Caste-based Discrimination and Earning Differentials: Theil and Oaxaca Decomposition Analysis for the Indian Labour Market

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Abstract

The primary focus of this paper is to interpret earning gaps between the forward caste and the non-forward caste workers in the Indian labour market using two distinct estimation methods. First, after briefly setting out worker characteristics based on education, participation and wages in the rural-urban and regular-casual labour markets for 55th, 61st, 68th and 75th NSS rounds, the paper empirically evaluates and interprets earning gaps using microdata from NSS 68th round (2011-12). Using STATAto interpret inequality indicators, this paper first calculates Theil index, and decomposes Theil to show "within" and "between" group inequalities. Second, to delve deeper, Threefold Oaxaca Decomposition is employed to break the earnings differentials between the forward and non-forward castes into components of "endowment", "coefficient" and "interaction". This is important in understanding to what extent does unexplained factors such as discrimination and bias manifest not only in the form of low incomes but also as lesser opportunities to earn for the traditionally disadvantaged. This study finds that though the forward castes continue to control a larger share in higher education and in higher occupations as compared to the lower caste workers, the magnitude of this disparity has very slightly eroded over time. Within group inequalities are found larger than between groups across variables; with a higher overall inequality for forward castes. Even though endowment is found more than discrimination and interaction, the latter two cannot be ignored. A high endowment indeed implies pre-market discrimination in investment in education, health or even nutrition. Inclusion of traditionally deprived classes into the mainstream through a mix of caste-specific and area-specific approaches will fill social gaps in the development process. (271 words)

Key words: Inequality; earnings differentials; Theil index; Theil decomposition; Oaxaca Three Fold decomposition; wage discrimination; NSSO (E&U) 68th round.

JEL Classification: J01, J08, J11, J15, J30, J31, J71

1. Introduction

Economic inequalities in wealth and income[1] is one of the most pressing issues in the world today. To conceptualise, measure, and interpret inequalities[2], an ever growing number of findings all across the world (kind of a common trend) seems to suggest in almost all economies: Almost all countries, regardless of their economic development, show a picture of increasing wealth and income inequality; and this not-so-hopeful scenario is gaining both

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[1] Wealth is defined as the sum total of/ or the value of all assets that an individual or household holds. This includes private pension rights, financial assets and property. Income on the other hand "is not just money received through pay, but all the money received from employment (wages,salaries, bonuses, etc." (The Equality Trust).

[2] Inequalities in income and wealth are quantified forms of economic inequality. Income inequalities will capture the disparity in income between the top decile and bottom decile of the population.

momentum and magnitude. It will not be wrong to mention that during the last few decades, there are certain common agents that have accelerated the scenario of inequalities in wealth and income across countries.

Discrimination fabricates a long run disadvantaged condition and limits the opportunities for one group with respect to another (Bourguignon et al., 2007). And there is little doubt that regardless of the form of dicrimination, whether based on "caste, race, gender or skin colour" it does lead to significant gaps in wages, disparities in earning opportunities (Esteve-Volart, 2009), begets economic and social inequalities and "alienation in the society" (Gupta et al., 2018). A complex and historical concept of societal hierarchy has manifested itself into grave differences in income between the scheduled castes (SCs), scheduled tribes (STs) and other backward castes (OBCs) on one hand and the traditionally advantaged forward castes on the other[3]. Not only has this contrast manifested in occupational divisions as a reflection of a highly unequal labour market, but also largely due to pre-existing 'visible' discriminations in education and 'implicit' ones as attitudes and behaviors of the overall labour market that elevates income disparities between the socially disadvantaged and forward group workers.

In the context of widening gaps in incomes and opportunities in the Indian labour market, the primary objective of this paper is to interpret earning differentials (and its components) between forward caste and non-forward caste workers in urban and rural regions. We focus on using two different empirical approaches in order to achieve our objective. First is the Theil index. Theil is one of the more popular and frequently used measures of inequality (Charles-Coll 2011, Allison 1978, Liao 2008); other being Gini however the former is more frequently applied in literature due to its decomposability (Liao 2016). We therefore utilise Theil Index to calculate aggregate disparities between castes segregated on the basis of gender, sector and region. Subsequently we decompose Theil into within and between groups- allowing us to factor which of the two is largely causing such disparities. This plays an important role, since research previously supports within groups to be a significant contributor in overall inequality in India.

A second way to interpret earning differentials is to decompose the observed gaps into endowments i.e., "observable characteristics" (Chakraborty, 2016; Deshpande 2015), coefficient

[3] Indian caste system is complex and hierarchical segregations are based on occupations. Only among Hindus, there are 3000 sub-castes NSS broadly consists of classifying the Hindu divisions into four parts SCs , STs and OBCs are classified as underprivileged/ marginalised groups while the FCs are classified as "others". They approximately represent 20%, 8%, 42% and 30% of the national population respectively (Arabsheibani et al 2018). Other than this, NSS specifies information and data by religions and other demographically distinct characteristics of gender, region, sector, occupations and industries among others.

i.e., “unexplained factors” and interaction (of the previous two) components. The indirect effect is the discrimination component and what is taken as an “indirect effect can be further decomposed into a pure indirect effect and a mediated interactive effect” (Weele 2013) called interaction: the third component. In standard literature studying labour market inequalities the wage gaps have been commonly decomposed between endowment and discrimination components. The former being the explained part, where earning gaps are attributable to (i.e., unexplained) components (Blinder, 1973 and Oaxaca (1973); Cotton and Newmark (1988); Oaxaca and Ransom (1994).

This paper is divided as follows: Section 2 presents review.of literature. Descriptions of the data sources and methodologies are presented in Section 3. In Section 4 we briefly present the trends in overall worker characteristics segregated on the basis of caste. Data for composition and participation of the labour force, trends in wages and educational levels over four NSS rounds i.e., 55th round, 61st round, 68th round and 75th round are extracted. This sets a stage before we start with empirical calculations in order to examine earning disparities specifically for the 68th round. Subsequently in Section 5, we explain the empirical calculations of Theil Index and it’s decomposition and Three Fold Oaxaca Decomposition methods. Results are presented in Section 6. Section 7 concludes with discussions on managerial and policy implications.

2. Literature Review

The notion of ‘job polarisation’ in India has significant implications for inequality since the workforce is heavily divided along traditional classes i.e., caste. Zacharias and Vakulabharanam (2011) highlight that economic differences among castes precisely conform to the caste hierarchy present in society. This suggests the existence of caste-based ‘group inequality’ in India, a concept developed in Jayadev and Reddy (2011) to measure within inequality between groups in a population. Findings from IHDS data support this theory, showing that group indicators such as average skill-level, wealth, consumption, etc. are all ordered hierarchically along caste lines (Bharti, 2018). In this context, caste can be both a cause and consequence of job polarisation. Lower educational attainment of backward castes mean that they are differentially impacted by loss of middle-skilled jobs, and the consequent inability to find work may make it harder for them to accumulate wealth and skills, thus aggravating inequality between castes.

The role of caste in the Indian labour market is well documented by Singhari and Madheswaran (2016), they find that Scheduled Castes (SCs) receive, on average “19.5 % and 31.7 % lower wages in the public and private sector respectively” (Singhari and Madheswaran, 2016). More importantly, the study concludes that these wage differentials were largely attributable to occupational discrimination which means discrimination in access to employment; rather than discrimination within an occupation. It is also interesting to note that in occupations witnessing the largest increases in wages (sectors such as IT, management, etc.), the share of marginalised workers is underrepresented, and as a result, job polarisation has resulted in greater wealth concentration among forward castes in the recent decades (Bharti, 2018).

While there has been extensive research on caste and wealth inequality, most papers have focussed on differences in inheritance, access to education and other institutions, and discrimination (Borooah, 2005; Tagade et al., 2018; Zacharias and Vakulabharanam, 2011). We find literature that has tried to understand the correlation between wage and education level of individuals from different socio-religious groups in the Indian context (Agarwal, 2011; Kingdom and Unni, 2010). But such studies are few and they focus on the effect of differential returns to education to explain labour market outcomes. The differences in the quality and amount of education are thus understood as the main factors determining one's ability to secure a regular salaried employment among the traditionally socio-disadvantaged classes.

Using the Indian NSS 50th and 66th rounds, some studies have estimated the degree of caste-based inequality in wages while considering demographic differences between groups. They find that "within different age cohorts" of forward caste and traditionally disadvantaged groups income gaps between them are increasing (Arabsheibani et al 2018). Sidkar (2019) attempts to determine earning differentials between the "formal and informal" sector for socio-religious group individuals, showing an significant relationship in case of socio-classified groups between wages and education levels, while considering all educational level, and yet persons belonging to general category with higher educational level are able to get better jobs, none of the other three groups, i.e., the SCs/STs and OBCs seem to show any substantial impact of higher education on wages.

In recent decades, many economies have undergone 'polarisation' of the labour force, a process wherein demand for high-wage and low-wage occupations increase while traditional middle-skilled jobs experience a decline. This has adverse effects on low-skilled members of the workforce, and studies have shown that changes in employment across jobs and sectors are major drivers behind increasing inequality in many countries (Böhm et al., 2019).

In Vashisht and Dubey (2018), the authors decompose the labour market in India with respect to their task content (tasks identified are: 'routine manual', 'routine cognitive', 'non-routine cognitive', 'analytical' etc.). Their analysis reveals that largely the employment of forward caste workers in 'non-routine cognitive' tasks is greater. SCs, STs, and OBCs, owing to their high incidence of poverty, are concentrated in occupations that are manual and repetitive. Since the overall demand for manual labour is declining, their results imply that job polarisation may result in large-scale unemployment for backward castes. Here, they recommend greater government investment into programs such as Skill India for socially disadvantaged groups.

Caste-based inequality present in the Indian formal urban sector is well documented (Madheswaran and Attewell, 2007) They study income and occupational gaps among workers with higher education showing that it is the prevalence of discrimination resulting in “15 % lower wages for the marginalized worker in comparison to the advantaged or forward caste worker”. It is interesting to note that not only such discrimination is prevalent across public and private sectors, is also found higher in the private sector. The paper however looks into the urban sector and a large portion of rural inequality remains undocumented.

Although caste is principally an Indian phenomenon, its effect on wages is studied in other countries like Nepal. Mainali et al. (2016) uses Blinder-Oaxaca decomposition techniques to find that wage-differentials due to caste are large, though this caste-based wage-differential is caused through difference in investments in “human capital” and also low opportunities to “high-paying” jobs. Their decomposition method is expanded to consider firm sizes, and they also find that underrepresentation of lower castes in larger firms contributes significantly to the overall wage differential. Karki and Bohara (2014) conduct a Blinder-Oaxaca as well as a non-parametric decomposition analysis on monthly earnings data from Nepal, and find that “differences in endowment” causes significant gaps in wages between Dalits and non-Dalits. Decomposition analysis conducted on data from Bangladesh also suggests the existence of a strong gender-based sticky floor effect i.e., wage-differentials due to discrimination are highest among low quintiles of the income distribution, and a “weaker glass-ceiling effect” (Faruk, 2019).

Within the Indian context, Blinder-Oaxaca decomposition has been employed to understand caste-based differences in various contexts. Sangwan (2020) conducted a decomposition analysis on India Human Development Survey data from 2005 to 2011-12 to find whether credit access varied on the basis of caste. Substantial evidence for caste-based differences in credit access is found after correcting for selection bias. Bhuyan et al. (2018) used Oaxaca-quantile decomposition techniques to analyse differences in food security of backward and forward castes in both rural and urban India. Unsurprisingly, they found that the incidence of food insecurity was higher among lower castes, though more of this differential was explained through differences in overall identity than caste.

Some recent studies reinstate the continuing influence of caste on wealth inequality. Thorat and Madheswaran (2018) find asset ownership differences to be the most enduring source of caste-based inequality in consumption spending (followed by differences in educational qualifications). Importantly, they find that the magnitude of the wage differential as a consequence of caste varies across the wage distribution: it is higher in upper quintiles and lower among bottom quintiles. This is in contradiction to Mainali et al. (2016) who finds that in Nepal, greatest discrimination occurs at the lowest quintiles of the wage distribution. As a support to Mainali et al. 's (2016) idea, Khanna (2012) finds, using Oaxaca-decomposition techniques, that in India too the gender wage differential is higher among lower quintiles of the wage distribution when compared to the uppermost quintiles. Recently, Kumar and Pandey (2021), have explained the factors contributing large discrimination caused by lack of formal employment in India using a three fold Blinder Oaxaca decomposition method.

Many studies have also assessed the impact of reservation policies on income inequality between castes (Brennan et al., 2006). Several have documented earnings' gaps in the formal Indian labour market segregated by sector or gender (Lama, 2018; Chakraborty 2016; Deshpande 2015; Sharma 2018). A few do attempt to understand the extent and implications of dicrimination that causes this persistence in wage inequality among the socially disadvantaged groups in Indian labour market (Madheswaran and Attewell 2007; Mukherjee and Majumder, 2011; Agarwal, 2013). However using a three-fold Oaxaca Decomposition method (Jann 2008, Jones and Kelly 1984) is not extensively utilised in Indian literature, and to the best of our knowledge has not been documented based on exclusive caste specific segregations for the Indian labour market.

Our attempt through this paper is to fill this gap in literature by examining the extent and composition of caste based wage inequalities within and between two groups, i.e., the FCs and NFCs and also extending the approach to assess discrimination between the FCs and the NFCs in urban and rural areas by using a Threefold Oaxaca Decomposition method.

3. Data Sources and Methodology

For this paper, data is extracted from 55th (1999 - 2000), 60th (2004 - 2005) and 68th (2011 - 2012) rounds of the quinquennial 'Employment and Unemployment Surveys'[4]. To analyse for a more recent year, we derive data from the 'Periodic Labour Force Survey' or PLFS (2017 - 2018). Micro-individual data file for the 68th round (2011-12) is accessed to calculate both Theil index and its decomposition, and subsequently Oaxaca decomposition; the detailed explanation for both is done subsequently under this section.

Data for wages in NSSO is available only for employed individuals from the regular salaried and for casual workers. Wages are given in rupees as 'received or receivable' on a weekly work done basis. For analysis purposes, we focus on wages paid in cash and kind and convert wage and salary earnings that are given as current weekly status (CWS) to a 'daily rate'. Daily rate[5] is thus derived as a ratio of the given weekly wage and the number of either half day or full day work for the given week. Using daily wage is understood to be important since it reflects the earning frequency and characteristics of the lower earning sections of the population well.

For our analysis, we include four social classifications: scheduled tribes , scheduled castes, other backward categories and 'others' or general category workers. For notification purposes we use

[4] These quinquennial surveys are one of the most important surveys conducted by the NSSO. Microdata provides comparable measures of annual incomes, employment and unemployment rates for prior rounds.

[5] Accordingly, the NSS survey considers 'full day' if an individual works on any activity in one day for four hours or more and it considers 'half day', if work is between one to four hours in one day.

FC for all forward caste (referred to as "Others") workers, and NFC for all those belonging to backward caste (including SCs, STs, OBCs). In NSS work is defined by two types of activity status: "primary and subsidiary activity status", this paper has taken both. We include both rural and urban workers in the regular salaried category of the Indian labour market. We exclude exclusive gender and religious segregation from this analysis. For occupations, Broad occupational divisions as per NCO 2004 is considered[6].

Three approaches are used in this paper to analyse discrimination in wage and occupations. First, using data for four rounds: 1999-00, 2004-05, 2011-12, 2018-19, we begin by briefly examining the trends in caste based inequalities and disparities manifested in form of labour participation ratios, educational levels, and wages. We build the case by presenting employment shares of workers belonging to backward castes and forward castes separately. This share of employment leads us to understanding the composition and extent of the caste factor in education, occupations and industry over these decades. The main idea behind this section is to establish a pattern of worker distribution segregated by caste and to test the hypothesis that labour-market inequalities are rooted in pre-existing discriminations say, in formation of human capital and to some extent this is reflected in educational attainments and subsequently in difference in wages for workers with similar educational attainments or workers employed in similar occupational divisions.

Second, we calculate the Theil index in order to analyse the level of aggregate disparities in distribution of wages, by employing unit record or 'micro' level data from NSS 68th Round. For this we use the STATA inbuilt command (^ineqdeco^) following Stephen P. Jenkins model of Theil Index. First we attain the subgroup summary statistics by calculating for each subgroup. Then Theil (GE1) index for each non-forward and forward caste groups is determined separately. We further expand our approach by calculating aggregate disparities by sector, region, activity status and gender of such workers. Subsequently we decompose the Theil index into 'within' and 'between' components (Liao 2008), calculating separately for the non-forward caste workers (NFC) and the forward caste workers (FC). Decomposing Theil Index is helpful since it allows us to show the extent of discrimination prevalent between non-forward caste and forward caste workers belonging to the same group.

The third approach is to employ a oaxaca decomposition technique. We use STATA inbuilt command (oaxaca) developed by Ben Jann[7]. This method allows us to essentially segregate the

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[6] See Notes for Occupational Divisions; NCO 2004.

[7] Ben Jann (2008) presented the method of decomposing wage gaps between groups (based on Blinder (1973) and Oaxaca (1973) original method). Ben Jann created a new command 'Oaxaca' in STATAthat utilises 'decomposition' by Blinder (1973). "Differences in wages are described as the overall gap between average earnings of two dissimilar groups. Further, this observed gap is broken down into endowments i.e., explainable parts and

differences in mean wages into "endowment" and "coefficient components". Differences in productivity variables represent differences in wages due to skill, whereas differences in coefficients represents potential discrimination. Mincerian Earnings Function (Mincer 1974) is calculated to study the impact of education and experience on wages. OLS regression is run separately for the four divisions of castes. Estimation of returns to schooling is a crucial piece in completing the study of unequal distribution of wages across the population since it helps in shedding light on why certain groups may remain disadvantaged in terms of earnings, and why education does improve earnings. Estimating Returns on education brings out the level of discrimination and inequality faced by the disadvantaged groups at each level of education. It also helps us analyse which group of the four divisions face more barriers (and whether they do at all) in climbing the education level.

Number of Observations, Use of dependent, independent variables and dummy variables

After filtering data from the unit level data files of NSSO, the total number of observations are 70,067 individuals, of which 20,125 are those belonging to forward castes (FC) and 49,942 are those belonging to the non-forward castes (NFC). For notification purposes, we use 'FC' for forward caste workers, and 'NFC' for non-forward caste workers. We take the value of the dependent variable of probit (selection) as 1 if an individual wage is > 0, and 0 otherwise. Therefore we include workers with non-zero income in the age bracket of 15 to 60 years and belonging to the regular salaried and casual labour market[8].

We take the dependent variable (outcome of interest) to be the natural log of daily wage. Daily wage reflects the earnings characteristics at the lower and middle income sections of the society well. Variables of age, levels of education, region, occupation and industry are taken as predictors. The data does not provide years of work experience (that can be an important variable), therefore we use age as an approximation to experience. We use different dummy variables for controlling the household characteristics such as gender (male/ female), type of employment (regular/ casual) and sector (rural/ urban) to get a better estimate for establishing relationship between education and wages for each caste category separately. (Please see Appendix 1 for details).

A previous round of NSS (64th round), documents participation and expenditure in education along with the years of formal schooling among the population covered in the survey between

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discrimination (coefficients) or unexplainable parts. Jann names them as "occupational segregation" and "direct discrimination" respectively (Ben Jann, 2008).

[8] Regular salaried categories of workers are coded as 31, 71 and 72 in the "Key Indicators" section of "Employment and Unemployment (2011-12)".

age 5 to 29 years. The level of 'general education' provides the maximum level of education completed, which is similar to the NSS 68th round (E&U) survey. *Codes*[9] assigned for all levels of education are as follows: "Primary (06)", "middle (07)", "secondary (08)", "higher secondary (10)", "diploma/ certificate course (11)", "graduate(12)" and "postgraduate and above (13)".

4. Characteristics of Workers

Indian labour market inequality is high and is extensively documented. Inequality is found across organised and unorganised sectors, rural and urban regions; from unequal access to the labour market manifesting in unequal wages and earnings, resulting as inequalities in both opportunities and outcomes.

Table 1 provides data on worker population ratio (WPR) by caste. In rural areas, scheduled tribes (STs) recorded the highest WPR for all years (41.4% in 2018-19), followed by scheduled castes (35.2% in 2018-19), other backward castes (35.0% in 2018-19) and others (33.7% in 2018-19). In urban areas, however, scheduled castes (SCs) had the highest WPR in 2018-19 (34.3%). In general, WPR is higher in rural areas for all castes, though this gap has reduced over time. Interestingly, all castes exhibit the same trend across time: WPR increased between 1999-00 and 2004-05 but following that, between 2004-05 and 2018-19, it has consistently fallen.

Table 1: Per Thousand Worker Population Ratio by Caste(1999-00 to 2018-19)

	1999-00		**2004-05**		**2011-12**		**2018-19**	
	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
SC	428	344	439	368	400	358	352	343
ST	498	342	513	384	460	356	414	322
OBC	417	349	433	369	388	348	350	337
Others	371	313	409	342	376	339	337	334

Source: Own compilations based on NSSO data various rounds.

This reduction is noted to be higher in rural areas, and this partly explains why the urban-rural differential in WPR has reduced over time. All lower castes (SCs, STs, and OBCs) have witnessed a decrease of roughly 16 percent in rural WPR between 1999-00 and 2018-19, while 'Others' have experienced only a 10 percent decline. In fact, it is only urban 'Others' that has recorded a net increase in WPR over time: from 31.3% in 1999-00 to 33.4% in 2018-19. However, despite this increase, 'Others' continues to have the lowest WPR among all castes.

[9] Please note that codes assigned are not the same as "average years of education".

Understanding trends in the distribution of workers by educational qualification can provide insight into the supply-side dimension of job polarisation. Studies suggest that variations in the "skill mix" in the population can contribute to changes in "routine jobs" (Goos and Manning, 2018; Salvatori, 2018)[10]. Studies from India however also argue that the oversupply of graduates could have caused the transition of middle-skilled workers to low-skilled jobs, resulting in greater wage polarisation (Kuriakose and Iyer, 2020).

A similar trend is portrayed for India from Table2. The number of graduates per 1000 for all castes have increased significantly over time. For instance, between 1999-00 and 2011-12, the number of graduates for urban SCs have increased roughly 2.5 times, from 45 to 111 per 1000. This has been accompanied by a consistent decrease in the number of illiterates and primary graduates.

Rural areas contain a greater share of workers with lower educational qualification (Illiterate, primary, and middle school), while urban workers are, on average, more highly qualified. 'Others' are overrepresented in higher educational brackets and underrepresented among lower educational groups. As of 2011-12, 'Others' accounted for 41.2 percent (rural) and 47.6 percent (urban) of all graduates despite constituting only 21.7 percent (rural) and 27.1 percent (urban) of the population respectively (NSSO, 2014). In percentage terms, OBCs appear to be most disadvantaged since they constitute 44 percent of the population but only 20.5 percent (rural) and 25 percent (urban) of total graduates respectively.

Over the decades, the trend of lower caste workers being overrepresented in lower educational qualifications while upper castes ('Others') having a greater percentage of higher educated workers has persisted, yet the magnitude of this disparity has reduced in urban areas. In 1999-00, SCs, STs and OBCs combined accounted for only 51.1 percent of all urban graduates (combined), but that figure increased to nearly 60 percent in 2011-12.

Table 2: Per Thousand Distribution of Workers by Levelof Education and Caste

	Illiterate		**Literate and up to primary**		**Middle**		**Secondary**		**Higher secondary**		**Graduate and above**	
	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
1999-00												

[10] Salvatori (2018), for example, showed that over the last three decades a greater increase in the number of graduates has resulted in a large shift of employment from middle to top occupations in the United Kingdom.

SC	392	615	220	193	176	108	109	50	58	22	45	12
ST	344	647	182	186	177	92	134	42	74	24	89	9
OBC	281	525	234	220	189	137	150	73	79	31	67	16
Others	153	373	168	243	167	175	193	117	127	54	192	38
2004-05												
SC	322	546	249	222	187	129	113	56	62	29	69	20
ST	288	587	182	229	183	111	132	40	103	21	113	14
OBC	244	457	232	236	195	158	139	82	83	39	108	30
Others	125	325	164	259	169	179	175	121	131	63	239	56
2011-12												
SC	247	436	199	242	188	157	156	93	101	49	111	25
ST	220	456	172	253	185	152	148	77	129	43	148	21
OBC	190	371	192	219	165	172	171	130	125	67	139	42
Others	105	254	135	231	146	177	185	159	153	99	280	80

Source: Own compilations based on NSS various rounds

In rural areas, however, the trend is reversed: Lower castes accounted for 58.2 percent of all graduates in 1999-00, but by 2011-12, the figure had reduced to 52.4 percent. In the same time, the combined share of illiterates for SCs, STs, and OBCs has remained roughly constant at 83 percent. This suggests that while literacy rates are increasing among lower-castes, their share in the middle-skilled workforce also improved over the years, especially in rural areas (since most of those literate workers do not reach senior-secondary or graduate levels). Thus, job polarisation is likely to have a differential impact on lower castes since they are more exposed to jobs that are at risk of automation (ILO, 2018).

Table 3 shows a stark difference in wages between regular and casual workers irrespective of castes. Interestingly, the differences in wage between regular and casual workers outweighs inter-caste wage differentials. While the regular-casual wage differential is highest for 'Others', the impact of it is experienced majorly by lower-castes since SCs, STs and OBCs are overrepresented in the casual workforce (NSSO, 2014). Madheshwaran and Attwell (2007) found that occupational discrimination is a more significant factor in driving inter-caste wage disparities than discrimination within an occupation. For policy implication this can suggest that access to regular employment can significantly improve chances of higher wage outcomes among the lower-castes.

Wages for ‘others’ are highest among regular workers, followed by STs, OBCs and SCs. Urban wages are higher than rural wages, though inter-caste disparity in wages are also higher in urban areas, especially among regular workers. For instance, as of 2011-12, daily wages for ‘Others’ was 1.6 times higher than SCs (lowest among lower-castes) in urban areas and 1.3 times higher in urban areas. Caste-based wage disparity is higher within the regular workforce, though overall, wage differentials between casteshave reduced between 2004-05 and 2011-12.

This may be a consequence of increased educational attainment of lower-castes, as Singhari and Madheswaran (2016) find that differences in wages among castes can be understood better with explaining the differences in average skill-level than pure discrimination between such workers. Lastly, it is interesting to note that within the urban casual workforce, ‘Others’ are not the highest earners: within males, OBCs have the highest average daily wage, while for females, ‘Others’ have the lowest wage among all castes. Here, SCs and OBCs have the highest average daily wage as of 2011-12.

Table 3: Daily wages by Regular and Casual Worker(real average wage, base year 2011–12)

		Rural		Urban	
		Regular	Casual	Regular	Casual
		2004-05			
Male	**Others**	330	103	420	133
	OBC	234	107	288	138
	SC	221	100	262	127
	ST	238	83	369	112
Female	**Others**	209	64	348	83
	OBC	142	63	194	76
	SC	109	65	165	78
	ST	144	60	220	77
		2011-12			
Male	**Others**	375	152	579	173
	OBC	297	158	383	193
	SC	284	150	362	180
	ST	337	122	445	160
Female	**Others**	251	100	504	104
	OBC	194	105	276	115
	SC	148	106	225	116
	ST	197	97	340	105

Source: Own calculations based on NSSO data various rounds.

5a. Explanation of Theil's Index and it's Decomposition Method

First, total inequality as measured by Theil[11] is given as:

$$T = \frac{1}{N}\sum_{j=1}^{N} \frac{x_j}{\bar{x}} \ln \frac{x_j}{\bar{x}} \qquad ...1$$

Here j = 1, …,n, with x_j = individual's (*j*) income, $\bar{x}$ = mean income and *N* = size of the population, w = weight

Equation (1) above can be additively decomposed into two parts:

$$T_B = \sum_{k=1}^{m} y_k \ln \frac{\bar{x}_k}{\bar{x}} \qquad ...2$$

one being the "between group" inequality here, y_k = subgroup K's income share as a proportion of total income of full sample, $\bar{x}_k$ = group *k's* mean income.

$$T_W = \sum_{k=1}^{m} y_k \sum_{j=1}^{N_k} y_{jk} \ln \frac{x_{jk}}{\bar{x}_k} \qquad ...3$$

other being the "within group" inequality. here, *jk* = income share of individual (*j*) within subgroup *k*, and X_{jk} = individual *j's* income within subgroup *k*.

5b. Explanation of Three-fold Blinder Oaxaca Decomposition Method

By using the three-fold Blinder-Oaxaca decomposition method we are able to break down the earnings differentials into components of "endowment", "coefficient " and "interaction" components. This method helps us to examine the wage gaps between two groups i.e., FC (considered as the high-wage group in this case) and NFC (considered as the low-wage group in this case). The endowment component measures the "expected change" in NFC's mean outcome, if NFC had FC's "predictor levels". In other words, this part is attributable to "differences in skills'' or explained differences. The coefficient term measures the contribution

[11] Please see Tim Liao (2008)

of “differences in the coefficients (including differences in the intercept)” (Ben Jann 2008). This component is attributable to discrimination and “cannot be explained by differences in skills or individual characteristics”. The third Interaction component basically is an overlap of endowments and coefficients and reflects that “differences in endowments and coefficients can exist simultaneously between the two groups” (Ben Jann 2008, STATA implementation).

First taking the gross *wage differential (denoted as W) between the FC and the NFC groups, is the difference in the predicted logarithmic daily wages of the two groups* (the *higher wage group: FC*; and the *lower wage group: NFC*)

$$W = E(\ln Y_{FC}) - E(\ln Y_{NFC}) \qquad \ldots 4$$

Here, *E(Y) is the “expected value” of the log of daily wage of the workers in the FC and NFC group as indicated by the subscript.*

Taking the logarithmic daily wage rate as dependent variable, and demographically different characteristics of age, education, sector and region as predictors, the OLS wage equation is written as:

$$\ln Y_k = X'_k \beta_k + \varepsilon_k, \; E(\varepsilon_k) = 0, \; k \in \{NFC, FC\} \qquad \ldots 5$$

Where *X is a vector containing the predictors in subgroup k, β is the slope parameter or the coefficient*, and ε*is the error term with zero mean and constant variance*. The *subscript k denotes subgroups of the previously defined FC and NFC workers.*

Since $E(\beta_k) = \beta_k$ and $E(\varepsilon_k) = 0$ as stated earlier, equation (5) gives us:

$$E(\ln Y_k) = E(X_k)'\beta_k \qquad \ldots 6$$

Combining the equations (4) and (6) we get

$$W = E(X_{FC})'\beta_{FC} - E(X_{NFC})'\beta_{NFC} \qquad \ldots 7$$

To break down the overall difference into contributing components, equation (7) can be rewritten as:

$$W = [E(X_{FC}) - E(X_{NFC})]'\beta_{NFC} + E(X_{NFC})'(\beta_{FC} - \beta_{NFC}) + [E(X_{FC}) - E(X_{NFC})]'(\beta_{FC} - \beta_{NFC}) \qquad \ldots 8$$

Of which, the first term or the endowment component shows how much of the earnings differentials between two groups are caused by the differences in regressors. This term will measure the expected change in an individual NFC's average earnings if he/she had FC endowments (or observable characteristics of human capital). Endowment component is written as:

$$E = [E(X_{FC}) - E(X_{NFC})]`\beta_{NFC} \qquad ...9$$

The second term or the coefficient component shows the contribution of differences in coefficients of the two groups. Simply put, a coefficient component will measure the "expected change" in NFC's average earnings if he/she had a FC coefficient. This is written as:

$$C = E(X_{NFC})`(\beta_{FC} - \beta_{NFC}) \qquad ...10$$

And the third term or the interaction component takes into account for the presence of endowments and coefficient differences at the same time, or occurring simultaneously. Interaction is written as:

$$I = [E(X_{FC}) - E(X_{NFC})]`(\beta_{FC} - \beta_{NFC}) \qquad ...11$$

Equation (8) is the Threefold decomposition and substituting (9), (10) and (11) we get

$W = E + C + I$

6a. Empirical Results: Theil Index and Wage disparities between and within group

First, by using a quantile based approach (Liao, 2016) we evaluate dispersions in wage inequality between groups at the top and bottom of the income distribution. The quantile method to measure dispersions in the top and bottom end of wage distribution are well documented in studies (Basu and Sinha, 2021, Faruk, 2019, Lioa, 2016, Christofides et. al. 2013, Khanna, 2012 and Melly 2005). The approach gives us what in literature is called as the "glass ceiling" and "sticky floor effects" that explains whether inequalities in wages are predominant at the top or bottom of wage distribution.

Table 4: Caste-based wage inequality using 90/10, 90/50 and 10/50 percentile ratios based on Theil's decomposition of average daily wage (2011-2012)

	p90/p10	***p90/p50***	***p10/p50***
All Observations (NFC)	9.332	3.889	0.417
Female	9.000	3.571	0.397

Male	8.000	3.810	0.476
Rural	5.200	2.275	0.438
Urban	10.305	4.122	0.400

Source: Author's own calculation.

In Table 4, we mention the 90:10, 90:50 and 10:50 percentile ratios that illustrate the earnings gap of different individuals belonging to the non-forward castes (NFC) in the income distribution. Percentile ratios are important measures of inequality and are widely used in social literature. Percentile ratios will estimate the income of one individual at one position of income distribution as a proportion of another at a different position of income distribution. The 90:50 ratio for example, will capture the income of one at the 90th percentile to the one at the 50th. The results show that inequalities are higher at the 90:50 ratio than they are at the bottom quantile. The evidence of "glass ceiling" among the NFC workers is not found to be very strong, however we find a slightly strong glass ceiling effect between males and in the urban sector within the socially disadvantaged groups. Rural sector shows a low wage inequality at all the quantiles. Our findings are in sync with standard literature over the years documenting evidence for "sticky floor effect" (Basu and Sinha, 2021, Khanna, 2012).

According to the World Bank Inequality Report, the top 10 % controls 55 % of the total wealth and the inequalities in wealth and income is significantly higher now (and is rising) than it was about four decades ago. Between 1980 and 1918, the top 10 percent population's control of wealth has increased from 31 % to 55 %. Segregating on the basis of caste, 26.6 percent of scheduled caste individuals, 18.3 percent of OBCs and 45.9 percent of ST individuals are in the bottom 10 percent of income distribution (NFHS 2015-16). Interestingly, among the FCs the inequality is higher as compared to the NFCs. Here, 60 % of the total FC wealth is controlled by the top 10 %.

As a next step to examine the overall inequality in wages we decompose Theil index into between group and within group inequalities. The results are presented in Table 5. While employment shares of NFC individuals (SC, ST and OBCs together) constitute about two thirds of the total employment share, the mean wages are significantly lower than the other caste (FC) individuals. It is interesting to note that between the socially disadvantaged groups, male workers earn higher wages than female workers and this is observed across region (rural, urban), sector (formal, informal), or even nature of work (regular, casual). Not just that the gender gaps are significant between the disadvantaged groups, we also note that among female workers there is higher wage inequality, and thisis true for both FC and NFC workers.

However, the inequality observed in Table 5, for non-forward caste individuals is less than that of forward caste individuals and this is true regardless of gender segregation. For example, the FC workers overall show a greater inequality in terms of Theil index which is 0.5515 for FC workers and a lower inequality 0.3909 for NFC workers. This trend is persistent throughout gender and sector. FC females and FC males both show higher inequalities as compared to NFC females and males respectively. In the rural sector, the FC workers show a higher inequality Theil index at 0.4359 and urban FC workers show higher inequality Theil index at 0. 4762 as compared to their respective NFC sectors.

Rural and NFC workers contribute to more than 80% employment share, yet they earn less than three fourth of what an average FC worker earns. Interestingly, we see a low rural inequality between NFC workers than in rural FC workers. Within group inequality is greater than between group inequalities across socially disadvantaged individuals. The urban NFC constitutes about 60% as employment share, while the average wage for such individuals is significantly lower than the urban FC individuals. Despite workers in the urban regions earning higher wages overall, there is a higher inequality prevalent in urban areas simultaneously and this is mainly attributable to “within group inequality”.

Over the years, between group inequalities are seen as important indicators that can evaluate how just societies are as these are seen contributing to caste based violence and unrest (Jaidev and Reddy, 2011). However, there are problems in the way in which these are measured, a few studies have tested how much of between group inequality can contribute to total inequality by using the concept of “sequence” and “representational” inequalities.

Among the NFC individuals, the share of other backward caste individuals is higher and that corresponds with a higher wage as compared to the rest of the NFC individuals. Inequalities observed for all social disadvantaged groups is much less than the forward group. And “within group” proportions are greater than between groups in total wage across the social groups. For rural regions, we see that the between group inequality contributes to less than 4% of total inequality, this inequality share remains low for urban segregation of NFC and FC individuals at less than 8% of total inequality. Rural regions as compared to urban shows lower inequalities in both within group and between group estimates.

Table 5: Wage Gap Decomposition based on Caste (2011-12)

Social Group	Employment Share	Mean Wage	Gini index	Theil index	Within Group	Between Group
Non-forward Caste	74.93%	186.71	0.4487	0.3909		
Forward Caste	25.07%	368.27	0.5457	0.5515		

Total Inequality			0.5059	0.5067	0.4547	89.74%	0.0518	10.22%
Schedule Tribe	9.48%	155.28	0.4717	0.4752				
Schedule Caste	24.96%	168.55	0.4192	0.3479				
OBC	40.49%	205.27	0.4529	0.3875				
Others	25.07%	368.27	0.5457	0.5515				
Total Inequality			0.5059	0.5067	0.451	89.01%	0.0557	10.99%
NFC Female	79.38%	123.9	0.4546	0.4399				
FC Female	20.62%	299.81	0.605	0.6644				
Total Inequality			0.5385	0.6108	0.5265	86.20%	0.0842	13.79%
NFC Male	73.62%	206.76	0.4295	0.358				
FC Male	26.38%	384.11	0.5302	0.5261				
Total Inequality			0.4857	0.4687	0.4252	90.72%	0.0435	9.28%
Rural NFC	81.89%	144.54	0.3816	0.2907				
Rural FC	18.11%	211.25	0.4801	0.4359				
Total Inequality			0.4103	0.338	0.3261	96.48%	0.0124	3.67%
Urban NFC	61.47%	295.42	0.4656	0.3814				
Urban FC	38.54%	511	0.515	0.4762				
Total Inequality			0.5069	0.468	0.4307	92.03%	0.0372	7.95%

Source: Authors own calculations based on NSS 2011-12 data.

Notes: non-forward caste (NFC) includes all scheduled castes, scheduled tribes and other backward caste workers for this analysis. FC includes others except all scheduled and backward castes. NFC female includes all females form scheduled castes, scheduled tribes and other backward castes. FC females include all forward caste females. Same approach applies for NFC males and FC males. The number of observations

6b. Empirical Results: Blinder Oaxaca Decomposition

Table 6 provides mincerian earnings function results for the year 2011-12 which compares earnings and human capital (used in this case in the form of level of education achieved) and other earnings-determining variables. The Ordinary Least Square Method (OLS) is used for our estimation. (We have shown descriptive statistics and dummy variables in Appendix 1 and discussed it under the methodology section). The NSS E&U provides us with the completed level of education for every individual. We use different dummy variables for controlling the household characteristics like gender (male/ female), type of employment (regular/ casual), sector (public/ private), and region (rural/ urban) to get better estimates for establishing relationship between education level and wages.

We run regression separately for scheduled castes, scheduled tribes and other backward castes. From table 6, first it is observed that education is significantly and positively related to log of daily wages, however for the exception of below primary levels across castes, and a negative relationship (see *below primary* coefficient) for the forward castes (*others*) signifying perhaps both opportunities and motivations for forward castes to pursue further education. It is observed that forward castes have an edge over the rest Higher coefficients for post graduation across the castes indicate greater returns to higher education followed by graduation giving the highest returns for the forward castes indicating that these workers do not have to achieve the highest education to start getting better incomes.

On the other hand the disadvantaged have to rise up the education ladder to maintain some standard of living. At low levels of education i.e., up to primary levels the returns are dismal, even though that of SCs and OBCs indicate the ratio of workers from these castes are finding access to low skilled manual work and this could very well be due to lack of opportunities even bias against such communities. For STs, ownership of land as an asset could explain lowest returns on education up to primary among all castes (Tagade et al., 2018; Zacharias and Vakulabharanam, 2011). Previous studies, using similar variables for successive years (or using more than one NSS round) show that the general category workers have overall achieved a constant returns on education at each level of education; however that is not true for disadvantaged castes where unless they attain a higher level of education, they are not able to increase their returns to education (S. Madheswaran and Paul Attewell, 2007).

In Table 6, other than education, we use “demographically identified personal characteristics” (Chakraborty, 2018) such as age, gender, sector and region in our estimation. Comparing earnings, gender gaps for those belonging to *SC* and *Others* are higher yet females earn less than males across castes. Specifically, an SC or forward caste female worker earns 50% less and the females in rest of castes earns around 40% less. Forward castes are observed to have an edge over the rest in urban areas as compared to rural (earning about 40% higher), thus depicting a greater gap in the urban regions as compared to rural overall.

In Table 7a we show results for "original formulation of E, C, U and D" (Blinder-Oaxaca, 1973). Along with portion of (i) endowment and (ii) discrimination, an "unexplained portion" of discrimination is given which is due to (iii) interaction or combination of (i) and (ii)[12]. The results indicate a high overall raw wage differential of 48.8%. This is important to reinstate that there are huge gaps or wage differentials between the two groups. Under representation of lower castes in higher occupations, higher paying jobs and also regular employment can significantly contribute to overall wage differentials. Raw wage differential is divided into three parts of which 43.1 % is attributable to endowment and a lower 6.1 % is attributable to discrimination (coefficient). The third unexplained "interaction term" is -0.4 %.

Table 7b summarises endowment, discrimination and interaction components as a percentage of total difference in wage. Results indicate a larger endowment component as compared to discrimination component. The endowment component is 71.24 percent as part of total difference in the wage gaps. Nevertheless discrimination explains 11.7 percent of lower wages and interaction explain about 17 percent lower wages for NFC workers than that of the FC workers. Together the total attributable difference is close to 50 percent (49.2) between the forward castes and non-forward castes workers andthis is very large.

Comparing the results with similar literatute using NSS data for previous rounds, show an increasing share of discrimination over the decades; with the share of unexplained difference- as part of total discrimination- reducing over the years. Using the data for 1999- 2000, Madheswaran and Attewell (2007) find that 79 % of the wage differentials is due to endowment and rest, 21 percent is due to discrimination, explaining the persistence of lower wages for the disadvantaged workers of SCs and STs. Here, the role of past discriminations measured in the form of human capital cannot be ignored, which does cause a difference in endowments itself yet is not easy to measure directly.

This understanding leads us to some important points that are worth mentioning here. A larger endowment difference in India implies a pre-market labour discrimination in terms of education, nutrition and health attainments, and these pre-market factors can be by far more important than discrimination itself in explanaing the differences in wages. Although the endowment difference seems to be decreasing over the years from 1983 to 1999-00.

[12] Details are covered in the explanation of Blinder Oaxaca Decomposition section.

Table 6: Earnings function OLS results in Regular salaried workers segregated by caste (2011- 12)

	Scheduled Castes				Scheduled Tribes				Other Backward Classes				Others			
	coeff	std err	t-value	P>|t|	coeff	std err	t-value	P>|t|	coeff	std err	t-value	P>|t|	coeff	std err	t-value	P>|t|
age	0.022625	0.002969	7.62	0.000	0.016663	0.003743	4.45	0.000	0.030794	0.002237	13.76	0.000	0.020773	0.002929	7.09	0.000
agesq	-0.000202	0.000041	-4.95	0.000	-0.000129	0.000052	-2.49	0.013	-0.000321	0.000030	-10.53	0.000	-0.000117	0.000039	-2.99	0.003
below-primary	0.023991	0.016200	1.48	0.139	0.012134	0.019158	0.63	0.527	0.027893	0.012372	2.25	0.024	-0.030159	0.019481	-1.55	0.122
primary	0.051652	0.014336	3.60	0.000	-0.013699	0.018708	-0.73	0.464	0.049378	0.011714	4.22	0.000	0.019409	0.016441	1.18	0.238
secondary	0.237148	0.018278	12.97	0.000	0.309578	0.026711	11.59	0.000	0.200062	0.012525	15.97	0.000	0.344197	0.015970	21.55	0.000
highschool	0.308350	0.024470	12.60	0.000	0.465028	0.032093	14.49	0.000	0.347976	0.016451	21.15	0.000	0.486816	0.018480	26.34	0.000
grad	0.730589	0.027823	26.26	0.000	0.780784	0.034458	22.66	0.000	0.844158	0.016221	52.04	0.000	1.065509	0.015611	68.25	0.000
diploma	0.680594	0.048218	14.12	0.000	1.030249	0.066691	15.45	0.000	0.737743	0.024044	30.68	0.000	0.924431	0.027240	33.94	0.000
post-grad	1.074412	0.043029	24.97	0.000	1.109383	0.059195	18.74	0.000	1.084990	0.022151	48.98	0.000	1.389023	0.019720	70.44	0.000
Gender:male Base_Female	0.522808	0.011777	44.39	0.000	0.396763	0.013809	28.73	0.000	0.516694	0.009005	57.38	0.000	0.529653	0.012224	43.33	0.000
Sector:public Base_private	0.591039	0.017786	33.23	0.000	0.645138	0.021927	29.42	0.000	0.513607	0.012850	39.97	0.000	0.508208	0.013457	37.77	0.000
Region:urban Base_rural	0.290183	0.012279	23.63	0.000	0.327365	0.018131	18.06	0.000	0.302432	0.008350	36.22	0.000	0.405578	0.010129	40.04	0.000
_cons	3.676148	0.052245	70.36	0.000	3.743405	0.065049	57.55	0.000	3.598352	0.039654	90.74	0.000	3.628384	0.053193	68.21	0.000
R-squared	0.3694				0.4218				0.4298				0.5555			
Adj- R2	0.3689				0.4211				0.4295				0.5553			
Observations	14,144				9,906				25,892				20,125			

Source: Own calculations using NSSO microdata 68th round

Notes: Natural logarithm of Daily wage is the dependent variable. Levels of education are predictor variables to determine the effect of human capital factors on earnings. Factors such as gender, age, sector, region are other demographically identified characteristics taken as predictor variables. p>0.10 = insignificant variable ; 0.01 < p < 0.05 = significant at 90% level of confidence; 0.01 < p < 0.05 = significant at 95%; p<0.01 = significant at 99% level of confidence.

Table 7a: Summary of Blinder-Oaxaca Decomposition Results (as %)

Components of Decomposition	NFC vs FC
Total differential:	49.2
- attributable to endowments (E):	43.1
- attributable to coefficients (C):	6.1
Shift coefficient (U):	-0.4
Raw differential (R) {E+C+U}:	48.8
Adjusted differential (D) {C+U}:	5.7
Endowments as % total (E/R):	**88.3**
Discrimination as % total (D/R):	**11.7**

Table 7b: Blinder-Oaxaca Decomposition Results Components as a percentage of Total Difference

Components of Decomposition	NFC vs FC	%
Due to endowment (E)	0.3475596	71.24%
Due to coefficients (C)	0.0571873	11.72%
Due to interaction (I)	0.0830914	17.03%
Gross Wage Differential (W = E+C+I)	0.4878383	100.00%

Source: Own calculations based on NSS microdata 68th round

Table 8 shows the relative contribution that each independent variable has on the wage gap. Here, decomposition results of endowment, coefficient (discrimination) and a third interaction components in the earnings function is shown. The results show that of the total difference in wages, how much is attributed to endowments and how much is attributed to differences in rewards[13]. Looking at levels of education, we see that except for below primary and primary level, all other (higher levels) favour forward caste workers.

Discrimination effect as part of total difference in wages is stronger at below primary, primary and secondary levels as compared to endowment effect. Moving up the educational levels reduces discrimination significantly. At secondary level, we see that the total difference in wage between FC and NFC is 4.35%, of which 2.34% is due to discrimination and 1.37% is attributable to endowment. At graduate level, the total difference is significantly higher at 28.10%, and

[13] 'Rewards' has been used in standard literature to show discrimination as a component of differential in Blinder Oaxaca decomposition.

discrimination component of the total is reduced. A similar pattern with effect to earnings differential and favourable treatment towards FC isnoted at postgraduate level.

Table 8: Earnings Gap Three Fold decomposition (Blinder-Oaxaca) between NFC and FC using different variables

	Endowments	%	Coefficients	%	Interaction	%	Total Difference
age	0.022625	4.64%	-0.191533	-39.26%	-0.004744	-0.97%	-35.60%
agesq	-0.015925	-3.26%	0.181389	37.18%	0.008575	1.76%	35.68%
below-primary	-0.001053	-0.22%	-0.006444	-1.32%	0.002327	0.48%	-1.06%
primary	-0.001220	-0.25%	-0.003415	-0.70%	0.000670	0.14%	-0.81%
secondary	0.006667	1.37%	0.011426	2.34%	0.003233	0.66%	4.37%
highschool	0.012214	2.50%	0.007159	1.47%	0.004437	0.91%	4.88%
grad	0.095075	19.49%	0.013709	2.81%	0.028306	5.80%	28.10%
diploma	0.011828	2.42%	0.003173	0.65%	0.002589	0.53%	3.61%
post-grad	0.065892	13.51%	0.007206	1.48%	0.017654	3.62%	18.60%
male	0.027385	5.61%	0.017945	3.68%	0.001281	0.26%	9.55%
public	0.047056	9.65%	-0.004398	-0.90%	-0.003311	-0.68%	8.07%
urban	0.077018	15.79%	0.025254	5.18%	0.022074	4.52%	25.49%
constant	0.000000	0.00%	-0.004283	-0.88%	0.000000	0.00%	-0.88%
Subtotal	0.347560	71.24%	0.057187	11.72%	0.083091	17.03%	100.00%

Source: Own calculations based on microdata from NSS 68th Round

After education, the wage differentials are substantially greater for the urban area and favour the FC, showing a more pronounced wage gap in the urban area as compared to rural ones. By taking wage structure of the FC, we see that 15.79% of the total wage difference in urban region is attributable to characteristics (or endowments) and 5.18% is attributable to discrimination. An unexplained part of the wage differential is 4.52%. Results in table 8 also show a positive number for the public (8.07%) indicating presence of comparatively smaller discrimination against the NFC in public sector. The adjusted differential of 1.58% shows a miniscule earning advantage favouring the disadvantaged workers in the public sector. The exceptions are public sector where the discrimination componet is negative and favours the NFC and lower levels of education, where both endowments and discrimination components are negligible but favour the NFC.

Similar pattern is observed for gender divide in wage differences, using the wage structure of the FC, a total differential in wage gap between male and female is 9.55% and favours the forward caste males. It is important to mention here that since our data does not fully account for differences in human capital, it will not be correct to assume that the full unexplained component is discriminatory even though in most variables, discrimination is less than endowment. Many women, for example, are excluded from the labour force due to caring and other "household obligations" (Kingdon 1998, Agarwal 2013).

Of course, pre-labour market discrimination does affect wages in some ways either due to lower "out of school investments", lack of good education or even lack of accessibility to higher education, poorer health outcomes or low nutrition levels, overall a "lower social capital" thus can be more important in explaining wage differences later on. (Das and Dutta 2007). Unequal labour market outcomes are stemming from some discrimination in the past that has limited the earnings and maintained deprivation and distress in the socially disadvantaged groups.

7. Discussion: Managerial and Policy Implications

The analysis presented in this paper shows a persistence of caste based inequalities regardless of whether we look into level of educational attainment, gender, region or sector. Earnings inequality is found across public and private sectors, rural and urban regions; in unequal access to the labour market manifesting in unequal wages and earnings, resulting as inequalities in both opportunities and outcomes. Lack of opportunities caused 93 million disadvantaged caste workers to relocate to areas in search of either employment or education in 2011. Such movements bar the workers from accessing certain state specific schemes, and also make them susceptible to poor nutrition, health and living conditions (Mitra, Damle and Varshney, 2019).

Our research question approached disparities using two approaches. Through the first approach, we find that lower wage inequalities are found at the bottom quantile and in rural areas as compared to the top quantile between the non-forward caste workers. Female workers belonging to the non-forward castes face greatest discrimination and this is evident from the higher Theil index found for this group. Comparing between the female forward castes and the female non-forward castes workers, higher inequalities are found for the females belonging to the forward caste groups. Interestingly, for all divisions the forward castes have shown greater within group inequalities as compared to the non-forward castes. Notwithstanding that standard deviations are seen high even in the forward caste groups, which means that not everyone in this class is better off. A World Bank study reports that inequality within the sub-castes could be a main factor in economic inequality (World Inequality Report, 2018). Such recent findings remain very similar to those that are shown in our paper, despite the gap in years between the two.

The Mincerian earnings function shows a rising premium to skill among the non-forward caste workers and this seems to be the trend post liberalisation of the indian economy. However, the gaps between the forward and non-forward castes are large However, also leading to increased wage inequalities more in urban areas as compared to rural areas. A substantial amount of labour market discrimination is found and it is also observed that in order to increase their standard of livings, the scheduled castes and scheduled tribes must move to a much higher level of education as compared to the forward caste workersand the other backward caste workers.

Comparing the levels of general education, a higher education is shown to favour the forward caste while the lower levels pre-primary and primary shows favour towards the non-forward caste workers. This is an important observation, that strengthens our argument that the endogenous work division, that is traditionally fabricated into the societal and economic structure, is very much existent and even domination the market discrimination against the socially backward and disadvantaged groups. Women, at all levels and in all social and sectoral divisions are in a disadvantaged situation.

Interestingly our findings suggest that despite education continuing to be seen as a significant and positive investment for both disadvantaged and forward classes, the returns are higher at middle and graduate levels for the disadvantaged sections while they are the highest at the postgraduate level for the forward classes. To add to this, the returns are declining while going from graduate to a diploma level for all the three disadvantaged classes, showing a lack of participation of such sections in diploma courses. Recently, returns to education are seen highest for postgraduate diploma courses and the lower levels of disadvantaged class participation suggests important policy implications. Policymakers should first invest in basic quality education and simultaneously expand post graduate diploma opportunities, subsequently increasing the participation in the labour force for the traditionally disadvantaged sections in disciplines and occupations where the forward castes have long dominated.

Providing educational empowerment in forms of pre-matric, post-matric scholarships, fellowships, free coaching services, to support the children of marginalised groups, will ensure quality education and lower the incidence of drop outs are strong policy tools. Closing the income inequality gaps will also call for entrepreneurship programs, skill training, refinancing loans, credit facilities with aim to encourage entrepreneurship will result in not just creation of jobs but also help bringing such sections into the mainstream of growth and development discourse. Several educational and economic initiatives are taken by the Ministry of Social Justice and Empowerment, such as the Post Matric Scholarship for Scheduled Caste Students (PMS-SC) that aims to assist students belonging to scheduled castes by providing scholarships, fellowships and free coaching services. Policies such as Credit Enhancement Guarantee Scheme for Scheduled Castes, SCDCs, NSFDC, SCSP are also initiated.

A newly developing trend where returns to education are seen higher at tertiary level, does have important policy implications for the deprived sections as the demand for tertiary education rises, so does the requirements of higher education where the enrollment of such sections have remained very low. The enrollment ratios (GER) for SCs at primary and upper primary levels are over 100, however starts dipping while moving up the education ladder, falling to 82.7 at secondary level, and a dismal 19.1 for higher education (Social Welfare Statistics, 2018). Policymakers should however continue to improve access to quality primary and secondary education that is an important prerequisite for entering higher education.

The decomposition results following Oaxaca-Blinder approach allowed us to identify endowment, discrimination and interaction componenets of wage differentials. Even though the endowment component is larger than discrimination, the magnitude of discrimination cannot be ignored. A large endowment difference could imply pre-market discrimination with respect to human capital investments in education, health and nutrition and therefore becomes critical in explaining earning differentials than labour market discrimination. These pre-market discriminations have deprived those belonging to NFC groups and policies to increase endowment of not just physical capital (for example providing of assets in form of cattle, land, irrigation wells, raw-materials etc.) but also human capital in forms of quality and affordable education and healthcare to begin with.

Narrowing the endowment component is crucial to "functioning of any democratic government" (Chakraborty 2019), this is an important issue because the pre-market disparities in human capital including quality education, skill development and training manifest as employer's bias against the disadvantaged groups leading to discrimination based on other observable characeristics such as "age, gender, disability and at times region" (Becker, 1957). Perceptions can be very challenging to change, nevertheless, continuous investments in high quality primary education initially and skill development and training later on can gradually improve commonly held perceptions against SCs, STs and OBCs.

Arguments against reservations that are based on so-called ineffectiveness and inefficiency of such policies are neither empirically documented nor supported. Such policies do have incentives for the non-forward caste individuals to access better and higher education, given that in absence of which most such individuals would have not pursued. The reservation policies can be seen as a "system that allocates resources such as seats in colleges and government jobs" (Munshi, 2016). Despite reservations policies seen as in fact "redistributing opportunities" (Bertrand et al., 2010, Munshi, 2016) and a range of reservations for SC, STs and OBCs in civil posts and services, the proportion covered by reservations remains miniscule. This could be due to the higher employment of such workers in informal, non-reserved non-government jobs.

In rural areas where inequalities are observed lower as compared to the urban areas, the opportunities for growth and increasing incomes are restrained and limited. The rural labour market has traditionally been castebased. Wage labourers and farmers belonging to the non-forward castes face discrimination in the sense that their goods and services are less demanded by the forward caste groups, or discrimination is found while buying raw materials and inputs, obviously affecting the wage of this group. Special emphasis is already given for inclusion of scheduled castes and tribes in providing awareness on MGNREGA and additional provisions must be made to NFC individuals to “undertake land development works, provision of irrigation facility, plantation and horticulture, etc.” (Ministry of Rural Development, GOI, NREGASoftV1.5).

As much as reducing visible disparities in education and income, bringing down discrimination remains a challenge. Caste based wage discrimination can counteract with the development process. In the past, caste related violence has reinstated the traditional differences between the so-called higher caste individuals and the socially disadvantaged individuals, acquiring new vigour and turning into violent and fierce struggle for power in our incessant hierarchical society. Margianalised and backward castes need to be brought into the mainstream of the ongoing development process in order to achieve holistic growth. An important policy implication is that there is a need to expand economic initiatives based on area specific approach rather than caste based approach, therefore targeting vulnerable populations in deprived areas regardless of their castes can narrow large gaps in inequalities and lessen communal tensions or caste-wars as well.

Appendix 1. Descriptive Statistics of selected variables

Variables	Description of the Variables	Scheduled Caste		Scheduled Tribe		Other Backward Caste		Others	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
lwage	Logarithm of daily wage (in rupees)	4.820057	0.7475881	4.659777	0.8025349	4.974421	0.7933116	5.371033	1.006541
Age	Age in years	34.67003	10.82573	34.2806	10.6227	34.91094	10.79073	35.61171	10.87655
agesq	Age squared	1319.199	787.6599	1287.99	768.6686	1335.209	792.6708	1386.487	809.9557
<Primary	if completed below primary education=1; 0 otherwise	0.1173098	0.3218004	0.1290705	0.3352949	0.113963	0.3177724	0.0747498	0.2629937
Primary	if completed primary education=1; 0 otherwise	0.1632851	0.3696387	0.1419318	0.3489978	0.1330588	0.3396448	0.1159301	0.320149
Secondary	if completed secondary education=1; 0 otherwise	0.092595	0.2898743	0.0631702	0.2432812	0.1162562	0.320538	0.1304215	0.3367749
HSC	if completed higher secondary=1; 0 otherwise	0.0479179	0.2136001	0.0452674	0.2079004	0.0619876	0.2411376	0.08939	0.285313
Grad	if completed graduation=1; 0 otherwise	0.0380705	0.1913732	0.0435283	0.2040534	0.0701238	0.2553605	0.1718776	0.3772834
Diploma	if completed diploma/ certificate course=1; 0 otherwise	0.0111947	0.1052149	0.008887	0.0938556	0.0263876	0.1602881	0.0846967	0.1830432
Postgrad	if completed post graduation=1; 0 otherwise	0.0145648	0.1198068	0.0121057	0.1093635	0.0336168	0.1802443	0.0347078	0.2784368
Gender-Male	base_female	0.7544501	0.430428	0.6979318	0.4591779	0.7743006	0.4180501	0.8121484	0.3906033
Sector-Public	base_private	0.1052055	0.3068288	0.1314364	0.3378941	0.1159791	0.320206	0.2004234	0.4003271
Region-Urban	base_rural	0.2425139	0.4286186	0.1601833	0.3667945	0.3302627	0.4703167	0.5238378	0.4994438
Occupation									
NCO_1	Base: otherwise	0.0160774	0.1257777	0.0154529	0.1233519	0.029184	0.1683252	0.0733345	0.2606912
NCO_2	Base: otherwise	0.0192926	0.1375561	0.0172562	0.1302312	0.0394305	0.1946206	0.0959298	0.2945023
NCO_3	Base: otherwise	0.0271227	0.1624467	0.0366705	0.187961	0.0388395	0.1932161	0.0798028	0.2709943
NCO_4	Base: otherwise	0.0241085	0.1533916	0.0227741	0.14919	0.0310898	0.1735639	0.0694625	0.2542454
NCO_5	Base: otherwise	0.0411633	0.1986748	0.0411049	0.1985428	0.0730739	0.2602627	0.0952546	0.2935736
NCO_6	Base: otherwise	0.0593044	0.236202	0.1243092	0.3299506	0.0751737	0.2636765	0.0587028	0.2350735
NCO_7	Base: otherwise	0.1552232	0.3621301	0.0920895	0.2891668	0.1781299	0.3826295	0.146478	0.3535936
NCO_8	Base: otherwise	0.058884	0.2354159	0.0347777	0.1832257	0.0849231	0.2787726	0.1073212	0.3095289
NCO_9	Base: otherwise	0.5959554	0.4907235	0.6129229	0.4871061	0.4485694	0.4973575	0.2674765	0.442654

Source: Own calculations based on NSS microdata 68th round

Notes: the sample consists of individuals aged 15 - 65 in the nss (2011-12) 68th round. Standard deviations are not reported for dummy variables.

Notes:

1. NCO Classifications (2004) are as follows: NCO1: Legislators, Senior Officials and Managers; NCO2: Professionals; NCO3: Technicians & Associates Professionals; NCO4: Clerks; NCO5: Service Workers & Shop & Market Sales Workers; NC06: . Skilled Agricultural and Fishery Workers; NCO7: Craft and Related Trades Worker; NCO8: Plant and Machinery Operators and Assemblers; NCO9: Elementary Occupations.
2. (According to Ben Jann) "The results from decomposition are presented using Blinder's (1973) original formulation of E,C,U and D; The endowments (E) component of the decomposition is the sum of (the coefficient vector of the regressors of the high-wage group) times (the difference in group means between the high wage (FC) and low wage (non-FC/NFC) groups for the vector of regressors); The coefficients (C) component is the sum of the (group means of the low-wage group for the vector of regressors) times (the difference between the regression coefficients of the high-wage group and the low-age group); U is the unexplained portion of differential (difference between model constants); D is the portion of differential due to discrimination (C+U); the raw (or total) differential is E + C + U".

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