80	9		31	75	-6
	50th	0.297	0.121	0.209	-0.033	0.421	0.088	0.336	-0.003	0.251	0.098	0.203	-0.050
			(0.025)	(0.022)			(0.024)	(0.022)			(0.029)	(0.022)	
			41	70	-11		21	80	-1		39	81	-20
	90th	0.860	0.335	0.424	0.101	0.916	0.169	0.588	0.158	0.644	0.270	0.350	0.025
			(0.057)	(0.054)			(0.051)	(0.048)			(0.059)	(0.062)	
			39	49	12		18	64	17		42	54	4

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.

Results obtained from both matched and unmatched sample are interesting and raise important concerns e.g., what are the important factors that could explain for higher discrimination in the Indian labour market. One explanation could be the occupational choices between the groups especially at lower quantiles in the marginalized groups. For instance, individuals from the marginalized groups (especially the poor in terms of income) choose the occupation for which human capital is not very important to reward their work at the labour market. Therefore they avoid jobs requiring large investment in skills that are unique to a particular occupational category because the return to specific attributes is reaped only if they stay longer in the same occupation. In this view, Munshi and Rosenzweig (2006), showed that marginalized groups who have been historically involved in the lower end of the labour-market are less likely to prefer investment in human capital and hence more likely to be discriminated by others in the workplace. Another potential reason could be higher social distance, higher poverty and economic inequality in marginalized groups which lead to higher discriminatory practice in the labour market for marginalized groups.

So far, we have analyzed the overall wage gap between two groups and the persistent discriminatory effect between the groups. However, one of the important aspect of this paper, and as a robustness test to main results, is to reveal the presence of discriminatory practice among young and old cohorts in the light of reservation policies, that was aimed to improve the participation in the labour force for deprived and privileged classes by way of reserving seats in various public places, e.g., in jobs, education, and other fields of life. However, these reservation policies are not directed towards 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).

In Table 5 and 6, we present the results of the counterfactual distribution obtained by MM decomposition for both matched and unmatched sample for young and old cohorts over time. First, comparing the overall wage gap for both cohorts and over time, our results provides a strong evidence of a rise in wage gap among both cohorts across the distribution. This confirms the validity of OB results. More importantly, we observed that this has not only increased over time but has been acuter among young cohorts when compared to old cohorts and in unmatched sample. Our main interest, however, lies in examining the unexplained part of the wage decomposition. From our results, it is clearly evident that there is the presence of higher discriminatory practices on both lower and middle quantiles compared to higher quantile and this has increased over time between privileged and marginalized groups for both cohorts.

In the existing literature, there is little evidence on the extent to which the young cohorts are subject to discrimination There are several possibilities for higher wage gap and persistent discrimination among young compared to old cohorts. One possible reason could be a difference in skills, i.e. young cohorts are less qualified than old cohorts. Second, could be linked to the consequent policy response in federal and state employment process which is often not the same case in private employments. Third, could be linked to informal economy where discriminatory practices are more often and difficult to control through the legal mechanism such as the reservation policies. Last but not least, this could be linked with the unemployment penalty rate among young cohorts which might contribute to higher wage discrimination through the potential employer to downgrade their skills and wage structure.

Table 5: 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
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Unmatched													
1993-94	*10th*	0.223	0.188	0.034	0.001	0.221	0.132	0.050	0.042	-	-	-	-
			(0.0436)	(0.0434)			(0.0430)	(0.0426)					
			84.10	15.46	0.44		59.16	22.22	18.62				
	50th	0.336	0.304	0.089	-0.057	0.370	0.199	0.170	0.000	-	-	-	-
			(0.0284)	(0.0235)			(0.0277)	(0.0257)					
			90.49	26.37	-16.86		53.86	46.03	0.11				
	90th	0.624	0.502	0.115	0.008	0.211	0.212	0.020	-0.022	-	-	-	-
			(0.0421)	(0.0368)			(0.0389)	(0.0425)					
			80.35	18.39	1.26		100.81	9.40	-10.21				
2010-11	*10th*	0.336	0.139	0.230	-0.032	0.377	0.125	0.306	-0.054	0.223	0.083	0.185	-0.045
			(0.0467)	(0.0488)			(0.0421)	(0.0400)			(0.0443)	(0.0447)	
			41.29	68.28	-9.57		33.17	81.20	-14.37		37.16	82.78	-19.94
	50th	0.431	0.219	0.229	-0.017	0.423	0.183	0.269	-0.029	0.357	0.149	0.195	0.013
			(0.0258)	(0.0209)			(0.0273)	(0.0274)			(0.0290)	(0.0234)	
			50.83	53.15	-3.98		43.32	63.49	-6.81		41.73	54.58	3.69
	90th	0.981	0.581	0.445	-0.045	0.470	0.347	0.227	-0.105	0.644	0.366	0.294	-0.016
			(0.0499)	(0.0433)			(0.0516)	(0.0584)			(0.0498)	(0.0487)	
			59.21	45.34	-4.55		73.88	48.40	-22.28		56.75	45.69	-2.44
Matched													
1993-94	*10th*	0.223	0.186	0.064	-0.027	0.182	0.047	0.170	-0.034	-	-	-	-
			(0.039)	(0.035)			(0.047)	(0.047)					
			84	29	-12		26	93	-19				
	50th	0.357	0.214	0.081	0.061	0.223	0.122	0.135	-0.034	-	-	-	-
			(0.026)	(0.023)			(0.026)	(0.021)					
			60	23	17		55	60	-15				
	90th	0.556	0.439	0.127	-0.009	0.357	0.307	0.174	-0.124				
			(0.036)	(0.038)			(0.037)	(0.049)		-	-	-	-
			79	23	-2		86	49	-35				
2010-11	*10th*	0.287	0.061	0.228	-0.002	0.560	0.063	0.456	0.041	0.357	0.064	0.249	0.043
			(0.047)	(0.049)			(0.056)	(0.049)			(0.044)	(0.037)	
			21	80	-1		11	82	7		18	70	12
	50th	0.288	0.099	0.184	0.004	0.446	0.080	0.367	0.000	0.182	0.057	0.178	-0.054
			(0.020)	(0.019)			(0.033)	(0.026)			(0.024)	(0.023)	
			35	64	1		18	82	0		32	98	-29
	90th	0.514	0.254	0.334	-0.074	0.341	0.108	0.500	-0.267	0.457	0.239	0.326	-0.108
			(0.040)	(0.054)			(0.047)	(0.114)			(0.041)	(0.051)	
			49	65	-14		32	147	-78		52	71	-24

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

			HC vs SC				HC vs ST				HC vs OBC		
		gap	explained	unexplained	residual	gap	explained	unexplained	residual	gap	explained	unexplained	residual
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Unmatched													
1993-94	*10th*	0.288	0.325	0.041	-0.079	0.357	0.223	0.207	-0.073	-	-	-	-
			(0.0448)	(0.0384)			(0.0448)	(0.0498)					
			113.03	14.40	-27.44		62.51	57.91	-20.42				
	50th	0.916	0.775	0.085	0.056	0.916	0.569	0.212	0.135	-	-	-	-
			(0.0408)	(0.0266)			(0.0379)	(0.0365)					
			84.62	9.26	6.12		62.14	23.12	14.74				
	90th	0.805	0.691	0.092	0.022	0.444	0.349	0.080	0.014	-	-	-	-
			(0.0358)	(0.0450)			(0.0343)	(0.0397)					
			85.86	11.39	2.74		78.70	18.06	3.25				
2010-11	*10th*	0.624	0.306	0.276	0.042	0.583	0.151	0.393	0.040	0.401	0.246	0.166	-0.010
			(0.0454)	(0.0410)			(0.0445)	(0.0517)			(0.0481)	(0.0384)	
			48.95	44.27	6.78		25.80	67.32	6.88		61.28	41.31	-2.59
	50th	1.050	0.627	0.365	0.057	0.876	0.354	0.445	0.077	0.973	0.486	0.357	0.130
			(0.0408)	(0.0306)			(0.0457)	(0.0390)			(0.0448)	(0.0313)	
			59.76	34.76	5.47		40.42	50.81	8.77		49.92	36.73	13.35
	90th	0.709	0.528	0.293	-0.113	0.437	0.230	0.208	-0.001	0.530	0.380	0.239	-0.090
			(0.0336)	(0.0503)			(0.0353)	(0.0387)			(0.0362)	(0.0413)	
			74.50	41.40	-15.89		52.62	47.59	-0.21		71.77	45.13	-16.91
Matched													
1993-94	*10th*	0.154	0.122	0.034	-0.002	0.069	0.057	0.018	-0.007	-	-	-	-
			(0.054)	(0.049)			(0.037)	(0.029)					
			79	22	-1		83	26	-10				
	50th	0.624	0.536	0.049	0.039	0.223	0.184	0.133	-0.094	-	-	-	-
			(0.037)	(0.022)			(0.032)	(0.026)					
			86	8	6		82	60	-42				
	90th	0.662	0.519	0.109	0.035	0.469	0.372	0.115	-0.018	-	-	-	-
			(0.040)	(0.048)			(0.042)	(0.048)					
			78	16	5		79	24	-4				
2010-11	*10th*	0.491	0.119	0.329	0.042	0.511	0.033	0.384	0.094	0.260	0.065	0.166	0.028
			(0.038)	(0.034)			(0.037)	(0.039)			(0.041)	(0.042)	
			24	67	9		6	75	18		25	64	11
	50th	0.405	0.205	0.248	-0.047	0.432	0.081	0.335	0.016	0.490	0.201	0.293	-0.003
			(0.027)	(0.025)			(0.020)	(0.020)			(0.033)	(0.023)	
			50	61	-12		19	77	4		41	60	-1
	90th	0.693	0.288	0.408	-0.003	0.778	0.163	0.499	0.116	0.665	0.239	0.322	0.105
			(0.051)	(0.033)			(0.050)	(0.042)			(0.065)	(0.062)	
			42	59	0		21	64	15		36	48	16

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

Fast-paced growth without stability is not sustainable. Although India's recent growth success story has motivated academics and policy makers to predict a faster pace of convergence in per capita income to the developed countries growth path within a time frame of less than three decades, the observed rise of social and economic differential in development has been a source of worry. Under this backdrop, this paper has investigated how discrimination across demographic cohorts and socially segmented groups is widening over time. Indeed, we argued that rising inequality between young and old cohorts and between social groups meant 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.

An important emphasis of the paper concerned quantifying the effects of caste discrimination by focusing exclusively on the cohorts' demographic distinctions, viz., young and old. Both demographic cohorts possess their own social affiliations and we hold that this has been endogenously determined within the Indian context, viz., whether they belong to a 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 this paper that the impact of caste discrimination has been felt more acutely among younger than the older age cohorts.

From a temporal perspective, this paper finds that there is a strong presence of discriminatory practices in India over the period 2010-11 compared to the one in 1993-94. Our finding thus raises an important question: whether the increasing effect of caste discrimination among all social groups is due to less effectiveness of the government affirmative policies *per se* or the notable division of labour between high caste and lower caste since independence. 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 practices, historical juncture and socioeconomic realities has reinforced or reshaped the nexus of caste-class relations in India. The distributional effect of age and the nexus of caste discrimination, thus, draw attention towards more studies. The effect of rising discrimination over time and more discrimination between younger and older workers reinforces the need for policy makers to review the existing affirmative policies for lower social groups and in particular pay attention to the plight of younger workers in those groups. Inclusive demography-driven affirmative policies may prove helpful in light of our findings.

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7 Appendix

- Machado and Mata (2005) Algorithm

Let $w(\tau), x(\tau), \tau = hc, lc$ denote wage distribution and the m covariates of group τ. Let $g(x;\tau)$ be the joint density of the covariates for group (τ). To generate a random sample for the wage density that would prevail for group (τ) if the conditional fitted model 5 were true and the covariates were distributed as $g(x;\tau)$. This can be described as follows:

Step 1 Generate a random sample of size m from a uniform (0,1): $\theta_1, \theta_2, \theta_3 \ldots \theta_m$

Step 2 For the data set for group τ (denoted by $x(\tau)$, a n_τ x k matrix of data on the covariates) , and each θ_i estimate

$Q_\theta(w|x:\tau)$

which yields m estimates of the QR coefficients $\hat{\beta(\theta)}$

Step 3 Generate a random sample of size m with replacement from the rows of the covariate matrix $x(\tau): x_i^*(\tau), i = 1, 2, 3, \ldots m$.

Step 4 Finally

$y_i^*(\tau) = x_i^*(\tau)'\hat{\beta(\theta_i)}_{i=1}^m$

is a random sample of size m from the desired distribution.

To construct the counterfactual density i.e., the density function of wage distribution for high caste corresponding to low caste distribution of covariates, we follow the algorithm above for hc, but in step 3, instead of drawing the sample from hc covariate x_{hc}, we replace the drawn sample with x_{lc}. After obtaining the desired counterfactual densities, we decompose the overall difference in wage between both groups in two parts: a part attribute to the coefficients and another to the covariates plus the residual term.

In equational form, let $f(w_{hc})$ denote the estimate of the marginal density of wage for the high caste based on the observed sample, and $f^*(w_{hc})$ denote the density of wage for high caste based on the generated sample. Under counterfactual distribution assumption, we may have $f^*(w_{hc}; x_{lc})$ that would have prevailed if all covariates would have been distributed as in low caste and the wage structure as in high caste. Under this assumption, the MM decomposition can written as:

$$
\begin{aligned}
f(w_{hc}) - f(w_{lc}) &= f^*(w_{hc}) - f^*(w_{lc}) + residual \\
&= \underbrace{[f^*(w_{hc}) + f^*(w_{hc}; x_{lc})]}_{covariateeffect} - \underbrace{[f^*(w_{hc}; x_{lc}) - f^*(w_{lc})]}_{coefficienteffect} + residual
\end{aligned} \tag{7}
$$

- $\tilde{N}$opo (2008) matching approach

  The $\tilde{N}$opo matching approach can be performed in the following way

  - *Step 1:* Select one low caste individual from the sample (without replacement).
  - *Step 2:* Select all the upper caste individuals that have the same characteristics as the low caste individual previously selected.
  - *Step 3:* With all the individuals selected in step 2, construct a synthetic individual whose wage is the average of all of them and match him to the original low caste.
  - *Step 4:* Put the observations of both individuals (the synthetic upper caste and low caste) in their respective new samples of matched individuals.
  - Repeat steps 1 through 4 until exhausting the original low caste sample.

  The new data set contains the observations of matched upper caste and low caste individuals based on the same empirical distribution of probabilities for characteristics. The advantage of such matching approach is that the modelling assumption that with the same individuals with the same observable characteristics should be paid the same regardless of their social status.