

Wages in India: Social Disparities and Discrimination

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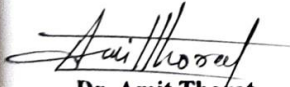
DECLARATION

I, **Sarika Chaudhary**, hereby declare that this dissertation entitled "**Wages in India: Social Disparities and Discrimination**" submitted by me for the award of **Master of Philosophy** at the Centre for the Study of Regional Development, School of Social Sciences, Jawaharlal Nehru University, New Delhi, is based on my original research work and has not been submitted so far in part or in full, for any other degree or diploma of any University or Institution.


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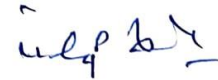
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List of Abbreviations

CWS	Current Weekly Status
EUS	Employment and Unemployment Survey
FCs	Forward Castes
FSU	First Stage Units
GDP	Gross Domestic Product
GoI	Government of India
IHDS	India Human Development Survey
ILO	International Labour Organization
LFPR	Labour Force Participation Rate
MGNREGA	Mahatma Gandhi National Rural Employment Guarantee
MMM	Machado, Mata and Melly
MoSPI	Ministry of Statistics and Programme Implementation
MPCE	Monthly Per Capita Consumer Expenditure
NSO	National Statistical Office
NSSO	National Sample Survey Organisation
OBCs	Other Backward Classes
OLS	Ordinary Least Square
PLFS	Period Labour Force Survey
QR	Quantile Regression
RBI	Reserve Bank of India
RIF	Recentred Influence Function
RWS	Regular Wage/Salaried workers
SCs	Scheduled Castes
SSA	Social Structures of Accumulation
SSS	Second Stage Strata
STs	Scheduled Tribes
UFS	Urban Frame Survey
UPSS	Usual Principal and Subsidiary Status
UR	Unemployment Rate
USU	Ultimate Stage Units
WPR	Worker Population Ratio

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Introduction

1. Background and the Statement of Problem

The COVID-19 pandemic has led to an extraordinary economic and health crisis and has impacted the economies across the globe. According to the National Statistical Office's provisional National Income estimates, India's Gross Domestic Product (GDP) decreased by 7.3 percent at current prices in the fiscal year 2020-21 (Annual Estimates, 2021). The massive decline in the GDP, as a result of the pandemic, is indicative of the severe crises rocking the Indian Economy, subsequently affecting adversely the lives of millions of Indians. The extent of the crisis is so deep that it has forced the masses to make a choice between their lives and livelihoods. The extent of the brutality of this crisis was evident during the mass exodus of migrant workers from big cities had happened during the first phase of the lockdown (Rajan, 2020). The second wave of the pandemic saw a massive rise in number of deaths due to unavailability of care facilities (Anand, Sandefur, & Subramanian, 2021). While the impact of the COVID crisis begs for deeper analyses, the current work is restricted to the pre-pandemic period since a fuller understanding the current crisis can only be captured with a better analysis of the situation at the onset of the pandemic.

The situation of the Indian economy was already deteriorating when the pandemic hit the country (Kishore, 2020). The decline in the India's GDP growth rate dates back to 2017-18. According to the annual report for the year 2020-21 of the Reserve Bank of India (RBI), the real GDP growth rate was 8.3 percent in 2016-17, which fell to 6.8 percent in 2017-18 and finally to 6.5 percent in 2018-19 before it was impacted by the COVID-19 pandemic (RBI, 2021). However, even these numbers have been contested by economists. While the official estimation of the annual average growth rate of the GDP between 2011-12 and 2016-17 was 7 percent, the former GoI's Chief Economic Advisor claimed in his two-paper that it was 2.5 percent overestimated (Subramanian 2019a and 2019b). Thus, the reversal in the growth pattern did not begin with the COVID-19 pandemic, but dates backs several years and economic policies like demonetisation lie at the heart of such crises (Srivastava & Padhi, 2020).

There are several indications of the declining economic performance of the Indian economy. The unemployment rate has risen to 6.1 percent in 2017-18, which is the highest in the last 45 years (NSO, 2019). Similarly, wage growth decelerated from 6.47 percent between 2004-05 and 2011-12 to 1.05 percent between 2011-12 and 2017-18 (Srivastava & Padhi, 2020). Thus,

the reversal in the growth pattern of Indian economy indicates a worsening situation for the working population particularly those belonging to the marginalised social and economic backgrounds. Moreover, the improvement in the lives of these groups was inadequate even during the times of high GDP growth. Most of the previous works on inequality in India suggests that it has risen in the post-liberalisation period, which has resulted into widening gap between the rich and the poor (Anand & Thampi, 2016; Chamarbagwala, 2010; Chancel & Piketty, 2019; Himanshu, 2018; Jayadev et al., 2007). The ILO Decent Work Team found that despite having a high GDP growth rate, the process of structural transformation was slow. Further, the majority of employment was found to be centred in agriculture and the informal economy (ILO, 2018). Hence, a majority of the working population still engages themselves in the low paying jobs. Moreover, the persistence of segmentation and fragmentation of the labour market has worsened the situation for the disadvantaged groups (Srivastava R. , 2019). As a result, low pay and wage disparity are two major roadblocks in India's quest for fair working conditions and inclusive growth (ILO, 2018).

The study of the problem of low pay and wage inequality become even more critical when the Indian economy is experiencing a slowdown. As pointed out by Marx (1844) in his Economic and Philosophic Manuscripts, “The worker need not necessarily gain when the capitalist does, but he necessarily loses when the latter loses” (p. 3). Wage employment is a vital source of livelihood today. In India, wage employment constitutes 47.8 percent of the workforce, which includes 22.8 percent regular/salaried employment and 25 percent casual employment (NSO, 2019, p. 62). These wage workers depend on their wages for their daily consumption. Hence, the level of wages is essential for the well-being of the wage earners and their family members. It is also a crucial indicator of social justice and economic progress (Papola & Kannan, 2017). The importance of wages becomes even more acute for developing countries because the income of a sizable population hovers around the poverty line. Several studies on poverty in India have shown a strong correlation between wages and poverty (Deaton & Dreze, 2002; Himanshu, 2007), where a decent wage can help in reducing poverty and inequality. It can also raise the living standards of the wage dependent population and their family members. Therefore, wages are a powerful tool for improving social equality and equity amongst the citizens by redistributing the wealth of the nation.

According to the neo-classical framework, it is supply and demand that governs wages (Borjas, 2016). It has been proposed that the identity of an individual play an insignificant role in the labour market. However, several empirical studies have suggested otherwise. This has led to a

debate within and outside the neo-classical framework regarding the persistence of inequalities based on social identity. While on the one hand, Becker argues that the discrimination based on identity will disappear as it is not profitable for the discriminating firms, other scholars have argued that identity is the basis for the persistence of inequalities and it helps capitalism in sustaining itself. Therefore, it is imperative to comprehend the role of identities in the labour market. Caste and gender identities affects every sphere of labour market from access to capital assets, enterprises, employment, schooling, civil liberties and political rights, and other social necessities (Thorat S. , 2008) and it might take the shape of job access, payment, and working environments.

To comprehend the significance of identity in the labour market, two mutually related concepts of exclusion and discrimination are important. Social exclusion is described as an individual's inability to engage in society's essential political, economic, and social functions as a result of denial of equal access to opportunities (Thorat S. , 2008). According to Amartya Sen, exclusion can take two forms of either unfavourable exclusion or unfavourable inclusion (Sen, 2000). While in the case of unfavourable exclusion, certain groups are left out, unfavourable inclusion is defined as inclusion under extremely unfavourable terms. In the mainstream economic literature, discrimination occurs when unequal treatment of an individual happens in the labour market based on non-economic characteristics like caste, gender, race, ethnicity and religious background. Further, the process of social exclusion and discrimination are embedded in social relations. Economic and social institutions play a critical role in mitigating exclusionary behaviours. Therefore, it important to locate discrimination based on caste and gender in its historical perspective and this would require re-examining the changing role of Patriarchy and Brahminism in controlling labour of women and Dalits under the current capitalist mode of production.

There have been studies that have acknowledged the existence of discrimination on the bases of gender and caste identities in the labour market. However, there is a lacuna in existing literature as to attempts to analyse the reasons for the persistence of such discriminations. Therefore, this study is an attempt not only to provide evidences of discrimination based on caste and gender in the labour market but to also critically analyse existing literature which provides an explanation for the persistence of wage discrimination among equally skilled workers. Because the neoclassical theories fail to explain the persistence of discrimination, other theoretical frameworks have been explored and utilised in an attempt to answer this question. The study begins by analysing the state of the Indian labour market and the changes

that has happened between 2011-12 and 2018-19 in terms of labour market outcomes like the labour market participation, rate of unemployment, worker population ratio, as well as quality of jobs generated. The study then analyses the distribution of wages based on caste and gender. It then estimates the extent of wage discrimination against socially disadvantaged groups like women and Dalits. In the end, this dissertation would present a critical evaluation of the various explanations with regards to persistence wage discrimination provided by several schools of thought.

2. Research Questions

In the light of the discussion made above, following questions would be taken up in this dissertation:

1. What changes have occurred in the labour market structure between 2011-12 and 2018-19?
2. Is there a wage disparity based on gender and caste identities in the Indian labour market between 2011-12 and 2018-19?
3. Are there significant discriminatory practices against women and Dalits in regular urban labour market? How does this behaviour vary across different percentile groups?
4. What do existing theories have to say about the persistent wage discrimination against women and Dalits?

3. Organisation of the Dissertation

The present research is divided into four chapters apart from the introductory and concluding remarks. The first chapter of the thesis makes a comparative analysis the 68th round of NSSO-EUS and the PLFS along with the methodology of the study. The second chapter consists of a comprehensive literature review of the theoretical and empirical studies done on the question of wage discrimination. The third chapter evaluates the state of the Indian labour market between 2011-12 and 2018-19. In the fourth chapter, the first section sheds light on the trends and patterns of the distribution of wages by gender and social group. Then, the second section analyses the extent of discrimination against Dalits and women using mean and quantile-based decomposition method. The final concluding section summarises the findings of the study and tries to put forth a possible policy intervention.

Chapter 1: Data Sources, Measurement Issues and Methodology of the Study

1. Introduction

There are several sources through which labour statistics are collected, compiled and disseminated in India, including several official sources. The official sources of wage statistics have been broadly divided into two categories based on the method of collecting data. The first is a set of data sources based on annual returns submitted under various labour regulations and the second one being survey-based sources (Papola & Kannan, 2017). Out of all the data sources on wages, the Employment and Unemployment Survey (EUS) carried out by the NSSO was the only data source that covers both wage and salary earners (Papola T. S., 2014). However, the NSSO-EUS has recently been replaced with a Period Labour Force Survey (PLFS) survey conducted by the National Statistical Office (NSO) under the same ministry. The NSO was created on 23rd May 2019 by merger of the NSSO and the Central Statistical Office (CSO).

There have been several debates since then regarding the comparability of the two data sets; therefore, this chapter is an attempt to comprehend the changes that were brought in PLFS data sets and its comparability with the EUS. In the process of understanding the compatibilities of the two data sets, the chapter also discusses the measurement issues that arise while using these data sets. In the end, we will discuss the methodology that would be employed for the measurement of wage disparities and discrimination in the Indian labour market.

2. NSSO-EUS to PLFS

The NSSO-EUS was one of the most comprehensive data sources for labour statistics. It covered all categories of workers in the economy, along with their industrial activity and occupational codes. The data could be further disaggregated by age, gender, social groups, region, and state. The conceptual framework for conducting such surveys is based on the suggestions of the Expert Committee known as the Dantwala Committee (NSSO, 2014).

The first such survey was carried out in 1972-73 and evolved as an integral part of the quinquennial household socio-economic survey, which included 'Household Consumer Expenditure' and 'Employment and Unemployment' surveys. Nine such surveys have been

conducted till now including the 68th round undertaken in 2011-12, which was to be last in this series. Despite the success of the quinquennial surveys, a need for a more frequent survey was felt. Therefore, an annual series was started in 1989 by the NSSO from its 45th round of survey. However, the sample size for the annual survey was much smaller and the two data sets were thus not comparable, because in the quinquennial surveys, the current weekly status is calculated from the daily activities of the reference week, whereas it was calculated by direct question in the annual rounds. Therefore, it was discontinued after the NSS 59th round (January - December 2003) and a different schedule on employment and unemployment was canvassed from the 60th round (January - June 2004), which was conceptually similar to the quinquennial rounds. However, they continue to suffer from the issue of comparability that arises due to different sampling design and smaller sample size (Himanshu, 2011). Similarly, the need for an annual survey had been recognised by the Ministry of Labour and Employment upon which they started conducting an annual survey from 2009-10 onwards. They continued collecting data till 2015-16 when all surveys on labour market statistics were virtually stopped by the Government of India and a task force was constituted on 11th May 2017 under the chairpersonship NITI Aayog's Chairperson to improve data on employment. It recommended replacing existing surveys with the Periodic Labour Force Survey (Panagariya, 2017). The main reason cited for this change was the stated need for making available statistics on the labour force at more regular intervals (NSO, 2019). While the NSSO-EUS was quinquennial, The PLFS's aim is to track quarterly changes in urban labour market statistics as well as to estimate the annual changes in labour market indicators for both rural and urban regions.

Besides the low frequency of the quinquennial NSSO-EUS surveys, the committee cited the time lag between data collection and availability of results as a reason for its recommendation to replace them with the PLFS. The NSSO-EUS surveys usually took a year for data collection and the tabulated results were made public only a year after that. Therefore, the requirement for more regular access of labour market statistics was long felt and a National Statistical Commission (NSC) on PLFS was first constituted by the MoSPI on 24th February 2009 with Prof. Amitabh Kundu as the head of the committee. The main objective of the committee was to provide statistical indicators on the labour market for the urban population on a quarterly basis. Following this, the NSSO established a standing committee chaired by Prof. S. P. Mukherjee on 12th November 2014. The standing committee decided that apart from generating quarterly estimates for urban areas, the PLFS would also be used to collect information on employment and unemployment status annually, which would encompass both rural and urban

regions. Finally, in May 2019, the first Annual Report of PLFS based on data gathered between July 2017 and June 2018 was released.

However, the PLFS gained much criticism after a report by daily newspaper in January 2019 was published that showed unemployment to be on a 45-year high (Ramakumar, 2019). Subsequently, the PLFS data and report was halted by the government, citing its unreliability. Later on, many articles were written by government officials and many economists stating that the PLFS is unscientific in design and not comparable with the Employment Unemployment Surveys (EUS) of the NSSO (Kant, 2019). Economists like Surjit Bhalla went to the extent of calling the PLFS survey a “statistical embarrassment” (Bhalla, 2019). However, the PLFS report was later released in May 2019, immediately after the 2019 Union elections. The report has itself compared the PLFS data with previous NSSO data with a precautionary note stating changes in the methodology of sampling design. Therefore, it is imperative to study the changes in sample design to understand the reliability and usability of the PLFS data.

The changes brought about in the questionnaire also require a detailed study as they raise questions regarding the comprehensibility of the two data sets. Hence, a thorough and critical comparison would be made in this section between EUS and PLFS with respect to sample design and preparation of the questionnaire. Simultaneously, a discussion will be undertaken on the measurement issues that are faced while measuring employment, unemployment, and wages in the labour market.

2.1. Sampling Methodology: A Critical Comparison between EUS and PLFS

There have been several contestations with regards to changes in the sampling methods of NSSO-EUS and PLFS surveys. These changes brought in the sampling methods have raised questions with regards to the comparability of the two surveys (Bhalla, 2019). Therefore, in this section, a detailed analysis of the changes in the sampling method brought by the PLFS from its predecessor EUS will be done. In the end of the section, an analysis with regards to the question of the comparability of the two data sets would be done.

2.1.1. Data Collection Mechanism

During the data collection for PLFS, the “paper schedule inquiry” used by the NSSO has been replaced by “computer-assisted personal interviewing (CAPI)” for the first time. The CAPI has

“in-built validation rules” where data is mostly validated at the time of the survey itself (NSO, 2019).

2.1.2. Frame of Sampling

The sample frame for urban areas was a latest list Urban Frame Survey (UFS) blocks. The 68th round of the quinquennial survey selected entire UFS blocks from the 2007–12 frame whereas in the PLFS, 50 percent of the towns were identified from the UFS 2012–17 frame and another 50 percent from UFS 2007–12 frame. While the rural sample frame for the 68th round of the EUS was a list of 2001 Population Census villages, it was 2011 Population Census for the PLFS.

2.1.3. Period of Sampling

Unlike the previous NSSO Employment-Unemployment Surveys, where the period of survey used to be for a duration of one year, the PLFS survey is supposed to be continuous without any break. In the 68th round of NSSO-EUS, the survey period was one year starting from 1st July 2011 to 30th June 2012. The period of survey was then divided into four sub-rounds and every sub-round was of three months duration. In addition, an identical First-Stage Units (FSUs), were assigned to guarantee a uniform distribution of sample FSUs throughout the survey period (NSSO, 2011).

2.1.4. Sample Design

Both the PLFS and the 68th round of the NSSO-EUS used a stratified multi-stage sampling design. The Urban Frame Survey (UFS) blocks were included in the FSUs for urban areas with a different frame of sampling for the PLFS and the EUS, as discussed in the above section. The ultimate stage units (USU) for both the PLFS and the 68th round of the NSSO-EUS were households. In the event of large FSUs, hamlet groups/sub-blocks were developed as intermediary stage units.

However, the method of canvassing the selected households was changed in the PLFS. As discussed above, the primary purpose of PLFS is to ensure availability of key labour market estimates at a frequent time interval. For urban areas, it would be available on a quarterly-cum-

annual basis and an annual basis in rural areas. In other words, yearly estimates were made available at the Usual Status (Usual Principal Status and Usual Subsidiary Status) and Current Weekly Status (CWS) for both urban and rural areas. The quarterly estimates at CWS were made available to capture the periodic changes in the estimates for urban areas. Further, a rotational panel sample design has been adopted to capture quarterly estimates for urban areas (NSSO, 2016).

2.1.4.1. Rotational panel design for urban areas in PLFS

In a rotational panel sampling design, each selected household was visited four times, with a visit schedule for the first time and with a revisit schedule for the subsequent three visits. However, at the outset, all of the selected First State Units (FSUs) had their households listed and selected. Only 25% of the First State Units (FSUs) of urban yearly allotment were covered in the first quarter (Panel P₁₁) of the initial rotating panel, which lasted two years. The first visit questionnaire was surveyed among the households selected for Panel P₁₁, where P_{ij} indicates panel associated with jth quarter and ith period of rotation in the year. Another 25% of FSUs was covered with first visit schedule in the second quarter (Panel P₁₂) along with the revisit schedule for the households covered under (Panel P₁₁).

Similarly, the next 25% of the FSUs were surveyed in the third quarter, where the first visit schedule and the households covered in the Panel P₁₁ and Panel P₁₂ were surveyed with revisit schedules. In the fourth quarter, the first visit scheduled was canvassed for a new Panel P₁₄ and Panel P₁₁, Panel P₁₂ and Panel P₁₃ were surveyed with revisit schedules. 75 percent of FSUs (3 panels - P₁₂, P₁₃ & P₁₄) were common in the following quarters of the second year, and an previous panel (P₁₁) was substituted with a fresh panel (P₁₅) for surveying the first visit questionnaire. Until the eighth quarter, this procedure continued.

Panel P₂₁ from the updated frame was chosen in the 9th quarter (first quarter of the next two-year period), while survey was conducted for panels P₁₆, P₁₇, and P₁₈ from the preceding frame. The same strategy was extended for two more years, with panels P₂₂ to P₂₈ being introduced every quarter for the next seven quarters until the conclusion of the fourth year (NSSO, 2016, pp. A-3).

Thus, from Table 1 we can observe that starting from the 5th quarter, this scheme of panel rotation generates estimates with 75% matching between consecutive quarters. Further, it was expected that this method would provide an estimation for successive quarters without any

break (NSSO, 2016, pp. A-3). The first visit schedule is canvassed for 25% of the FSUs in each quarter, similar to the NSSO-EUS sub-rounds.

Table 1: Rotational Panel Survey Design for Urban Areas in PLFS

Panels for the first 2-year period								Panels from updated frame for the next 2-year period			
During the four quarters of the first year				During the four quarters of the second year				During the four quarters of the third year			
Qtr1	Qtr2	Qtr3	Qtr4	Qtr1	Qtr2	Qtr3	Qtr4	Qtr1	Qtr2	Qtr3	Qtr4
P₁₁*	P ₁₁	P ₁₁	P ₁₁	P ₁₅ *	P ₁₅	P ₁₅	P ₁₅	P ₂₁ *	P ₂₁	P ₂₁	P ₂₁
	P ₁₂ *	P ₁₂	P ₁₂	P ₁₂	P ₁₆ *	P ₁₆	P ₁₆	P ₁₆	P ₂₂ *	P ₂₂	P ₂₂
		P ₁₃ *	P ₁₃	P ₁₃	P ₁₃	P ₁₇ *	P ₁₇	P ₁₇	P ₁₇	P ₂₃ *	P ₂₃
			P ₁₄ *	P ₁₄	P ₁₄	P ₁₄	P ₁₈ *	P ₁₈	P ₁₈	P ₁₈	P ₂₄ *

*Panel canvassing first visit schedule

Source: Annual Report of PLFS for July 2017-18

2.1.4.2. Sample Design for Rural Areas in PLFS

In rural areas, the selected households were visited only once with the first visit schedule. As pointed out in Table 2 the two-year survey period was divided into eight quarters, and the samples for all of them were selected before the commencement of the survey. Only 25 percent of annual allocation was covered in each quarter, similar to each sub-round of NSSO-EUS surveys. Independent estimates for each quarter were ensured by multiplying the quarterly allocation for drawing interpenetrating sub-samples by two.

Table 2: Survey Design for Rural Areas in PLFS

Panels for the first 2 year period								Panels from updated frame for the next 2 year period			
During the four quarters of the first year				During the four quarters of the second year				During the four quarters of the third year			
Qtr1	Qtr2	Qtr3	Qtr4	Qtr1	Qtr2	Qtr3	Qtr4	Qtr1	Qtr2	Qtr3	Qtr4
R₁₁*	R ₁₂ *	R ₁₃ *	R ₁₄ *	R ₁₅ *	R ₁₆ *	R ₁₇ *	R ₁₈ *	Fresh rural samples in third year from the updated frame			

R_{ij}* indicates sample covered in rural areas for ith two-year period in jth quarter.

Source: Annual Report of PLFS for July 2017-18

It is important to note here that such rotational panel design could have been beneficial for the rural areas too as it would have helped in capturing seasonal variations in the rural labour market. However, there are no revisits for rural samples.

2.1.5. Stratification

The sampling for both the NSSO-EUS and the PLFS are based on NSS regions. NSS regions are made up of many districts within a state that have comparable agro-climatic and socioeconomic characteristics. In rural areas, each NSS region constituted rural stratum for PLFS. However, within each NSS region, strata were constructed based on the size classification of towns according to their population as determined by the 2011 Population Census.

Stratum 1:	All towns with population less than 50,000.
Stratum 2:	All towns with population 50,000 or more but less than three lakhs.
Stratum 3:	All towns with population three lakhs or more but less than 15 lakhs.
Stratum 4, 5, 6,... :	Each city with a population of 15 lakhs or more.

Source: Annual Report of PLFS for July 2017-18

The stratification of the first stage units in the 68th round of NSS-EUS was undertaken within each district of a State/UT. The following were the two basic strata that were formed:

- i. **Rural stratum** included all of the district's rural areas, and
- ii. **Urban stratum** included all of the district's urban areas.

If there were more than one town in an urban area with a population of 10 lakhs or more, each of them was treated as a distinct basic stratum, with the remaining urban regions of the district being treated as a separate basic stratum.

2.1.6. Sub-stratification

In the urban areas sub-stratification has not been done in the PLFS. In rural regions, “r/8” sub-strata were constructed for every rural stratum, where “r” is the total number of samples assigned for each rural stratum. Within each stratum, villages were initially organised in ascending order of population size. The sub-stratums were then delineated from 1 to “r/8” in a such a way that every sub-stratum constitutes of villages with similar populations.

The procedure for sub-stratification for the 68th round of the NSSO was similar for rural areas. But instead of forming “r/8” sub-strata, “r/4” sub-strata were created. A district’s villages were initially arranged in ascending order according to their population size and then form sub-strata consisting of villages with similar population.

On the other hand, “u/4” sub-strata were defined for urban areas, where “u” is the sample size of that stratum. The sub-strata were created by organising towns in ascending number of households available in each town in accordance with UFS. After that ‘u/4’ sub-strata were generated using the organised frame of UFS blocks, with each sub-stratum consisting of about the same number of households.

2.1.7. Sample Size

In comparison to the 68th round of NSSO-EUS, the PLFS has better coverage with relation to the total number of FSUs and households surveyed. However, its coverage of rural areas is less extensive. The total number of FSUs covered for the PLFS 2017-18 is 12,800, including 7,024 villages and 5,776 UFS blocks while in the 68th round of the NSSO-EUS 12,737 FSUs with 7,469 villages and 5,268 UFSs were covered. The total households surveyed were 1,02,113 and 1,01,724 for the first visit of PLFS and 68th round of the NSSO respectively.

2.1.8. Sample Selection for First Stage Units

The selection of FSUs in rural areas was done through the method of probability proportional to size with replacement (PPSWR) scheme with size consists of village population according to the censuses of 2001 and 2011 respectively for the 68th round NSSO and the PLFS respectively. For both surveys, samples were taken at random from each stratum/sub-stratum in the form of two independent sub-samples.

However, for urban areas, the method for selection of urban FSUs was simple random sampling without replacement (SRSWOR) for 68th round of NSS-EUS. In contrast, it was PPSWR scheme for PLFS. To confirm the rotating system was implemented in PLFS, a random sample of four sets of sample FSUs of identical size were selected. For both surveys, samples were taken from each stratum/sub-stratum and two independent sub-samples were formed.

2.1.9. Sample Selection for Second Stage Units

With regards to large FSUs hamlet groups/sub-blocks were created based upon the size of the population. Following that, in each FSU and its hamlet groupings, the second stage strata (SSS) were developed based on an index that roughly represents their socio-economic condition.

Table 3: Criteria for the Formation of Second Stage Stratum for PLFS and 68th round of NSSO-EUS

SSS	Criteria for the Formation of SSS	Number of Members	Number of Households to be Surveyed	
			FSU without hamlet group (HG) formation	FSU with HG formation (for each hg)
PLFS (Urban)				
SSS 1	number of members in the household having level of general education as secondary (10th standard) or above	3 or more	2	1
SSS 2		2	2	1
SSS 3		1	2	1
SSS 4		0	2	1
PLFS (Rural)				
SSS 1	number of members in the household having level of general education as secondary (10th standard) or above	2 or more	2	1
SSS 2		1	4	2
SSS 3		0	2	1
NSS 68 th Round (Urban)				
SSS 1	relatively affluent households	-	2	1
SSS 2	of the remaining, households having principal earning from non-agricultural activity	-	4	2
SSS 3	other households	-	2	1
NSS 68 th Round (Rural)				
SSS 1	households having MPCE* of top 10% of urban population	-	2	1
SSS 2	households having MPCE* of middle 60% of urban population	-	4	2
SSS 3	households having MPCE* of bottom 30% of urban population	-	2	1

*Monthly Per Capita Consumer Expenditure (MPCE) obtained from NSS 66th round (2009-10) for each NSS region was used

Source: Annual Report of PLFS for July 2017-18

While the number of second stage strata remained three for rural areas, it has been increased to four for urban areas in the PLFS. By taking samples from each socio-economic group, the possibility of sample biases is reduced. Further, the level of education has replaced the criteria of economic affluence represented by Monthly Per Capita Expenditure (MPCE) used in the 68th round of the NSSO-EUS as discussed in Table 3.

2.2. Changes Made to the Questionnaire

The changes brought about in the methodology of sample selection have created a lot of debate, but these are not the only changes made to the PLFS. Apart from the sample selection methodology, there were several changes made in the PLFS questionnaire. While NSSO introduced many new parameters, many existing questions were removed. We'll look at that in the next section, the changes made in the questionnaire and thus consequent changes in the database on employment and unemployment, including wages.

2.2.1. Information related to Household Characteristics and Demographic Particulars of Household Members

Questions regarding household for example size of household, religion, household type, and social group remained unchanged between the two surveys. Similarly, questions on household members' demographic characteristics, such as their name, relationship to the head of the family, marital status, age, general educational level, and technical educational level, have remained unchanged. However, several other questions with regards to household characteristics and demographic particulars have been altered. First of all, the PLFS has recognised the third gender for the first time, making the survey more gender-inclusive. Secondly, a whole new section of follow-up questions has been added to the questionnaire for those who have received formal vocational/technical training. The PLFS now includes questions on training completion, training period, training field, and source of funding for training, giving improved coverage for skill-related data. Thirdly, a question with regards to the number of years in formal education, has been added. However, other equally important aspects of information on general education such as institutional type (governmental or non-governmental) and registration with placement agency have been removed.

There are several questions regarding household characteristics such as the principal occupation of the household, principal industry, access to land, questions related to the Mahatma Gandhi National Rural Employment Guarantee (MGNREG) scheme and accessibility of banking facilities have been removed, which made the socio-economic enquiries less comprehensive. Access to land is particularly important as it is one of the primary determinants of socio-economic status of a household in rural areas. Even the MGNREG scheme is an important source of income in rural areas. The removal of these crucial questions makes the survey more skewed towards urban areas.

2.2.2. Questions Related to Availability, Accessibility and Intensity of Work

Many indicators regarding the availability, accessibility, and intensity of work have been modified in the PLFS questionnaire. For example, the query on “mode of payment” for the regular salaried and casual wage earners was removed along with queries like “period of seeking / available for work during last 365 days”, “whether unemployed in all the seven days of the week,” and “duration of present spell of unemployment.” This was important information for examining the severity of the unemployment situation. Even detailed data on the types of economic activities has been removed. Furthermore, the PLFS only records two major activities taken out by household members throughout the course of the reference week. However, work intensity is measured through actual hours worked in PLFS instead of half or full-day assigned for work done for ‘1 hour or more but less than 4 hours’ and ‘4 hours or more’ respectively in NSSO-EUS.

2.2.3. Modifications made to wage related inquiries

Apart from the information regarding daily/weekly wages available previously, the PLFS has added the gross monthly earnings of the regular salaried and self-employed. This addition would help in estimating the household’s total income received through employment. However, the nuances of wage payment are lost as the PLFS has removed inquiries related to “mode of payment” that answered whether payment was made in cash or in kind. For those working in usual status, the PLFS has also deleted all follow-up inquiries on job availability, the existence of unions/associations, and the nature of employment.

2.2.4. Other Alterations

The NSSO-EUS was more than mere employment data. It can be termed a socio-economic survey as it included detailed questions with regards to both employment data as well as consumption data. However, the PLFS is limited to questions related to employment and has removed comprehensive information on consumption and expenditure. In order to ascertain the usual consumer expenditure per month, the first question put forth to the informant by the NSSO-EUS was “What is your usual expenditure for household purposes in a month?”. Subsequently questions regarding the purchase of any durables during the previous year would be asked. This gave an estimate of expenditure in a year. Then, the expenditure on durables would be divided by 12 to get monthly expenditure. In addition, any consumption out of (a) payments in-kind, (b) homegrown stock, and (c) free collection was determined. Lastly, by adding these three values the usual monthly consumer expenditure was calculated. However, it has been replaced with a single question regarding the household’s monthly consumer expenditure (Rs.) in the PLFS. This limits the examination of the socio-economic status of a household.

3. Comparability of PLFS and NSSO-EUS

In the previous sections, a discussion was undertaken regarding differences in the sampling methods and questionnaires of the PLFS survey and the NSSO-EUS. We discovered that both surveys encompassed over 1,00,000 households across India's whole geographical region. Above that these two surveys also used multilevel stratified random sampling. Both surveys gathered data over the course of a year in four unique phases (sub-samples) to account for seasonality.

One of the most significant differences between the surveys is their criteria to select second-stage stratum. For the PLFS, the basis for the identification of second stage stratification is household members with at least secondary educational attainment. On the contrary, the NSSO-EUS employs the MPCE of households as a criterion. However, in both surveys, the FSUs and village groupings (sub-blocks in case of big FSUs) are chosen based on the same population size criterion, resulting in a comparable sample composition (Mehrotra & Parida, 2019). Therefore, the two data sets are comparable to one another.

Furthermore, it was discovered that, while the questionnaire had been modified, both surveys employed identical questionnaire to collect data on the status of employment, as well as

household and individual data on the social and economic status. As a result, the PLFS data acquired during the survey's first visit is comparable to the NSSO-EUS data. Therefore, this study would use 68th round of the EUS and the first visit data of PLFS for 2018-19. While the study would use the data from across India to estimate Unemployment Rate (UR), Labour Force Participation Rate (LFPR), and Worker Population Ratio (WPR); however, the final chapter on wage discrimination and disparities would limit itself to Regular Wage/Salaried (RWS) employment in the urban labour market as it is considered to be the ideal form of work. It is generally held as an underlying principle applying to economic justice that wages should be based upon the merit or the capacity of an individual and the social identity of the individual should not have any role to play in the same. Furthermore, individual across social identities employed in the same category of work should be paid wages that are comparable. Given that the two data sources are comparable, with the exception of the caveats listed above, the next section would discuss the methodology employed in this dissertation.

4. Methodology of the Study

The primary objective of this dissertation is to determine the existence of wage disparities and discrimination in the labour market based on group identity with a particular focus on caste and gender identities. The dissertation primarily relies on quantitative methods for the same purpose. The first objective is to study the changes have occurred in the labour market structure between 2011-12 and 2018-19 and for the same purpose, LFPRs, WPRs and URs are calculated for social groups and gender. Further, the percentage distribution of workers in different segments is calculated. Then to understand the wage level for different segments of the society, average wage rates have been calculated, both at mean and percentile levels. We have also calculated the average wage by level of education and type of enterprises. However, to estimate wage disparities and discrimination, the following methodologies have been used.

4.1.Wage Ratio

The second objective is to determine the existence of wage disparity based on social identities. The wage disparities based on gender and caste identity have been shown firstly by calculating average mean wage for workers and then by estimating wage differentials using wage ratios. A wage ratio of a value less than one indicates the existence of a wage differential among various groups. In other words, it shows that the disadvantaged groups are getting lower wages

than that of advantaged groups. A wage ratio of 1 or more indicates the absence of any wage differential.

4.2. Ordinary Least Squares (OLS)

In this study, the OLS regression is used to identify the role of dependent variables in explaining the changes in independent variable. The wage equation for the urban labour market has been further calculated for those workers employed in the RWS employment for the period 2011-12 and 2018-19. The study used human capital equation for wage proposed by Mincer (1974), with the log of real monthly wage as the explained variable and the control variables included education, experience, and other household and individual attributes. The required statistical tests to correct for heteroscedasticity and multicollinearity have been applied to the data sets for both the time periods to ensure that the variables are accurate and significant. A semi-log model has been used for OLS regression. For a given absolute change in the regressor's value, the slope coefficient estimates the relative change in Y. (Gujarati & Sangeetha, 2007). The OLS equation on wage may be written as follows:

$$\ln(\text{wage}) = f(\text{Experience, Religion, Social Group and Sex, Educational level, availability of job contract, type of enterprise, other control variables})$$

in the above equation, $\ln(\omega)$ represents the log of real monthly wage of workers employed in the regular labour market in urban areas. In this equation, the log of real monthly wage is the response variable and age and age square, social group, and gender identity, availability of job contract, educational level and the type of enterprise are explanatory variables. The linear regression estimates the change in Y with respect to one unit change in X variables (Torres-Reyna, 2007).

This type of wage equation has the drawback of not accounting for what is known as ‘selection bias’. Selection bias happens because the wage equation applied to only those people who are already working. In other words, selection bias happens due to non-randomness of participation in the labour market. This is due to the lack of (anticipated) wage statistics for people who are either unemployment or out of the labour market altogether. It is reasonable to suppose that individuals who are employed earn more than those who are now jobless would have earned if they worked. The absence of such jobless people in the data causes unobservable factors that regulates their participation in wage employment to be overlooked. The link between these

unobserved variables and the explanatory variables might lead the estimated coefficients to be either positively or negatively skewed.

4.3. Heckman Sample Selection Correction

This study employs the two-step model proposed by Heckman to correct for sample selection bias (Heckman, 1979). The first step in this model is to estimate the selection equation, which has dependent variables that determine the participation in wage employment. Given employment, wage equation is estimated in the second step. The inverse Mills ratio is derived in the selection model using the projected likelihood of labour force participation. In the second stage selection bias is corrected by including the calculated inverse Mills ratio in the wage equation. The selection equation is identified by compulsorily including minimum one variable that is not included in the wage equation. If the variable is same, it will result in the collinearity between the explanatory variable of the equation on wage and the predicted inverse Mills ratio from selection equation. Therefore, one variable which affects participation in the labour market and simultaneously does not affect the determination of the wages is required. The most appropriate identifying variable suggested by theory is the non-labour income of individuals or households. However, such variables are generally missing in empirical data. Therefore, instead the literature frequently uses the number of dependents, which includes children between age 0 and 14, as well as seniors above 60 years of age. It is reasonable to assume that the number of dependents in a household is unlikely to affect the wage rate in the Indian labour markets.

4.4. Blinder-Oaxaca Decomposition

Following Becker's (1957) theory of market discrimination, Ronald Oaxaca and Alan Blinder in 1972 developed a methodology to decompose wage difference into two components. According to Becker, in the absence of discrimination and nepotism, the equilibrium wage rates of males and females would be equal in a perfectly competitive labour market. Thus, the percentage differential in wages between the two types of labour that are perfect substitute is defined as discrimination coefficient.

Blinder-Oaxaca Decomposition method divides wage gap into two components: the first component represents differences that can be explained by disparities in individuals' human

capital and another component which unexplainable by these differences, is therefore indicate the prevalence of labour market discrimination (Kumar & Hashmi, 2020; Madheswaran & Singhari, 2017).

Let us discuss the mathematical logic of this decomposition method in detail:

The gross wage gap can be expressed as:

$$G = \frac{Y_a - Y_b}{Y_b} = \frac{Y_a}{Y_b} - 1 \quad (1.1)$$

Where, Y_a and Y_b represent average (mean) wages of individuals belonging to two mutually exclusive groups. When the labour market discrimination is absent the difference between the average wage between two group would reflect pure productivity differences.

$$Q = \frac{Y_a^0}{Y_b^0} - 1 \quad (1.2)$$

Here the superscript zero signifies that the labour market discrimination is absent. The proportional difference between $G+1$ and $Q+1$ is therefore defined as the market-discrimination coefficient (D).

$$D = \frac{\left(\frac{Y_a}{Y_b}\right) - \left(\frac{Y_a^0}{Y_b^0}\right)}{\left(\frac{Y_a^0}{Y_b^0}\right)} \quad (1.3)$$

Thus, above equations combined together indicate logarithmic decomposition of gross wage gap as described below:

$$\ln(G + 1) = \ln(D + 1) + \ln(Q + 1) \quad (1.4)$$

The semi-log wage equation can also be decomposed as follows:

$$\ln \bar{Y}_a = \alpha_a + \sum \beta_a \bar{X}_a + \varepsilon_a \quad (1.5)$$

$$\ln \bar{Y}_b = \alpha_b + \sum \beta_b \bar{X}_b + \varepsilon_b \quad (1.6)$$

Where geometric mean of wages is denoted by $\ln Y$, X represents the vector of mean value of the regressors, α represents the intercept, β is the coefficients' vector and the error term is denoted by ε . The log of wage gap in this framework can be represented as follows:

$$\begin{aligned}\ln(G + 1) &= \ln\left(\frac{\bar{Y}_a}{\bar{Y}_b}\right) = \ln \bar{Y}_a - \ln \bar{Y}_b \\ &= \sum \beta_a \bar{X}_a - \sum \beta_b \bar{X}_b\end{aligned}\quad (1.7)$$

The Oaxaca (1973) decomposition expands equation (1.7) and the difference in the coefficients of the two equations provides evidence of prior discrimination. In the absence of prejudice, females will be remunerated in accordance with wage structure for males at similar endowment levels, the hypothetical female earnings function would be

$$\ln \bar{Y}_b = \sum \beta_a \bar{X}_b \quad (1.8)$$

Substituting equation (1.8) in equation (1.7) provides the following equation:

$$\ln \bar{Y}_a - \ln \bar{Y}_b = \sum \beta_b (\bar{X}_a - \bar{X}_b) - \sum \bar{X}_a (\beta_a - \beta_b) \quad (1.9)$$

The above decomposition equation can be expressed as follows:

$$\ln \bar{Y}_a - \ln \bar{Y}_b = \sum \beta_a (\bar{X}_a - \bar{X}_b) - \sum \bar{X}_a (\beta_a - \beta_b) \quad (1.10)$$

In the above two equations (1.9) and (1.10), the right-hand side terms represent endowment difference. The second terms in these equations are considered as discrimination component.

4.5. Machado, Mata, and Melly (MMM) Decomposition Method

The limitation of mean-based decomposition method has led several studies to propose Quantile Regression (QR) decomposition, which a generalised Oaxaca-Blinder mean decomposition that decomposes at quantiles rather than mean. There are several quantile-based methods. However, the modification of Machado and Mata (MM) decomposition done by Melly is used in this study.

The decomposition method proposed by Machado and Mata (MM) uses quantile regression to estimate the marginal distribution of wage that are consistent with a conditional distribution. Let $Q_\theta(y_i|x_i) = X_i \beta_\theta$ for $\theta \in (0,1)$ denote the θ^{th} quantile of the wage distribution. Counterfactual exercises can be done by comparing the marginal distributions produced by various covariate distributions. The following four steps are taken in the MM approach for generating a counterfactual log wage distribution:

1. A uniform distribution $U[0,1]$: u_1, u_2, \dots, u_n creates a random sample of size n .
2. n different quantile regression coefficients: $\beta_{u_i}^m, \beta_{u_i}^f$; $i = 1, 2, 3, \dots, n$ is estimated for both the groups.
3. The covariate distribution of the two groups then provides a random sample with sample size being n . This random sample can be expressed as follows:

$$\{x_i^m\}_{i=1}^n \text{ and } \{x_i^f\}_{i=1}^n$$

4. The counterfactual distributions are estimated as

$$\{\ln \tilde{Y}_i^{cf} = x_i^f \hat{\beta}_{u_i}^m\}_{i=1}^n \text{ or } \{\ln \tilde{Y}_i^{cf} = x_i^m \hat{\beta}_{u_i}^f\}_{i=1}^n$$

In Melly decomposition method, the unconditional distribution is estimated by integrating conditional distribution over the range of the covariates. If the number of simulations employed in the MM process reaches infinity, the Melly's decomposition estimator will be quantitatively equivalent to the MM decomposition. Further, Melly estimate has a lower mean square error in comparison to MM estimation. The convergence of these two mean square errors occurs when simulations in MM is extremely large. Further, estimator proposed by Melly is normally distributed and consistent. The gross wage differential for the θ^{th} quantile can be decomposed into two segments as follows:

$$\hat{Q}_m(\theta) - \hat{Q}_f(\theta) = [\hat{Q}_m(\theta) - \hat{Q}_{cf}(\theta)] + [\hat{Q}_{cf}(\theta) - \hat{Q}_f(\theta)] \quad (1.11)$$

Where, $\hat{Q}_m(\theta) - \hat{Q}_f(\theta)$ represents the wage gap estimation for the θ^{th} quantile of the unconditional distribution of log wage; and using the male coefficient, $\hat{Q}_{cf}(\theta)$ is the estimated counterfactual unconditional quantile of the log wage distribution for female. It depicts the female wage distribution that would have prevailed if females were paid similarly to males.

The right-hand side of the equation (1.11) constitutes of two components. The first component is the endowment or characteristics effect. It shows the wage difference between the two gender groups that can be explained by the differences in endowment represented by covariates in the θ^{th} regression quantile. The second component reflects the coefficients effect or discrimination.

An important point is being raised by this decomposition at different wage segments: Do discriminated group faces a "glass ceiling effect" or a "sticky floor effect"? The phenomenon of "glass ceiling effect" and "sticky floor effect" is tested by using criteria specified by Arulampalam et al. (2006). If the projected wage disparities in other parts of the income

distribution are at least 2 percentage points greater than the 90th percentile, the “Glass ceiling effect” is considered to have occurred. The “sticky floor effect” occurs when the wage disparity at the 10th percentile is greater than the 25th percentile.

5. Conclusion

This chapter started with an important debate regarding the comparability of the NSSO-EUS and the PLFS data sets. The chapter then conducted a comparative analysis of changes between the two data sets and found that despite all the changes brought to the PLFS data, it is comparable to the NSSO-EUS. Then a discussion was undertaken regarding the several methodologies that would be employed in this dissertation in later chapters. It was discussed that since there are several heterogeneities in the distribution of wages; therefore, it is important to go beyond the mean-based decomposition method. Hence, apart from Oaxaca-Blinder Decomposition method, the study would also employ MMM decomposition method to get a more accurate picture regarding discrimination at different wage levels.

Chapter 2: A Survey of Literature on Disparities in Wages and Labour Market Discrimination

1. Introduction

Inequality is one of the greatest problems of our times. Previous studies have shown that economic inequality in India is consistently rising (Anand & Thampi, 2016; Himanshu, 2018). While the top 1 percent households in India own almost one-fourth of the total wealth and the 20 percent wealthiest households possess around 75 percent of the total wealth, only 3.4 percent is owned by the bottom 40 percent of the households (Tagade, Naik, & Thorat, 2018). Furthermore, it was found that the Hindu high castes have highest wealth concentration in comparison with other social groups (Tagade, Naik, & Thorat, 2018).

Steward (2005) has categorised inequality into horizontal and vertical inequalities. She defines horizontal inequality to indicate inequalities that exists between culturally defined groups and differentiates it from vertical inequality, which places individuals or households in a hierarchy, vertically and measures inequality over a range of individuals. The literature on social exclusion and discrimination suggests that socially-determined identities like gender, caste, ethnicity, religion, and race have considerable relevance for the life chances and the well-being of an individual (Stewart, 2005). The social exclusion and discrimination faced by certain groups are based on their identity. This is reflected from the definition of social exclusion itself. The definition of the social exclusion provided by Buvinic is, “The inability of an individual to participate in the basic political, economic, and social functioning of society and the denial of equal access to opportunities imposed by certain groups in society on others” (Thorat & Newman, 2007). Three things are important in this definition of social exclusion: first, the unit of analysis is a culturally defined “group”; second, the process of partial or complete social exclusion of a member of a group or groups to be embedded within “social relations”; and lastly, it describes the costs of exclusion (Thorat & Newman, 2007). The study of horizontal or group inequality is not only important to understand its impact on the well-being of the excluded group but also an inter-group conflict that may arise (Stewart, 2005).

India continues to be a highly stratified society where inequality persists along socio-cultural and economic axes. The previous studies have also found that disparities among social groups are substantially high in India (Jayadev, Motiram, & Vakulabharanam, 2007; Tagade, Naik, & Thorat, 2018; Zacharias & Vakulabharanam, 2011). The identities of class, caste, gender,

religion, and region are some of the most significant facets of socio-economic disparities in India (Deshpande, 2000). Caste is one of the oldest institutions and an important social characteristic that denotes a hierarchical positioning of social groups. It is believed that caste system in India originated around 3,000 years ago. However, it still plays a central role in defining the social organisation of Indian society (Deshpande, 2000). The ritual hierarchical positioning of social groups often overlaps with occupational hierarchy, where the lowest castes occupy the bottom rung in the occupational structure. The social system of castes tended to impose significant barriers to occupational choices and exit and entry into the labour market. But these barriers to mobility have been considerably lowered under the impact of modernization (Madheswaran S. , 2006). Early caste society separated the populace into four distinct and mutually exclusive, endogamous, hereditary, and occupation-specific caste groups or *Varnas*. Four varnas are defined in the Hindu social order as described by the *Manu Smriti*¹ and each of them are assigned specific human, social, cultural, economic, political rights and therefore permissible occupations (Vaid, 2014). The Brahmins, who are considered to be the highest caste have been assigned with intellectual occupations like that of priests, bureaucracy, etc.; and Kshatriyas have been assigned to become rulers and warriors; and Vaishyas have a monopoly over trade and allied occupations, and Shudras ostensibly the ‘lowest’ in the varna hierarchy have been restricted to performing manual labour and artisanal occupations. The Ati-Sudras were excluded from the Varna hierarchy. The system forced them to perform manual and ‘polluting’ jobs like cleaning, manual scavenging, etc. They were marginalised by the other varnas and were considered outcastes and untouchables. The Varna hierarchy was relatively straightforward and clearly compartmentalized, with the ‘upper’ three tiers being considered superior to the ‘lower’ two.

However, studies on caste suggest that the caste system has evolved with changes in economic and social organisation of production. In the present context, the study of the Jati (translates to sub-caste) system plays a more significant role since it more comprehensively captures the complexities of the Indian social structure. Deshpande (2000) has raised certain important points regarding the Varna and Jati; first, jatis are not exact subsets of varnas; second, there are

¹ Manu Smriti, is a compilation of religious laws based on various earlier *Dharma-sutra*’s, or documentations pertaining to Hindu religious laws. Manu, a saint is credited with compiling these various laws into one document, known as the Manu-Smriti.

considerable regional variations in the evolution of specific jatis. This has led to graded caste inequality among different jatis. This division is instituted based on unequal economic, educational, and civil rights. The Brahmins at the highest place in this pyramid with the greatest rights and privileges. Consequently, rights and privileges diminish gradually from Brahmins to Kshatriyas, Vaishyas, Shudras, and finally to the 'untouchables', who are accorded the lowest position in the caste ladder according to legal texts of the Hindu tradition. However, for constitutional measures to guarantee affirmative action, the population is divided into SCs, STs, OBCs, and Others. The Scheduled Castes (SCs) are a constitutional category that has clubbed together all the ex-untouchable castes. These Castes have been historically marginalised and, not only have they faced an extreme form of social exclusion but they have also faced the worst form of unfavourable inclusion by being compelled to engage themselves in occupations related to clearing animal carcasses, cleaning of excreta, and other "unclean" tasks. Although SCs and the Scheduled Tribes (STs) are often clubbed together, the source of social exclusion for the Scheduled Tribes is distinct from that of SCs. While unfavourable exclusion and unfavourable inclusion in social, economic and educational systems are the causes of marginalisation among SCs, the STs are marginalised because of their geographical isolation and various other socio-economic reasons and historical factors. According to the National Commission for Scheduled Tribes, there are over 700 STs in India.

There are socially and economically backward groups that are neither SCs nor STs. The Constitution of independent India did not clearly define the Other Backward Classes (OBCs) either. However, after the SCs were listed as a separate category, the terminology 'Backward Classes' was associated with two meanings: firstly, as a cluster of all groups that required preferential treatment, and secondly, as castes that were accorded a lower position in the socio-economic hierarchy, but higher than the untouchables (Deshpande & Ramachandran, 2014). The first Backward Classes Commission (which had Kaka Kalelkar as its chairman) came into being in 1953, which was given directions to determine the criteria to be used to ascertain whether a section of the population (other than the SCs and STs) would be considered backward, and then, in accordance with these criteria, prepare a list containing the names of such classes. It was largely understood that the nature of the groups recognised by the commission would be castes or communities. Nevertheless, at the last hour, the chairman renounced the report prepared by the commission, stating that he found the use of caste to be antithetical to democratic norms and the ideal of an ultimate formation of a casteless and classless society.

The second Backward Classes commission was setup in 1978 under the chairmanship of B.P. Mandal to re-examine the issue of backwardness entirely, where the criterion for identification of backwardness would be re-ascertained. The Mandal Commission employed the use of 11 criterion to establish admissibility, which were further grouped under three heads: social, educational, and economic. Weights were assigned to the groups (social criterion were given a weight of three, while educational criterion got two and economic criterion were given a weight of one). This was completed for all Hindu communities. For non-Hindus, the commission used another set of criteria: all persons from an untouchable caste who had converted to other religions (other than Buddhism and Sikhism, which are included under the definition of SCs) but were still associated with their traditional occupations, for which their Hindu counterparts were already included in the list of SCs, also got enlisted. Based upon this enumeration, the commission identified 3743 caste groups as backward, which it estimated to be 52 percent of the total population (Mandal, 1980).

Apart from these, religion and gender of an individual also has implications on their social and economic positioning. Although there are multiple religions in India, the analysis of the Muslim community is particularly important because of the nature of conflict that arose in India. The Hindu-Muslim conflict has not only aggravated in recent times but has also become one of the focal points in the political arena. Muslims in India are relatively more deprived than any other religious community. The Sachar Committee Report (Sachar, et al., 2007) has pointed out that in certain instances, the relative share of Muslims of India is less than Hindu Dalits in education.

Gender as a category cut across all groups and plays an important role in determining the socio-economic position of an individual. Gender disparities in socio-economic outcomes have captured the imagination of scholars in developed and developing economies alike. The culturally determined social reproduction responsibilities placed upon women are the reason for many forms of gender-based exclusion.

Although group inequality is multidimensional and affects almost all spheres of human life, this dissertation specifically focuses upon the disparities and discrimination in the distribution of wages among these culturally defined groups. According to neo-classical theory of wage determination, wage differentials among workers would not exist in a perfectly competitive labour market (Borjas, 2016). However, contrary to this postulation the existence of wage differential among workers across industries, occupations, sectors, regions, castes, races, etc. is commonly observed. In neo-classical economic theory, wage differentials are understood

only through the lens of differences in individual productivity. On the one hand, the theory of compensating wage differentials argues that wage differential arises because jobs are different, and on the other hand theory of human capital argues that it arises because workers are different (Borjas, 2016). However, they failed to explain wage differentials that exist between two workers having the same employment, education, and training. The later kind of wage differentials are called wage discrimination if the differentials arise due to differences in non-economic personal characteristics. Arrow (1971) states that discrimination in labour market arises when the valuation is done based on worker's personal characteristics, which has no relation to the productivity. While most of the works on labour market discrimination in developed countries are focused around race and gender, such discriminations in the Indian context exist due to the intersections between the caste, gender, and religious identities of individuals.

There have been several national and international studies to understand wage discrimination. In this chapter, a comprehensive literature review has been conducted. For the sake of expediency, the review of literature has been divided into two sections of theoretical literature and empirical studies. In the following first part, a critical assessment of theories of labour market discrimination is presented. Economic thought regarding discrimination is chiefly split in two major schools, presenting a broad explanation for the existence of the labour market discrimination. The first one is neo-classical theories encompassing the "Taste for Discrimination" theory by Becker (1957) and the theory of "Statistical Discrimination" given by Phelps (1972). The alternative and a more critical theory of discrimination is segmented labour market approach (Doeringer & Piore, 1970). The second part of this chapter will presents a summary of important empirical studies done analysing the existence of labour market discrimination in the Indian context. The first part of this section discusses discrimination based upon gender in the labour market and the second part discusses the discrimination based on socio-religious identity.

2. Theoretical Literature on Labour Market Discrimination

Although most literature in mainstream economics is formulated upon the hypothesis that the social identity of an individual has ceased to matter in the market, there are however a few exceptions that discuss the impact of social identity on economic outcomes. The two main neo-classical theories taking into account group identity are "taste for discrimination" (Becker,

1957) and “statistical discrimination” (Arrow, 1971). However, they approach discrimination from opposite ends.

The “taste for discrimination” theory was first formulated by Gary Becker in 1957 in which he argued that the employers, customers or workers may have a “taste for discrimination”; which indicates that they have a preference for a particular group of people (England & Lewin, 1989). Thus, he combined the discrimination in the conventional neoclassical theory to propose that “taste for discrimination” is one of the factors in the utility function. It was suggested by Gary Becker that economic agents, who have a “taste for discrimination”, would be willing to pay a price to discriminate. For example, supposing that workers are divided in two groups mutually exclusive groups of black and white workers. An employer faces constant price in a competitive labour market; the wage for white employees is represented by W_W and for black employees it is represented W_B . Thus, if an employer has a taste for discrimination, meaning that he is biased against black workers, the employer would get disutility from employing them. Alternatively, although the cost of hiring a black worker for an hour is W_B , the employer will then conceive costs to be $W_B(1 + d)$, where d being a positive discrimination coefficient (Borjas, 2016).

It is important to note here that Becker’s theory conceptualises ‘prejudice’ as something that arises from a belief or value system that is formed without an “objective consideration or fact”. It is not necessary that the prejudice have its origin in the employers’ taste and preference; it can also originate when co-workers are prejudiced against each other on the basis of caste or when the consumer discriminates based upon the identity of a worker while making economic exchanges in the market. The discrimination coefficient, thus, “monetises” prejudice, without regard to the source of the prejudice, which may either be the employer (called as “employer discrimination”), or the employee (called as “employee discrimination”), or even the customer (called as “customer discrimination”). A different scenario is presented through the example mentioned above where occasionally black employers prefer hiring black workers. This type of prejudice is called nepotism, and it suggests that the utility-adjusted cost of employing a worker from a preferred group is equal to $W_B (1 - n)$, in which the “nepotism coefficient” n being a positive number. In the hypothetical situation where the black employers in the abovementioned example favour black employees than they will rather perceive that hiring a black employee is relatively inexpensive. In Becker’s theory, the stronger is the prejudice or nepotism, the higher is the value of d and n within the non-market realm and suggests that labour market discrimination will inevitably affect the profitability of the firm that discriminates. Thus, the ultimate analysis of this theory also suggests that, in a competitive

labour market, the discriminatory firms will lose out to non-discriminatory firms and wages will settle around the equilibrium wages (Borjas, 2016).

In a situation when the job market is not differentiated into discriminatory and non-discriminatory firms and all the firms are discriminatory towards a particular group, the Becker theory then suggests that all firms will tend to be segregated on the basis of the identity that is the basis of discrimination, that is in the above mentioned example, such firms that have a small discrimination coefficient become firms with overwhelming black workers (thus black firms) and the firms that have a higher discrimination coefficient will employ a majority of white workers (thus white firms). Suppose that the labour market is dominated by one group, say white employers, and all of them have a positive discrimination coefficient and no employer wants to employ a black worker. When the wages of black workers exceed that of the white workers such that the ratio of wages of black workers to the wages of white workers (W_B/W_W) is more than one, no employer, even the employers with the lowest discrimination coefficient would want to hire black workers. When the real charge of employing black workers is higher than the price of employing their white counterparts, the utility-adjusted price of labour of black workers would be even higher. In fact, even if the wage for a black worker were slightly less than the wage for a white worker, the utility-adjusted wage for a black worker would probably exceed the wage for a white worker, consequently employers will not employ any black employees. Now, let us look at another a situation, where the relative wage of black workers further decreases. At certain point, the firm that has the smallest bias crosses a minimum level when firm becomes a black firm because wage of workers from black community are relatively cheaper than that of white workers - even post-adjustment for the disutility that the employer incurs from hiring black workers. Thus, the demand and supply curves intersect at lower point where the wage ratio for black and white employees is equal to one, so the employer discrimination leads to the generation of a wage gap between employees of equal skill.

In defence of Becker's theory, Arrow (1971, 1998) defines discrimination with regards to the perception of reality of the employer. Unlike the taste-based theory of discrimination, the model proposed by Arrow assumes no bias on the part of the employers. According to him, employers tend to discriminate against a group because the worker's value to the employer is not known with a degree of certainty. Using consumer choice theory and theory of the firm, he constructs a theoretical model where on condition of employers having preconceived notions

regarding female workers possessing a productivity lower than male workers, employers will only be ready to employ female workers at wages less than that of their male counterparts.

Following Arrow, Phelps (1972) developed a statistical discrimination approach, which states that even in the absence of prejudice, discrimination can arise. It is then ascribed to the presence of imperfect information in the labour market. It is a deviation from the general equilibrium theory that supposes that the availability of information is perfect and costless. However, this theory says that, in reality, this assumption of the general equilibrium theory does not hold and employers can't determine the productivity of a worker prior to employing them. Therefore, the theory suggests that discrimination happens when information about the productivity of a worker is estimated grounded upon the productivity of the group they belong to. In other words, the employers use group identity like race or gender and group averages are taken as indicators for individual productivity (England & Lewin, 1989). For example, suppose that there are two applicants for a job with identical résumés differing only with regards to their gender identity. In such cases, a colour-blind, gender-blind and profit-maximizing employer would seek group statistics to decide which employee to hire. Let us suppose a review of statistical records display a likelihood for women to leave their employment in their later twenties. There is no way for the employer to know, with any certainty, whether a particular female applicant intends to work beyond their late twenties. Nevertheless, the employer deduces based upon the statistical data that women have a higher likelihood of leaving their work. Hence, employer chooses to hire the male applicants over their female counterparts. This example shows how applicants from a high productivity group, by virtue of their membership in said groups, are privileged over applicants from low productivity groups.

In the above example, groups averages are employed to determine the productivity of an individual. Employers tend to regard members of a particular group to be endowed with equal abilities while using and propagating dominant stereotypes to determine group abilities. For example, employers might assume that women are generally less productive than men and use this belief to decide their wages. George Akerlof used the same theory to explain the correlation between caste identity and economic outcomes and explains “the caste identity of the agent perceived by other agents is seen as an indicator of merit or worth, which in turn, determines their labour market outcomes in terms of hiring and wage” (Thorat S. , 2012, p. 32). Thus, where such discriminatory practices are extant, the important neo-classical postulate that holds workers' payment to be in accordance to their marginal productivity does not hold water. Hence, changing just one of the several assumptions of the neo-classical general equilibrium

theory severely alters the conclusion and shows that profit-maximising agents can discriminate. In this sense, it is a very powerful theory. An employer with negative stereotypes against a particular group is less likely to assign a member of that group to a high position (Coate & Loury, 1993). Thus, an economy with discriminatory practices tends to divide workers with similar abilities along the lines of social identity. This echoes strongly with Ambedkar's understanding of "the caste system being a system of division of labourers rather than one of labour" (Ambedkar B. R., *Annihilation of caste*, 2014).

The two neo-classical theories of labour market discrimination question the assumption of existence of a perfectly competitive labour market. While the availability of information plays an important role in statistical discrimination theory, has no role in Becker's theory. In the taste for discrimination theory, the employer chooses to discriminate even when all information is available to them and they are aware of the consequent loss of income. But discrimination being recognised in these neo-classical theories of labour market discrimination, it is ascribed to individual behaviour and do not take into account the historical and structural factors that are central for the production and perpetuation of inequality across groups, both in terms of opportunities and outcomes.

The neo-classical theories of labour market discrimination have been criticised for their ahistorical analysis of discrimination and for their ignorance to institutional and systemic structures. The "competitive labour market" analysis of discrimination is unable to explain discrimination's persistence against disadvantaged groups in the long run. An alternative understanding is posited by J. S. Mill in 1885, who whilst rejecting Smith's notion of competition argued for analysing non-competing groups in the labour market. Mill argued that institutional realities are so widely prevalent and important that they cannot be characterized as mere departures from otherwise competitive markets.

Developing upon Mill's argument, the theory of the segmentation posits that the market for labour is split into relatively isolated sectors on the basis of sex, caste, and racial origin, and that there exists miniscule interaction between these sectors. There are two variants of this approach to discrimination: the hypothesis of "job crowding" and that of the "dual labour market". While the "job crowding" hypothesis suggests "job segregation" is based on group identity, the hypothesis of the "dual labour market" recognises primary and secondary segments of work.

The “job crowding hypothesis”, also termed as employment segregation. The theories proposed by Fawcett in 1918 and Edgeworth in 1922 are early instances of such an analysis which have argued that the over representation of women in certain occupational categories consequently depressed wages in those occupations. Thus, such kinds of discrimination could lead to exclusion of women from jobs which they have the capability to be employed in. If there exists a tendency for such jobs to be high paying, then this would lead to the creation of pay disparities between males and females. In their investigation of job segregation, women face barriers to access to certain jobs especially ones that highly specialised and high paying jobs. Such barriers to entry into the labour market may not always present themselves as a straightforward ban on hiring women; the criteria for the entry may be set in such a way that it’s disadvantageous for women like lengthy periods of training or the requirements for a specific employment history which inadvertently excludes a disproportionate number of women. Hence women face unfavourable inclusion by being forced to employ themselves in ‘easily accessible jobs.’

The dual labour market theory is a relatively recent and popular formulation developed by Piore and Doeringer (1970), where they have differentiated between the primary and secondary sections within the labour market. They have comprehensively elucidated upon the definitions of the segments as follows: Employment in the primary segment possesses multiple of the given features like better conditions of work, high wages, probability of promotion, employment stability, and proper regulation of management of the rules of employment. In contrast, employment in the secondary segment, tends to be associated with lower wages and minimal benefits, low working conditions, lower probability of promotion, high labour turnover, and arbitrary rules and regulation. The crux of the labour market segmentation approach is that segmentation in the labour market does not exist due to skill differentials, rather institutional rules act as a substitute for market processes. The implications of such segmentation in the labour market are that the mechanisms of price do not function properly either in the primary or the secondary segments.

A clear distinction is made here between discrimination in the labour market and segmentation. Discrimination arises when certain employees are either less paid than others (wage discrimination) or their chances of employment are diminished altogether in comparison to others (job discrimination) due of factors such as gender, race, or any such personal characteristics not related to their productive capacity. Segmentation here refers to the division into separate parts of the labour market where recompense and work conditions differ, and mobility between the separate parts remains limited. The groups at the receiving end of the

discrimination are pushed to the low wage segments, despite possessing an equal level of human capital. If there is free mobility across segments, the wage differentials should vanish. But, in practice, we find wage differentials persisting for decades implying that the market is not competitive enough. There exist intersections between discrimination and segmentation, as certain factors determine the access of certain social groups to certain labour market segments (although in principle, this can be random). On the contrary, it is possible for discrimination to exist without the existence of segmentation. This research is an attempt at analysing the issue of discrimination in a segmented structure of the labour market in India. The study would establish dualism in the labour market manifesting as a dichotomy between regular and casual employment. Besides, studies have shown that the characteristics of regular and casual labour markets are analogous to the primary and secondary segments, as per literature on the dual labour market. The study would further demonstrate that the existence of discrimination based on caste and gender identity even within the regular labour market, which is considered to be less prone to arbitrary wage determination. However, before starting our own empirical analysis the next section would conduct a comprehensive literature review of the empirical analyses undertaken in India regarding the discrimination in the labour market. This will provide us with the insights that have been informed by empirical analyses and would provide us with the possible literature gap in the study of discrimination in Indian context.

3. Wage Discrimination across Social Groups: A Review of Empirical Studies

Discrimination against marginalised group prominently manifests itself through the labour market which, consequently, results in inequity and inequality. There are two important methods through which discrimination in the labour market manifests itself; first, entry and exit barriers into particular labour markets which leads to the segregation of social groups into particular occupations; and second, through discrimination in wages with regards to similar work. While the mechanism of social exclusion in labour markets turns into a direct barrier to entry into specific labour markets, wages, and earning discrimination discourages marginalised groups to join in specific labour markets.

Analysing the phenomena of ‘wage discrimination’ and ‘job segregation’, its causes and its effects are crucial in understanding not only the workings of labour markets in India but also in forming better understanding about the position and mobility of individuals from different social groups in it. Several scholars have engaged in examining the extent of disparities and

discrimination prevalent within the labour market by the use of different statistical methods. These studies have recurrently shown the continued existence of striking discrimination in wage and earning in India against marginalized groups. The following review of empirical studies is divided into two parts: the first part concentrating on the issue of gender wage disparities, and the second part on the discrimination based upon social identity. Both sections are further divided into two main parts, one exploring direct or wage discrimination for similarly placed workers and the other examining job segregation as discrimination. The second section explores caste discrimination in the labour market, a separate section on the private sector has been provided so as to question the assumption that caste holds no relevance in 'modern' workplaces.

3.1. Labour Market Discrimination based on Gender

Wage disparities, irrespective of labour status, sector, region, or occupation is a major characteristics of the labour market (Papola & Kannan, 2017). Several studies have examined the gender wage gap using mean-based decomposition method. One of the most popular mean-based decomposition methods is the Oaxaca-Blinder decomposition method. However, other studies have recognised the limitations of the Oaxaca-Blinder decomposition method and have used least squares and quantile regressions methodologies.

A number of studies have been done in India using Oaxaca-Blinder decomposition method estimating the extent of labour market premised upon gendered discrimination (Agrawal, 2013; Bhaumik & Chakrabarty, 2008; Deshpande et al., 2015; Deshpande & Ramachandran, 2014; M. Duraisamy & Duraisamy, 1996; Khan, 2016; Kingdon, 1998; Kingdon & Unni, 2001; Padhi et al., 2019). In such studies, persistence of the wage gap between genders is decomposed into an "explained" part, consists of endowment difference and an "unexplained" part, also called as discrimination.

The original attempt to estimate gender discrimination was done by Duraisamy and Duraisamy (1996). The study was done for the technical and scientific labour market segment, using the Degree Holders and Technical Personnel (DHTP) survey data for the year 1981. It was found that discrimination accounts for almost 67 to 77 percent of the wage differentials for all fields of specialisation. It was further observed that while getting more education is advantageous for women, gaining experience is advantageous for men in the labour market. It was also found that a substantial part of the wage discrimination against women occurs at the entry level. Using

the same DHTP survey for the year 1981, Duraisamy and Duraisamy (1999) did a comparative survey of Tamil Nadu and Kerala. They found that while 40 percent of the wage differential is attributed to discrimination in Tamil Nadu, it is 45 percent in Kerala.

Kingdon (1998) studied the labour market discrimination in India using Oaxaca-Blinder decomposition method. The study mainly focused on the issue of lower female schooling in India, and tried to explain it through labour market discrimination. The data was collected through a primary stratified sample survey of 993 households conducted in the Lucknow district of Uttar Pradesh in 1995. The study found that almost 45 percent of the gender wage gap is “unexplained” and thus accounts for discrimination in the labour market. An analogous study was undertaken by Kingdon and Unni (2001) using the 43rd round of NSSO’s survey data for 1987-88 for Madhya Pradesh and Tamil Nadu. Through the utilisation of the Oaxaca decomposition method, the study found that a major part of the gender wage differential is due to discrimination.

The PhD dissertation submitted by Jacob (2006) to the University of Maryland has analysed the gender wage gap based on NSSO’s unit level data for 1983, 1987-88, 1993-94, and 1999-2000. The unexplained component of wage gap for urban wage workers are 63 percent, 65 percent, 73 percent, and 54.5 percent respectively for years 1983, 1987-88, 1993-94, and 1999-2000.

Bhaumik and Chakrabarty (2008) have studied the wage gap on the basis of gender in the urban India using NSSO’s 43rd round and 55th round of employment and unemployment survey data. The study found that pay gap based on gender between 1987 and 1999 has declined considerably in the formal sector, irrespective of earning deciles and education cohorts. The decline in wage gap is largely due to higher endowment for women with tertiary education and a sharp upsurge in earnings to the experience of women workers. A similar inspection has been done by Agrawal (2013) through the utilisation of the India Human Development Survey (IHDS) data for 2005 using the Blinder-Oaxaca methodology. The study finds that the pay gap based on gender is higher in rural areas. They also observed that the majority of the wage gap is explained by discrimination component for both the sectors, with the discrimination component accounting for 67 percent of the wage gap in the rural areas and 81 percent in the urban areas. A similar pattern was found regarding the extent of gender discrimination while cross classifying gender and caste categories. It was observed that, while the gender pay gap is greater among non-SC/ST groups in the rural areas, the reverse is true for the urban areas.

The Oaxaca-Blinder decomposition methodology uses mean-based decomposition method, which would be misleading as it doesn't take into account heterogeneity that exists across wage distribution. It has been noted that the gender wage gap is larger among high paying workers than their lower paid counterparts (Albrecht et al., 2003). Therefore, the mean pay gap hides larger or smaller gaps that exist for high-paying and low-paying workers. A few other methods have been developed to overcome this limitation of the Oaxaca-Blinder decomposition method. One of them was developed by Machado and Mata in 2005 and Melly in 2006 using quantile regression decomposition method. This method is helpful in differentiating "glass ceiling effect" and "sticky floor effect". The "glass ceiling effect" is defined as the process by which gender wage gaps increase with an increase in distribution of wages and accelerates at the upper segment (Albrecht et al., 2003), and the "sticky floor effect" happens when gender pay gaps are greater at lower end of wage spectrum than other parts (Deshpande, Goel & Khanna, 2015).

There are several recent studies that have taken cognizance of this limitation of the Oaxaca-Blinder decomposition method and have used other methodologies to decompose wage gap at quantile levels (Deshpande et al., 2015; M. Duraisamy & Duraisamy, 2016; Khan, 2016; Khanna, 2012; Padhi et al., 2019). The "glass ceiling" and "sticky floor" effect has been analysed by Khanna (2012) by the use of the MMM decomposition method. The study analysed the wage gaps for regular wage workers across different wage distribution quantiles using the 66th round of the NSSO-EUS for 2009-2010. It was found that the "sticky floor effect" is more prominent in explaining gender wage gap.

Another effort to verify the existence of gender discrimination was done by Deshpande and others in 2015. The study used EUSs for 1999-2000 and 2009-10 to discover the prevalence of gender pay gaps among the RWS employees. The study found evidences for a decline in human capital differences among gender groups. Therefore, majority of the gender pay differential is "unexplained", thus persistence of high labour market discrimination was found. By utilising the MMM decomposition method, this research found that, for both the years of 1999-2000 and 2009-10, women who were at lower wage spectrum experienced a higher discrimination than those women at the higher end. A similar study was done by Duraisamy and Duraisamy (2016) by means of the same MMM decomposition method. The research uses NSSO-EUS data for the years 1983, 1993-94, 2004-05 and 2011-2012 to analyse gender pay differential throughout the wage spectrum for several sectors likes regular, casual, public, private, rural, and urban sectors. The study's findings suggest the prevalence of "sticky floor effect" in all sectors except rural areas. Similar to the study conducted by Deshpande et al. (2015), they also

found that the extent of higher discrimination in the lower wage quantiles than at the upper wage quantiles and the endowment difference was declining over the years irrespective of wage quantiles.

Using the Recentered Influence Function (RIF) quantile decomposition analysis, Padhi et al. (2019) has studied the gender pay gap at different levels of wage spectrums. Padhi et al. (2019) have analysed the pay gap based on gender for both regular and casual employees. The data used for the study was taken from unit level data of 50th, 61st, and 68th NSSO-EUS surveys. The study found that the discrimination component's role is greater than that of the endowment component for both workers in regular and casual employment.

Another form of discrimination faced by women and other marginalized groups in the labour market is through labour market segregation. The gender segregation, generally leads to lower payment and worsening of the working conditions for women. It is therefore important to conceptualize labour market segregation as a form of discrimination. The statistical method decomposes the discrimination into two parts namely wage discrimination and job segregation has been developed by Brown et al (1980). The Brown et al. decomposition technique identifies discrimination into two parts: one part that can be explained by wage differential in a given occupation, which is called “vertical segregation” or “wage discrimination” and another portion identifies of wage differentials that arises due to differences in wage recompense across occupations and calls it “horizontal segregation” or “job discrimination”.

Using the Brown et al decomposition, a few studies have dealt with the question of job gender segregation in India (Agrawal, 2015; Agrawal & Agrawal, 2015; M. Duraisamy & Duraisamy, 2016; Jacob, 2006). Using the Brown et al. decomposition method, Jacob (2006) obtained a negative value for job discrimination and it was found to be insignificant while the wage discrimination was more pronounced than job discrimination in the labour market irrespective of the periods of study. However, there are a few studies that have found that occupational segregation plays an important role in determining gender wage gap (Agrawal & Agrawal, 2015).

Agrawal and Agrawal (2015) have studied the gender segregation in occupation using the NSSO data for 1987–1988, 1993–1994, 1999–2000, and 2004–2005. Using the Gini index, dissimilarity index, and square root index for measuring occupational segregation, the study found occupational segregation has increased over the years. They also found occupational segregation is more prominent in urban areas. Similarly, using the Alonso-Villar and del Río

(2010) method for measuring occupational segregation, Agrawal (2015) found that the urban sector has higher occupational segregation than the rural sector. Alonso-Villar and del Río (2010) measure overall and local segregation where the overall segregation looks into simultaneous assessments of all the occupational subgroups and the local segregation studies a comparison of the target group distribution with the total employment distribution. By using the EUS for 2009-10, Agrawal (2015) concluded that the contribution of occupational segregation for female workers are 76 and 78 percent respectively for the rural and urban areas. The study also found that the lowest level of segregation was among self-employed workers. While in the urban sector self-employed and casual workers are found more segregated, regular workers are found in the rural sector to be more segregated.

3.2. Discrimination in the Labour Market based on Socio-religious Identities

In Indian society, caste identity is one of the most significant factors determining the social and economic position of an individual and discrimination in the labour market is one of many facets through which caste system manifest itself. As discussed in the introduction section of this chapter, the institution of caste has historically been rigid and has assigned permissible occupations to various castes. The age-old institution uses ascriptive status to place entry and exit barriers (Thorat & Newman, 2007) in the labour market in India making it one of the prime axis along which discrimination occurs.

The decomposition method is one of the most popular methods utilised to examine the degree of discrimination in the labour market by decomposing the caste-based wage gap. The studies on decomposition can further be divided into the studies looking at ‘wage discrimination’ and ‘job segregation’. The studies looking at ‘wage discrimination’ divides the wage gap into two parts one that can be explainable through endowment difference while the other is the ‘unexplained’ component, which is attributed to discrimination (Agrawal, 2013; Das & Dutta, 2007; Deshpande, 2012; P. Duraisamy & Duraisamy, 2017; Ito, 2009; Kumar & Hashmi, 2020). Besides, other studies have dealt with the issue of caste based occupational segregation in the labour market (Banerjee & Knight, 1985; Kijima, 2006; Jacob, 2006; S Madheswaran & Attewell, 2007). However, some other studies have also used audit and correspondence studies to understand the magnitude of “direct discrimination” (Deshpande & Newman, 2007; Jodhka & Newman, 2007; Siddique, 2008; Thorat & Attewell, 2007).

Although decomposition analysis is important to quantify the discrimination in labour market, correspondence and audit studies are important to gain clearer insights into the process of labour market discrimination. The first major correspondence study in India to find out the extent of discrimination in the private sector was carried out by Thorat and Attewell (2007) to show that discrimination can happen even in so-called 'modern' jobs. The focus of the study was to find out the discriminatory hiring practices in the private sector and therefore, it focused on highly educated university graduates. They sent applications to multiple national and regional English-language newspapers, like The Times of India, Hindustan Times, The Hindu, Deccan Herald, and Deccan Chronicle, for entry- or near entry level positions. These were jobs that a fresh college graduate could apply for. They sent identical applications with respect to educational qualifications, job experience, and skills but with three different caste (and religious) identities which were identifiable through stereotypical names; one was a Hindu upper caste name, the second was a Muslim name, and the third was a Dalit name. Their results indicate that both caste and religion have an important bearing on whether the response is successful or not. The odds of a successful response for Dalit applicants were found to be 0.67 times that of upper caste applicants and those of Muslims were 0.33 times that of upper caste applicants.

Subsequently, Siddique (2008) also conducted an audit study from March to December 2006 in Chennai to determine the extent of caste-based discrimination in the hiring practices in the Indian private sector. Two identical résumés were sent out, one with an upper caste sounding name and the other with a lower caste one, for each of the advertised job vacancies. The study found that while an upper caste applicant had to send 6.2 résumés on average to get one response, it took 7.4 résumés for a deprived caste to get one response, a difference of roughly 20 percent. Furthermore, the call-back chances were even less for office/ administrative jobs for deprived castes.

It is important to note here that caste also functions as networks that enable access to information and links for better job opportunities. Deshpande and Newman (2007) in their college-to-work study examined the role of caste networks in personalised recruitments, where networks of acquaintances are often more important than capabilities affecting productivity. In this study, Deshpande and Newman took a collection of educationally comparable university students from JNU, DU, and JMI with different caste backgrounds and at the time of entry into labour market, they were compared in terms of their methods of searching work, job expectations, final appointments, and the roles that social networks in deciding their choices in

the labour market. Later, these students were studied for a span of 2 years and were interviewed every six months in order to keep track of their progress and to see how many of them had gotten jobs and what were the means employed to do so. In the end, the outcomes were compared to what the students had initially said in the questionnaire. Almost all the students have reported that they were asked questions related to their family background and many students have also reported that questions related to their views on affirmative action were asked by interviewers. These questions are of no relevance to such 'modern' jobs but are being used to indirectly determine caste and economic identities of the students. This indicates that the social group identity of an applicant plays a crucial role when they seek jobs in modern workplaces as well. Interviewers, while pretending to only consider the 'merit' of a candidate, did discriminate on the basis of the social identity of the applicant. The study found that cultural and social network is vital part in the urban and formal sector labour market as well. The existence and pervasiveness of unequal social-systems affect labour market outcomes not merely with regards to wages but also with regards to varying service-conditions, differential treatment by employers, and discriminatory work-contracts. Similarly, a survey gauging employer attitude conducted by Jodhka and Newman (2007) found out the universal prevalence of the language and logic of merit among employers, including MNCs. But employers often ignore pervasive social inequalities whereby the existing definition of merit inadvertently benefits dominant groups. The employers' allegiance to merit often masks their deep biases wherein they favour people of privileged castes and religious backgrounds. Apart from these audit or correspondence studies, many studies have been done using large scale sample survey data to quantify labour market discriminations based on caste and religious identities. The use of Oaxaca-Blinder method is the most common in such studies. However, other decomposition methods have also been used. Das and Dutta (2007) have explored prevalence of caste discrimination in wage distribution using NSSO-EUS 2004-05. The study found that caste is still a determining feature for payment of wages. The extent of the wage gap between SC and General Category workers was at 0.37 log points of which, 35 percent was attributable to discrimination. It increased to 59 percent after correction for selectivity bias. Similarly, the extent of wage gap between OBC and General Category workers was about 0.33 log points, of which around 40 percent could be said to be because of discrimination, which increased to 56 percent after correction for selectivity bias. The caste-based wage gap in the casual labour market, however, was found insignificant. A larger proportion of wage difference was explained by differences in characteristics. The study also found evidence for occupational segregation based on a descriptive analysis.

In another study, Agrawal (2013) has examined difference concerning SC/ST using the IHDS for 2005. Employing the Oaxaca-Blinder decomposition method, the study found that the wage gap between SC/ST and Non-SC/ST is higher in urban areas. The caste-based wage gap was mostly attributed to endowment differences. However, these are mostly found due to pre-labour market discrimination. Only a few studies that analyse religion based discrimination using the decomposition method have been undertaken (Bhaumik & Chakrabarty, 2009; P. Duraisamy & Duraisamy, 2017). Bhaumik and Chakrabarty (2009) have examined the wage discrimination between Hindus and Muslims. The study used the Oaxaca-Blinder decomposition method to find that educational disparities between Muslims and Hindus. It was observed that the huge difference in proportion of population with tertiary education is the reason behind variations in the average wages of the two religious communities irrespective of the study periods. Overall, the study found that the contribution of endowment difference between Hindu and Muslim workers is more than that of discrimination component.

Similarly, a study done by Duraisamy P. and Duraisamy M. (2017) using the Oaxaca-Blinder decomposition analysis for the NSSO data for 1983, 1993-94, 2004-05 and 2011-12 found that, except for STs, the discrimination component is positive and statistically significant for all social groups irrespective of the study periods. Additionally, it was found that discrimination component was greater for OBCs than for SCs and STs where the discrimination component between SCs and others (including OBCs) shows an upward trend over the period from 1983 to 2011-12. The study has understood the limitations of the Oaxaca-Blinder decomposition method as mean decomposition method, and has also used a quantile regression decomposition analysis to show that the discrimination component as well as wage differential against socially underprivileged groups diverge markedly throughout the wage distribution. The study found that the gross wage gap increases with the increase in the wage level till to 70th or 80th percentile and afterwards remains constant or declines marginally. In the case of STs, it declines up to the 60th or 70th percentile and then increases. So, the variations in the attributes of human capital explain majority of the wage differential across wage levels. The unexplained wage gap is found to be less at the bottom of the distribution than at the top, except for STs. In the case of STs, the low-wage earners experience higher discrimination than their counterparts earning a high wage. The study points out that the low wage earners are mainly low-educated regular contract workers with low bargaining power. On the other hand, high-wage earners may find it difficult to compete with higher caste workers and hence, are vulnerable to discriminatory practices.

There are other studies that have used the Brown et al. (1980) decomposition method divide the component of discrimination into wage and occupational discrimination. Using the same, Banerjee and Knight (1985) have examined the issue of discrimination against SC migrant workers in urban India. The study has used the data collected through a primary survey conducted in Delhi from October 1975 to April 1976. The study found that the discrimination to be responsible for two-thirds of the gross wage discrimination. It also found that wage discrimination is more relevant than job discrimination in defining overall discrimination. They observed that the discrimination against Scheduled Castes was highest in manual jobs which required direct contacts for recruitment, and less in white collar jobs where contacts were more formal methods of recruitment were used.

Madheswaran and Attewell in their 2007 study have examined the wage gap based on caste using NSSO data for the regular urban labour market. The study found that the wage gap amongst various caste groups is mainly attributable to endowment differences. Thus, it makes a clear point about the prevalence of pre-market discriminatory *behaviour* against disadvantaged social groups vis-à-vis educational and health benefits. However, the study also found out that there is a declining trend of endowment differences. But, the percentage of the wage different between SC/ST and forward castes due to discrimination, has expanded from 13.5 percent in 1983 to 30.4 percent in 1993-94. Moreover, the OBC and forward castes wage gap attributed to discrimination was found to be at 31.9 percent in 1999-00. The study also analysed the extent of caste-based discrimination for private and public sectors separately. The study found that the prevalence of discrimination against SC/ST workers is higher in the private sector when compared to the public one. It was further found that the extent of the wage difference attributable to discrimination has declined in the public sector over the years.

Another method used to understand discrimination is the expanded method, originally put forth by Brown et al. (1980), which decomposes the gross wage difference into both job discrimination and wage discrimination. A further comprehensive decomposition analysis of occupational and wage discrimination was proposed by Madheswaran and Attewell (2007) by combining Oaxaca and Ransom methodology with that of Brown and others. Using this expanded decomposition method, the study found that occupational discrimination or job segregation prominent in explaining discrimination.

4. Conclusion

The existing literature on labour market discrimination suggests that, while endowment difference or pre-labour market discrimination has vital to explain wage difference among social groups, the unexplained component or discrimination plays a central role in setting a wage gap for women workers. In addition, occupational segregation another important aspect of wage discrimination. Further, it was found that wage discrimination differs with the distribution of wage. We have found that although there are several studies on the issue of labour market discrimination caused by socio-religious and gender identities, there is a lack of studies that estimate the extent of labour market discrimination using recent PLFS data released by the NSO. Therefore, we find a lack of research on the current state of labour market discrimination particularly after the release of PLFS data sets of 2018-19. It was also observed that most of the studies used the Blinder-Oaxaca (B-O) methodology to analyse the degree of discrimination and very few studies have used quantile decomposition methodology to analyse the extent of discrimination at different wage levels. The heterogeneity with regards to the distribution of wages requires us to understand the nature of discrimination at differing levels of wage distribution. Therefore, this study would use the MMM Decomposition method apart from B-O method of decomposition to understand the existence of “glass ceiling effect” and “sticky floor effect”. Further, the research would limit itself in the urban regular employment because it is considered to be highest paying jobs and the wages are supposedly determined based on ‘merit’ of an individual rather than the identity. The existence of discrimination in the regular employment raises a question towards the “segmented labour market” theory which presents itself as a critique of neo-classical theories of discrimination. The segmentation theory assumed that the existence of discrimination can be explained by the occupational segregation into primary and secondary sectors. However, the existence of discrimination within the primary sector remains unexplained. Therefore, this study would also try to understand the possible theoretical explanations for the persistence of wage discrimination within the so-called ‘primary’ segments.

Chapter 3: The State of the Indian Labour Market: A Survey of Changes from 2011-12 to 2018-19

1. Introduction

The distribution of wages is determined by the labour market structure, the pattern of employment, and the labour market institutions. Therefore, a detailed study of the structure of the labour market becomes inevitable to better understand the question of wages. The question of employment or the lack of it has become the centre point of political debates in recent times, particularly after the release of the PLFS report of 2017-18, which pointed out that the unemployment rate is at 6.1 percent, which is highest since the beginning of NSSO's data collection. It has now been well established that the Indian economy failed to generate sufficient jobs during the post-liberalisation period particularly during the high economic growth period after 2004-05. Studies on employment suggest that there has been a significant decline in employment elasticity with respect to growth. In other words, employment generation over the years has not only been less than the growth rate but has also been declining continuously. A 1-percent growth rate was generating less than 1 percent increase in the employment between 2004-05 and 2011-12, with this trend continuously decreasing till 2011-12, when it was close to zero; the growth rate in employment as a proportion to the growth rate in GDP has been negative since then. The process of near-zero employment growth during a time when India's economy was expanding rapidly between 2004-05 and 2011-12 has led many economists to call it a "jobless growth" (Kannan & Raveendran, 2019). Following this logic, Kannan and Raveendran (2019) suggests that the period between 2011-12 and 2017-18, which has shown a negative growth in employment should be called as "Job-loss growth regime". However, as discussed in the introductory section, the time period between 2011-12 and 2017-18 has not only seen a decline in growth rate but also experience shocks like demonetisation. Therefore, it can be said that the growth in GDP was ineffective in generating employment between 2004-05 and 2011-12 but the declining growth rate has led to a loss of employment.

Indian society has a complex structure comprising of a diversity of social groups. However, this diversity within society has been hierarchical in nature, with caste, class, gender, language, religion, region, and ethnicity forming the bases for stratification. The NSSO and the subsequent PLFS data-sets divide social groups into Scheduled Castes (SC), Scheduled Tribes (ST), Other Backward Classes (OBC) and Others. The 'Others' category consists of all the

social groups that fall into none of other categories. The 'Others' group is largely comprised of the so-called 'upper castes', which includes all those groups who form the upper strata of the Hindu social order. The 'Others' groups shall be henceforth referred to as Forward Castes (FC). Although the basis for caste-based hierarchy can trace its roots to Hindu religious texts, today its prevalence can be observed throughout the region, with caste and caste-based discrimination being practiced by non-Hindus as well (Thorat & Newman, 2007).

A majority of the country's population, of around 69.63 percent, reside in rural areas, whereas only 30.37 percent population reside in urban areas according to the PLFS data 2018-19. The PLFS 2018-19 data also suggests that the gender distribution is such that males constitutes 51.02 percent of the population, while females constitute 48.98 percent. The social group-wise distribution of the population is such that ST, SC, OBC, and FC constitute 9.05 percent, 19.87 percent, 43.93 percent and 27.14 percent respectively. A larger proportion of STs (89.31%), SCs (78.45%) and OBCs (70.21%) live in rural areas. On the other hand, only 55.66% of FCs reside in the villages. Thus, the chances of residing in rural areas are higher for individuals from socially marginalised groups.

The caste system affects all spheres of life including labour market. Similarly, gender identities are vital in determining labour force participation of women. Hence, it is impossible to separate the question of caste and gender, as overlapping identities generate more complicated outcomes. Scholars like Uma Chakravarti and Sharmila Rege have pointed out that control over women's labour and sexuality is important for caste system to survive (Velaskar, 2016). Therefore, not only does the caste system dictate the social division, but also governs the sexual division of labour. Thus, the intersectionality of caste, class, and gender determines the social and economic position of an individual in the Indian society. Thus, in the context of declining job growth between 2011-12 and 2018-19, an attempt has been made in this chapter to analyse the role of social identity in determining access to employment, type of employment, and nature of work.

2. Demographic 'Window of Opportunity' for India

There have been fierce debates amongst social scientists about the economic impact of population change, which led to three different positions postulating negative, positive, and neutral impacts of population growth on economic growth. The negative impact of population on economic growth is associated with the theories of Thomas Malthus (Bloom, Canning, &

Sevilla, 2002). His postulations have had a deep impact upon economists and policymakers, resulting in coercive policies like one-child policy in China and the forced sterilisations in India during 1975-77 (Mehrotra, 2016). Other theories like Allen Kelley claim that economic growth is independent of the population, and there is no correlation between the two (Bloom, Canning, & Sevilla, 2002). Lastly, some theorists like Amartya Sen and Ester Boserup suggest a that population and economic growth is positively related. They suggest that with an increase in population, human ingenuity also increases. However, an important point that has been missing in these debates as pointed out by Bloom et al (2002) is the changing age structure.

The theory of demographic transition presented by Frank Notestein and Kingsley Davis in 1944-45 suggests that all the developed nations have passed through three stages of population growth. These stages are as follows; the first stage is characterised by constant or extremely sluggish population growth as a result of high birth rates and high mortality rates coexisting. At this stage, the country is at its lowest in terms of economic modernisation. The country enters the second stage with economic development, leading to higher incomes and improved health facilities and access to said facilities, which in turn lead to a low mortality rate. However, the birth rate still remains high as in the previous stage, leading to a rapid increase in population. Finally, the third is reached when the fertility rate declines with economic development and modernisation, which again leads to a stable population growth. The process by which a society transitions from a high fertility and mortality scenario to a low fertility and mortality one is known as demographic transition (Kapila, 2017). These changes in the fertility rate and mortality rate also change the age structure of a country.

Over the last few decades, there have been rapid demographic changes in India. The share of the working-age population between 15 and 64 years has been increasing continuously since the 1980s. While the working-age population of India was 65.21 percent in 2011-12, it had risen to 68.19 percent in 2018-19. The share of this section of the population is expect to increase until 2050, as predicted by the World Bank's population projections (Thomas, 2020). The growth in the magnitude of the working-age population is termed as the demographic window of opportunity because dependent population is relatively smaller. As the dependency ratio is low during this period, there is a possibility of increasing the growth in savings, which will lead to an increase in investment. Therefore, India must harness the power of human capital before the population starts ageing, for which gainful employment is a must.

3. Characteristics of the Indian Labour Market

The low participation of workers in the labour market is one of the major characteristics of India represented by a low Labour Force Participation Rate (LFPR) and Workforce Participation Rate/Worker Population Ratio (WPR). The LFPR for 2019 in India was 49.2 percent in comparison to 68 percent for China and 64 percent for Brazil (ILO, ILOSTAT database, 2020). Because to the low LFPR, a large portion of the population is unable to engage in the labour market. Therefore, this section attempts to understand labour market dynamics, along with the issue of employment and unemployment which are responsible for a low LFPR. We would further analyse the situation of different social groups and gender groups in the labour market.

3.1. Labour Force Participation Rate, 2011-12 to 2018-19

The LFPR is one of the indicators to assess labour market conditions, which indicates the ratio of the population that participates in labour market. In other words, it indicates the population proportion that is either economically active or unemployed but actively seeking a job. In India, the labour force is often assessed by the usual status, which is calculated by combining the usual principal status with the subsidiary status. The usual principal status denotes an individual's status throughout a one-year reference period, and a majority criterion is adopted to classify if an individual belongs to the labour market or not. An individual is considered to be in the labour force if he or she works or seeks for job for a significant portion of the year, that is, for more than six months in a year. The subsidiary status of employment means that a person is engaged in employment for a minimum 30 days in a given year. This criterion is essential to determine the seasonality of employment in the Indian labour market. Thus, the usual status (ps+ss) includes both the major time criterion as well as the priority to work status. In Table 4, the changes in the Labour Force Participation Rates are disaggregated by caste, gender, and sector. The LFPR has dropped from 39.5 percent for the year 2011-12 to 37.48 percent for 2018-19. When disintegrated at the sector level, we find that while the urban LFPR is stable at around 36 percent, the rural LFPR has declined from 40.62 percent to 37.71 percent. The broader trend in the LFPR disaggregated by gender suggests that the LFPR for males has been stable from 1983 to 2011-12 at around 55-56 percent. However, it has declined continuously for females from 30 percent in 1983 to 22.5 percent in 2011-12 (Kapila, 2017). The evidence from PLFS data of 2018-19 suggests that, while the female LFPR has further

declined to 18.58 percent, the male LFPR has remained at 55.62 percent. The fall in the female LFPR has been the major contributing factor to the fall in the overall LFPR. From Table 4, it can also be seen that the LFPR for urban females has increased marginally, by one percent, from 15.47 percent to 16.1 percent. Thus, we can say that the massive drop in the LFPR of rural females, from 25.27 percent to 19.65 percent, that has led to an overall decline in the LFPR.

Furthermore, on disaggregation at social group level suggest that the decrease in the LFPR for women is not uniform. Table 4 suggests that the LFPR has remained stable for males from different social groups. However, the decrease in the LFPR is higher amongst STs and SCs than OBCs and FCs women. We further find that only ST women experienced a particular decline in their LFPR in urban areas. The LFPR has either remained constant or increased marginally in urban areas for women from other social groups. As previously discussed, it is rural areas that have seen a maximum decline in the female LFPR. However, the amount of decline differs depending upon the social group and the decline has been most drastic among ST women at around 8 percentage points. While the decline for SC women was 7 percentage points, it was 5 percent each for OBCs women and FC women between 2011-12 and 2018-19. Thus, we see that the decline in LFPR is highest for ST women from rural areas. However, we also find that the decline in LFPR was relatively lower for FC women, which reinforces observations regarding the stigma attached to women leaving their home for work, particularly among FCs (Deshpande A. , 2019).

3.2. Worker Population Ratio (WPR), 2011-12 to 2018-19

The WPR is indicate population proportion that is employed. In other words, the WPR is a measure of the share of the population that has found employment. Similar to the LFPR, we observe from Table 5 that a decline in the WPR from 38.64 percent in 2011-12 to 35.29 percent in 2018-19 has taken place. However, the decline is for both males and females. The decline in the male WPR is from 54.43 to 52.25 percent between the two time periods. However, the female WPR declines from 21.95 to 17.61 percent between 2011-12 and 2018-19. The WPR is considerably less for women in both urban and rural segment.

The WPR for males and females in 2018-19 was 52.06 percent and 18.96 percent respectively, which declined from 54.34 percent and 52.84 percent respectively in 2011-12 for the rural segment. Similarly, in urban areas, the WPR for males and females in 2018-19 was nearly 52.7

percent and 14.51 percent respectively, which declined from 2011-12 when the WPRs for males and females was recorded at 54.64 percent and 14.66 percent respectively. However, the decline in WPR is much higher among females than males. In addition to that, the decline in female WPR is marginal among urban female workers with a drop of just 0.15 percentage points, while it has been a steep decline among rural female workers with a decrease of 6 percentage points.

Therefore, the decline in WPR, similar to the decline in LFPR, is mainly due to the decline in rural female workers. However, the WPR differs amongst social groups as well. The decline in WPR is highest among STs from 45.2 percent in 2011-12 to 40.64 percent in 2018-19. Further, the WPR declines from 39.49 to 35.41 percent for SCs, from 38.16 percent to 34.85 percent for OBCs, and from 36.8 to 34.13 percent for FCs. However, as discussed earlier, the decline is more significant among female workers. But when seen at a disaggregate level, we find that the decline is sharper amongst ST women, with a massive drop of 8 percentage points from 34.57 to 26.71 percent. Similarly, the decline in the WPR among SC women is also high at 6 percentage point from 24.57 to 18.42 percent. However, the decline is relatively less among OBC women and FC women at 4 percentage points each.

Further, we find the pattern of decline in WPR is unique for the two areas. In rural areas, the decrease in women WPR irrespective of their social groups, the decline is limited to socially marginalised groups viz. STs, SCs, and OBCs in urban areas. Further, a marginal increase in the WPR has been observed for women from FC in the urban areas from 12.89 to 13.1 percent. Although the WPR has declined for women from all social groups in rural areas, it is sharper among scheduled caste women. In summary, the female LFPR and WPR is significantly lower than male and it shows a declining trend over the years. Further, the decline is sharper in rural areas.

The drop in the LFPR and WPR in the rural segment began after 2005, which has generated considerable academic interest (Mehrotra & Parida, 2019; Dubey, Olsen, & Sen, 2017; Mehrotra & Parida, 2017; Sanghi, Srija, & Vijay, 2015; Abraham, 2013; Kannan & Raveendran, 2012; Hirway, 2012; Himanshu, 2011; Mazumdar & Neetha, 2011; Abraham, 2009). The decline in the female LFPR has led many scholars to claim that India is going through the process of “de-feminisation” (Abraham, 2013). However, there seems to be no consensus amongst scholars about the source of such drop in the rural female LFPR. One point of view suggests that the rise in enrolment in higher education amongst women is the reason behind such withdrawal (Mehrotra & Parida, 2019).

Table 4: Labour Force Participation Rate (in percent) according to the usual status (ps+ss) by sector, gender and caste (all ages), 2011-12 to 2018-19

Social Group	Rural						Urban						Rural+Urban					
	Male		Female		Person		Male		Female		Person		Male		Female		Person	
	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19
ST	56.45	57.29	36.85	28.73	46.87	43.26	53.77	54.28	20.21	18.37	38.02	36.5	56.14	56.97	35.05	27.61	45.87	42.54
SC	54.98	55.15	26.53	19.45	41.1	37.69	56.33	57.24	18.06	18.36	37.73	38.39	55.28	55.6	24.67	19.22	40.36	37.84
OBC	54.7	54.12	24.32	19.57	39.78	37.06	56.05	56.42	15.86	16.62	36.7	36.93	55.07	54.81	22.06	18.7	38.95	37.02
FC	56.22	56.03	20.59	15.1	38.93	36.08	56.83	57.04	13.76	14.52	36.31	36.48	56.47	56.48	17.79	14.85	37.84	36.26
All	55.31	55.14	25.27	19.65	40.62	37.71	56.33	56.72	15.47	16.1	36.73	36.94	55.61	55.62	22.48	18.58	39.5	37.48

Source: Computed from Unit Level Data NSSO-EUS 2011-12 and PLFS 2018-19

Table 5: Worker Population Ratio (in percent) according to the usual status (ps+ss) by sector, gender and caste (all ages), 2011-12 to 2018-19

Social Group	Rural						Urban						Rural + Urban					
	Male		Female		Person		Male		Female		Person		Male		Female		Person	
	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19
ST	55.71	54.78	36.44	28.04	46.28	41.64	51.97	48.57	19.24	15.71	36.61	32.3	55.28	54.12	34.57	26.71	45.2	40.64
SC	53.89	51.56	26.17	18.86	40.36	35.57	54.54	51.78	17.24	16.77	36.41	34.81	54.03	51.61	24.21	18.42	39.49	35.41
OBC	53.78	51.06	23.91	18.92	39.11	35.19	54.65	52.36	15.12	14.96	35.62	34.04	54.02	51.45	21.56	17.75	38.16	34.85
FC	55.18	53.14	20.08	14.22	38.15	34.17	54.9	53.71	12.89	13.1	34.89	34.07	55.06	53.4	17.14	13.72	36.8	34.13
All	54.34	52.06	24.84	18.96	39.92	35.8	54.64	52.7	14.66	14.51	35.47	34.11	54.43	52.25	21.95	17.61	38.64	35.29

Source: Computed from Unit Level Data NSSO-EUS 2011-12 and PLFS 2018-19

Other point of view states that the rise in the LFPR was distress driven in the first place and, with increasing rural wage levels, women have withdrawn from the labour force (Himanshu, 2011). The third point of view posits the decline in employment opportunities in rural areas due to an increasing agrarian crisis (Abraham, 2009), as having led to a fall in female LFPR in the villages of India. Lastly, some scholars have claimed that the so-called “missing labour force” is not missing in reality, but they have moved to lower productive informal work and subsistence work that is “difficult to be measured” by the NSSO (Hirway, 2012). Although there are disagreements regarding the exact cause of the declining labour force and workforce, one thing is sure that the burden of household work and care work is disproportionately laid upon women, which prevents them from contributing to the labour market.

As we have discussed earlier, women are heterogeneous and therefore, we must assess the variation of their interaction with the labour market across different social groups. It is mainly out of economic compulsion that women from socially and economically marginalised group seek work outside their homes. As a result, there is more vulnerability in the labour market. The vulnerability is exacerbated by the fact that women from socially marginalised groups have low human capital endowments as a result of their lack of education (if literate). In addition, the majority of women in India, particularly in rural areas, engage in a variety of part-time economic activities in addition to their home responsibilities. These works are often not considered as economic activity and are therefore, not included in the calculation of GDP. Thus, it results in an under-reporting of the economic participation of women (IHD, 2014; Hirway, 2012).

3.3. Unemployment Rate, 2011-12 to 2018-19

The Unemployment Rate (UR) is defined as the percentage of the labour force that is unemployed. Recent years have seen an unprecedented increase in unemployment rates from 2.19 percent in 2011-12 to 5.84 percent in 2018-19. This increase in the unemployment rate has generated a heated debate amongst politicians and academicians alike. While opposition parties have blamed the BJP-led ruling government for its inability to generate required employment, the government along with many economists favouring them have responded by denying the comparability of PLFS data with previous quinquennial rounds of EUS surveys. Several scholars have asserted that the two data sets can be compared “without any doubt or distrust” (Mehrotra & Parida, 2019). The rise in UR is particularly concerning because of its coincidence with a rise in proportion of working-age group associated with the demographic

‘window of opportunity’. The proportional increase in employment opportunities required to provide employment to an increasing number of people seems lacking. Thus, it can be stated that the increase in the UR has had an adverse impact on the economy in general.

From Figure 6, it can be observed that the increase in the Unemployment Rate is higher among males than females, though the increase in the UR among females is not negligible by any standard. The male UR saw a rise from 2.12 percent in 2011-12 to 6.05 percent in 2018-19. On the contrary, the increase was from 2.38 percent to 5.19 percent for the female Unemployment Rate. When disaggregated at the sector level, we find that the rise in the UR is higher in urban areas at 4.23 percentage points when compared to rural areas which are at 3.33 percentage points. Moreover, the UR was higher in urban areas in the first place, leading to a massive UR of 7.68 and 5.06 percent for urban and rural areas respectively. In urban areas, the female UR increased from 5.24 percent in 2011-12 to a massive 9.88 percent in 2018-19 while the male UR rose from 3 percent in 2011-12 to 7.09 percent in 2018-19. In rural areas, the increase in female UR was from 1.68 percent in 2011-12 to 3.52 percent in 2018-19 while the male UR rose from 1.75 percent in 2011-12 to 5.59 percent in 2018-19. Thus, female unemployment sees a higher increase than male unemployment in urban areas; while the increase in male unemployment was higher than female unemployment in rural areas.

Furthermore, when disaggregated according to social groups, we find that, while the variation of increase in the UR in rural areas lies between 2 and 4 percentage points, it is comparatively massive in the urban areas, varying between 2 to 10 percentage points. In urban areas, the increase in the male UR is higher among STs than SCs, which in turn is higher than OBCs. The rise in the UR is lowest among the FCs. In other words, the increase in the UR increases as one moves from dominant castes to oppressed castes for males in urban areas. For females in the urban areas, the increase in the UR is higher among ST and OBC women than among SC and FC women. Thus, we find that the UR is higher among the marginalised groups in the urban areas.

Table 7 presents the disaggregated data for unemployment by educational levels for 2018-19. The “Secondary and Above” educational group forms the majority of the unemployed both in rural and urban areas. We further find that an increase in the educational level, the unemployment rate increases. We also observe that, for those individuals who have completed a ‘Secondary and Above’ level of education, they are more likely to be unemployed if they are females. However, in every other level of education, the vice versa holds true.

Table 6: Unemployment Rate (in percent) according to usual status (ps+ss) by sector, gender, and social group (all ages), 2011-12 to 2018-19

Social Group	Rural						Urban						Rural + Urban					
	Male		Female		Person		Male		Female		Person		Male		Female		Person	
	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19
ST	1.31	4.39	1.13	2.4	1.24	3.74	3.36	10.52	4.81	14.46	3.72	11.5	1.54	5.01	1.36	3.26	1.47	4.45
SC	2	6.51	1.37	3.01	1.8	5.63	3.18	9.53	4.52	8.65	3.49	9.32	2.26	7.19	1.87	4.16	2.15	6.44
OBC	1.68	5.66	1.71	3.33	1.69	5.06	2.51	7.2	4.67	10.01	2.96	7.82	1.91	6.14	2.28	5.09	2.01	5.88
Others	1.85	5.15	2.44	5.87	2	5.3	3.39	5.84	6.29	9.79	3.91	6.6	2.5	5.46	3.66	7.56	2.76	5.88
All	1.75	5.59	1.68	3.52	1.73	5.06	3	7.09	5.24	9.88	3.45	7.68	2.12	6.05	2.38	5.19	2.19	5.84

Source: Computed from Unit Level Data NSSO-EUS 2011-12 and PLFS 2018-19

Table 7: Unemployment Rate (in percent) by sector and gender (all ages) with different educational attainments, 2018-19

	Rural			Urban			Rural + Urban		
	Male	Female	Person	Male	Female	Person	Male	Female	Person
Not literate	1.5	0.03	0.87	3.63	1.07	2.64	1.83	0.18	1.14
Literate & up to Primary	3.05	0.67	2.46	3.69	2.23	3.38	3.2	0.99	2.67
Middle	5.36	1.73	4.75	5.49	4.36	5.31	5.4	2.44	4.91
Secondary & above	10.15	16.61	11.22	9.17	17.62	10.81	9.72	17.1	11.04

Source: Computed from Unit Level Data NSSO-EUS 2011-12 and PLFS 2018-19

We also discovered that while the UR is greater in rural areas for men, it is higher in urban areas for females. The social group wise disaggregation of UR at secondary and above level as seen in Table 8, suggests that the UR among females is higher than male counterparts for all social groups. Further female UR is higher among SCs and STs than OBCs and FCs while for males it is higher among SCs and OBCs, than STs and FCs. Thus, unemployment among the educated population is a bigger challenge in front of Indian economy.

Table 8: Unemployment Rate (in percent) according to usual status (ps+ss) by social groups (all ages) for those with education level, secondary and above, 2018-19

Social Group	Rural + Urban		
	Male	Female	Person
ST	9.73	19.12	11.58
SC	12.96	19.32	14.05
OBC	10.52	17.56	11.79
FC	7.49	15.3	8.85
All	9.72	17.1	11.04

Source: Computed from Unit Level Data NSSO-EUS 2011-12 and PLFS 2018-19

4. Changing Employment Structure of India, 2011-12 and 2018-19

India saw a massive decline in the employment growth, from 12 million per annum during 2000-2005 to about 2 million per annum during 2005-12. This decline has led to a heated debate. It was found that the sharp fall in agricultural employment (Himanshu, 2011; Mehrotra et al., 2014) and a rise in educational enrolment at Secondary and Higher education (Thomas, 2012; Kannan & Raveendran, 2012; Mehrotra & Parida, 2017) was the primary reason behind the slow growth in employment between 2004-05 and 2011-12. However, it was anticipated that overall employment would rise after 2012, particularly in the non-farm sectors, as the educated youth would have joined the labour market. It was further expected that this would have sustained the structural transformation that India is experiencing. Since 2004-05, the Indian economy has been at a critical period of development, with the share of workers in agriculture dropping and the non-farm sector increasing at the same time (Thomas, 2020; Mehrotra et al., 2014). This stage of structural transformation, when “surplus labour” from the traditional sector (agriculture or informal) moves to the modern sector (industry or formal sector), has been modelled by Arthur Lewis and is defined indicative of the modernisation of a country.

But unfortunately, total employment has declined between 2011-12 and 2018-19. It was estimated that the decline in total employment is around 9 million between 2011-12 and 2017-18 (Mehrotra & Parida, 2019). Further, the share of those attending educational institutions has dropped from 27.5 percent for the year 2011-12 to 26.32 percent for 2018-19. Thus, unlike 2004-2005, when the share of those attending educational institutions increased when LFPR decreased, between 2011-12 and 2018-19 the decline in LFPR is happening along a with decline in participation in educational institutions. Further, women withdrew from the labour market *en masse*, leading to an increase in the share of those who have declared themselves as attending domestic duties from 10.81 percent to 16.14 percent. But this significant job loss will have a different effect on different sections of society and as we know, the Indian social structure is highly fragmented along the lines of caste and gender. Therefore, in this section, a detailed analysis of the changing employment structure of India between the years 2011-12 and 2018-19 will be analysed, particularly examining its impact on different social groups.

4.1. Distribution of Households by Household Type

Before moving to the analysis of the changing employment structure of India, a general overview of how households are distributed by household type is provided in this section using the PLFS data to get a broad understanding of the economic position of the population depending on their caste and gender identity.

Table 9: Percentage Distribution of Households by Household Type in Rural Areas in 2018-19

	ST	SC	OBC	FC	All groups
Self-employed in Agriculture	45.45	23.96	39.44	39.27	36.62
Self-employed in Non-Agriculture	7.95	13.35	16.28	18.13	15.06
Regular Wage/Salary Employed	11.36	12.82	12.11	16.2	13.1
Casual Labour in Agriculture	13.83	19.27	9.82	6.67	11.7
Casual Labour in Non-Agriculture	13.99	21.76	11.89	7.74	13.42
Others	7.42	8.84	10.46	11.99	10.09
Total	100	100	100	100	100

Source: Computed from Unit Level Data of PLFS 2018-19

The PLFS categorises families into distinct groups according to their source of income in last one year. In rural areas, households are divided into self-employment both in farm and non-farm, regular employment and casual employment again both in farm and non-farm. Households are further divided into self-employed, regular wage/salary earning, casual labour, and others in urban areas. Table 9 indicates that about 50 percent of the households in the rural

segment are engaged in agriculture with 36.62 percent being self-employed in agriculture and 11.7 percent working as casual labour. Another 15.06 percent households participates in self-employment in non-agricultural work and 13.42 percent households are in casual labour and 13.1 percent of the households are engaged in regular wage/salary earning. Furthermore, 45.45 percent of ST households in rural areas participate in self-employment in agriculture, while roughly 28 percent engage themselves in casual employment. Only 11.36 percent of ST households rely on regular wage/salary employment. Similarly, we find that the majority of OBC households and FC household are employed in self-employment is agriculture. While more than 50 percent of ST, OBC and FC households are in self-employment in both agriculture and non-agriculture, it is only 37 percent for SC households. The majority of the SC households are engaged in casual labour with 19.27 percent engaged in casual labour in agricultural sector and 21.76 percent in non-agricultural sector.

Table 10: Percentage Distribution of Households by Household Type in Urban Areas in 2018-19

	ST	SC	OBC	FC	All groups
Self-employed	22.76	24.22	32.97	33.75	31.75
Regular Wage/Salary Employed	42.38	44.25	39.41	45.89	42.77
Casual Labour	14.52	19.35	12.96	5.81	11.02
Others	20.34	12.17	14.66	14.54	14.46
Total	100	100	100	100	100

Source: Computed from Unit Level Data of PLFS 2018-19

In urban areas, households are divided into self-employed, regular wage/salary earning, and casual labour, which constitute 31.75 percent, 42.77 percent and 11.02 percent respectively of all households as provided in the Table 10. The share of self-employed for OBC and FC households are 32.97 and 33.75 percent respectively, while it is 22.76 and 24.22 percent for ST and SC households. Households that are dependent on casual labour are majorly among ST, SC, and OBC households at 14.52, 19.35, and 12.69 percent respectively; it is, however, relatively less for FC households with a mere 5.86 percent households engaged in casual labour. Thus, we find that households dependent on casual work are most prominent among socially marginalised groups whereas households engaged in regular work is more prominent among FC. Thus, caste is a major factor is determining employment. In the next section, a detailed analysis would be taken up on the status of employment for different segments of the society.

4.2. Status of Employment

The workers are grouped into three broad categories of self-employment, RWS work, and casual labour according to their status in employment (NSO, 2020). Table 11 demonstrates that the proportion of regular workers has risen. Further, it shows a decline in the number of casual workers. The number of those involved in self-employment is nearly stagnant. The first half of the 2000s shows a massive increase in the numbers of the self-employed. The trend reversed between 2004-05 and 2009-10 with a decrease in self-employment and a rise in the casual workers category (Thomas, 2012). Another reversal occurs after 2011-12, when the percentage of regular workers increases.

According to the PLFS data for 2018-19, more than 50 percent of male (51.63 percent) and female (53.38 percent) workers are engaged in the self-employed category (Table 11). While male workers are highly represented in the Own-Account Workers/Employers, female workers overwhelmingly employed as a helper in household enterprises. When compared to the year 2011-12, we find that the proportion of self-employed is constant at around 52 percent. However, disaggregation on the basis of gender suggests that the self-employed has increased by one percentage point for males, it has decreased by three percentage points for females. We also discovered that, while the proportion of regular work in total employment has risen for both gender groups, the share of casual employment has fallen across the board.

The disaggregation by the social group suggests that the percentage of SCs involved in self-employment is lowest at 38.03 percent while for all other groups, self-employment forms the majority of employment with more than 50 percent of the population of STs, OBCs and FCs engaging themselves in self-employment. On the other hand, we find that the proportion of population engaged in casual work is highest among SCs at 41.19 percent followed by STs at 30.53 percent. While 22.04 percent of OBCs engaged in casual employment, it is only 12.2 percent of FCs.

When we look at social group wise involvement in RWS Employment, which is in comparison better than other two kinds of job we find that the proportion of FCs is highest. The proportion of FC involved in RWS employment is highest at 32.99 percent followed by OBCs and SCs at 22.2 percent 20.77 percent respectively. The proposition of STs involved in RWS employment is lowest at 12.97 percent.

***Table 11: Distribution of Workers (in percent) according to usual status (ps+ss) by Status in Employment
(Rural + Urban)***

Gender	Year	Own Account Worker and Employer (1)	Helper in Household Enterprises (2)	Self-Employed (1+2)	Regular Wage/Salaried Employee	Casual Labour
ST						
Male	2011-12	38.62	13.6	52.22	10.83	36.96
	2018-19	43.49	10.5	53.99	14.46	31.54
Female	2011-12	11.1	44.94	56.04	5.21	38.75
	2018-19	13.49	48.25	61.74	9.85	28.4
Person	2011-12	28.36	25.27	53.63	8.73	37.63
	2018-19	33.79	22.71	56.5	12.97	30.53
SC						
Male	2011-12	28.07	6.26	34.33	16.78	48.89
	2018-19	33.07	4.51	37.58	20.86	41.56
Female	2011-12	17.29	25.1	42.39	11.85	45.75
	2018-19	19.31	20.08	39.39	20.51	40.1
Person	2011-12	24.85	11.89	36.74	15.31	47.95
	2018-19	29.57	8.46	38.03	20.77	41.19
OBC						
Male	2011-12	41.58	12.35	53.93	17.6	28.47
	2018-19	46.99	8.37	55.36	22.91	21.73
Female	2011-12	19.39	39.58	58.97	11.08	29.95
	2018-19	24.61	32.35	56.96	20.07	22.96
Person	2011-12	35.46	19.86	55.32	15.8	28.88
	2018-19	41.37	14.38	55.75	22.2	22.04
FC						
Male	2011-12	44.59	11.44	56.03	27.84	16.13
	2018-19	47.31	7.68	54.99	32.5	12.52
Female	2011-12	29.29	34.34	63.63	21.28	15.09
	2018-19	27.29	26.79	54.08	35.03	10.9
Person	2011-12	41.16	16.57	57.73	26.37	15.89
	2018-19	43.4	11.41	54.81	32.99	12.2
All						
Male	2011-12	39.67	11.06	50.73	19.82	29.44
	2018-19	44.01	7.61	51.63	24.4	23.97
Female	2011-12	19.99	36.14	56.14	12.68	31.18
	2018-19	22.54	30.83	53.38	21.89	24.73
Person	2011-12	34.24	17.99	52.22	17.85	29.92
	2018-19	38.76	13.29	52.05	23.79	24.16

Source: Computed from Unit Level Data of NSSO-EUS 2011-12 and PLFS 2018-19

***Table 12: Distribution of Workers (in percent) according to usual status (ps+ss) by Status in Employment
(Rural)***

Gender	Year	Own Account Worker and Employer (1)	Helper in Household Enterprises (2)	Self-Employed (1+2)	Regular Wage/Salaried Employee	Casual Labour
ST						
Male	2011-12	40.83	14.88	55.71	5.77	38.52
	2018-19	45.44	11.37	56.81	10.72	32.47
Female	2011-12	10.59	46.82	57.41	3.33	39.26
	2018-19	12.93	51.13	64.06	6.96	28.98
Person	2011-12	29.19	27.18	56.37	4.83	38.8
	2018-19	34.68	24.53	59.21	9.48	31.32
SC						
Male	2011-12	28.82	6.89	35.71	8.91	55.38
	2018-19	35.08	5.21	40.29	13.57	46.15
Female	2011-12	17	27.35	44.35	5.02	50.63
	2018-19	19.48	23.54	43.02	11.45	45.53
Person	2011-12	25.08	13.36	38.44	7.68	53.88
	2018-19	31.03	9.96	40.99	13.02	45.99
OBC						
Male	2011-12	43.67	14.15	57.82	9.43	32.74
	2018-19	52.05	10.08	62.13	13.73	24.14
Female	2011-12	17.39	43.9	61.29	5.59	33.12
	2018-19	24.19	38.91	63.1	10.52	26.39
Person	2011-12	35.78	23.09	58.87	8.28	32.86
	2018-19	44.65	17.74	62.39	12.87	24.74
Others						
Male	2011-12	49.42	14.35	63.77	14.13	22.11
	2018-19	55.48	10.17	65.65	17.89	16.47
Female	2011-12	29.82	43.53	73.35	8.29	18.37
	2018-19	27.7	40.54	68.24	16.04	15.71
Person	2011-12	44.41	21.8	66.21	12.64	21.15
	2018-19	49.84	16.33	66.17	17.51	16.31
All						
Male	2011-12	41.68	12.79	54.47	10.04	35.49
	2018-19	48.23	9.17	57.41	14.25	28.34
Female	2011-12	18.56	40.7	59.26	5.61	35.13
	2018-19	21.78	37.86	59.64	11	29.36
Person	2011-12	34.64	21.28	55.92	8.7	35.38
	2018-19	41.35	16.63	57.99	13.41	28.61

Source: Computed from Unit Level Data of NSSO-EUS 2011-12 and PLFS 2018-19

Table 13: Distribution of Workers (in percent) according to usual status (ps+ss) by Status in Employment (Urban)

Gender	Year	Own account Worker and Employer (1)	Helper in Household Enterprises (2)	Self-Employed (1+2)	Regular Wage/Salaried Employee	Casual Labour
ST						
Male	2011-12	20.53	3.15	23.68	52.03	24.29
	2018-19	25.06	2.26	27.32	49.93	22.75
Female	2011-12	18.99	15.62	34.61	34.56	30.83
	2018-19	21.7	5.78	27.48	52.66	19.86
Person	2011-12	20.15	6.23	26.38	47.72	25.9
	2018-19	24.25	3.11	27.36	50.59	22.05
SC						
Male	2011-12	25.47	4.08	29.55	44.3	26.15
	2018-19	25.85	2.02	27.87	47.03	25.11
Female	2011-12	18.9	12.92	31.82	48.84	19.34
	2018-19	18.62	5.77	24.39	57.92	17.68
Person	2011-12	23.96	6.11	30.07	45.35	24.58
	2018-19	24.16	2.89	27.05	49.57	23.37
OBC						
Male	2011-12	36.16	7.67	43.83	38.79	17.38
	2018-19	35.45	4.45	39.9	43.84	16.25
Female	2011-12	28.07	20.86	48.93	34.88	16.19
	2018-19	25.9	12.63	38.53	48.8	12.66
Person	2011-12	34.51	10.37	44.88	37.99	17.14
	2018-19	33.4	6.21	39.61	44.91	15.48
Others						
Male	2011-12	37.85	7.36	45.21	47.02	7.77
	2018-19	37.24	4.6	41.84	50.51	7.65
Female	2011-12	28.09	13.71	41.8	50.45	7.75
	2018-19	26.72	7.91	34.63	61.09	4.28
Person	2011-12	36.13	8.48	44.61	47.62	7.76
	2018-19	35.28	5.22	40.5	52.48	7.02
All						
Male	2011-12	34.83	6.89	41.72	43.4	14.88
	2018-19	34.54	4.11	38.65	47.17	14.17
Female	2011-12	26.12	16.72	42.84	42.81	14.35
	2018-19	24.86	9.6	34.46	54.79	10.75
Person	2011-12	33.1	8.84	41.94	43.28	14.77
	2018-19	32.54	5.25	37.79	48.75	13.47

Source: Computed from Unit Level Data of NSSO-EUS 2011-12 and PLFS 2018-19

The trend of increasing regular work and declining casual work is true for all social groups. However, the share of those employed in casual work is larger among SCs and STs. Further, the share of those employed in regular work is highest among FCs. Thus, a division on the

basis of caste in jobs is observed, where the chances of getting well-paying regular jobs are higher among higher castes and chances to be restricted to low paying casual work are higher among lower castes. Further, we find that a division on the basis of gender is persistent across caste lines, with female workers mostly employed either as a helper in household enterprises or as a casual worker. Interestingly, female workers from FCs have a decent share in RWS employment at around 35 percent.

From Table 12 and Table 13, we find that, while the majority of the rural workers are employed in the self-employment and casual employment, the share of the population employed in regular work is more in urban areas. We further find that while female workers are engaged slightly more as casual labourers in rural areas than their male counterparts, male workers are engaged more in casual labour in urban areas. The disaggregation at the sector level suggests that while the proportion of the female worker engaged as a helper in household enterprises is more prominent in rural areas. Thus, a majority of the women workforce is employed as helpers in the agricultural. The trend of declining share of casual work and increasing share of regular work has remained true for urban as well as rural areas.

Although the proportion of workers receiving regular wages is less in rural areas, it is even less among socially marginalised groups like SCs, STs, and OBCs. However, this share has increased marginally over the years. The further analysis suggests that the proportion of the self-employment is higher among FCs than among SCs, STs, and OBCs. But the share of the self-employed has increased for males in the FC category while for females it shows a declining trend. The proportion of workers engaged in casual labour in rural areas is lower than those in self-employment or regular work. However, the share of the population employed in the category of casual worker is higher for socially marginalised groups and lower for FCs. While the share of casual labour is as high as 30 percent for ST women, it is only four percent for females belonging to the FCs. Table 13 shows that while the share for male and female FCs engaged in regular work has increased, it had decreased for ST males from 52.03 percent in 2011-12 to 49.93 percent in 2018-19. Thus, the identity of caste and gender has a deep bearing upon the status of employment.

5. Quality of Employment

In the previous section, we looked at the status of employment. We found that regular employment has increased marginally, which is a silver lining in the otherwise grim situation

of the labour market. However, it is imperative to examine the exact nature of regular work to better understand the labour market situation. Therefore, in this section, we will look at the quality of the jobs, particularly in the RWS employment, as this category comprises of some of the highest paying jobs. For this purpose, the absence of a written contract and ineligibility of paid leave among the regular workers have been studied.

The absence of a written contract indicates the precarity of such employment. An employee without any formal written contract can be subjected to harsh working condition and may have to face extreme vulnerabilities and exploitation. Further, the lack of legal contract deprives them of their claim over entitlements and protections provided by labour laws and regulations. It is worrisome to find that an increase in the share of RWS employees without contract from 64.66 percent in 2011-12 to 69.92 percent in 2018-19 (Table 14). The share of the regular male worker without any written contract has increased from 64.86 percent to 70.6 percent. However, it has increased from 63.82 percent to 67.52 percent for females (Table 14).

When disaggregated at the social group level, it was found that SCs and OBCs are worse off in terms of having a written job contract. In 2018-19, while the share of RWS employees without a written contract was at 72.57 and 73.39 for SCs and OBCs respectively, it was 66.07 and 65.45 percent for the STs and FCs respectively (Table 14). Moreover, a clear regional divide can be observed regarding the availability of regular jobs without any written contract. Urban areas have a larger proportion of RWS workers without a job contract at 71.05 percent, which is three percentage points more than rural areas. The rural-urban divide is sharper when looking at female workers whereby 72.47 percent of female RWS employees in urban areas are without any job contract, while 58.83 percent of female RWS employees are without any job contract in rural areas.

Another indicator of the quality of employment and decent work is the access to paid leave. According to the PLFS for the year 2018-19, while 69.92 percent of RWS employee are without any written job contract, the share of RWS employee with no paid leave constitutes 54.22 percent.

Table 14: Regular Wage/Salaried Employees (in percent) according to usual status (ps+ss) without a Written Job Contract

Social Group	Rural						Urban						Rural + Urban					
	Male		Female		Person		Male		Female		Person		Male		Female		Person	
	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19
ST	55.34	68.9	53.82	56.22	54.94	66.04	52.22	63.89	63.13	72.81	54.15	66.13	53.59	67.2	57.82	62.37	54.52	66.07
SC	69.56	73.59	68.42	64.91	69.33	71.65	63.59	71.97	69.57	77.57	65.03	73.47	66.02	72.79	69.17	71.9	66.73	72.57
OBC	69.6	72.74	66.23	60.25	68.97	70.19	71.08	74.78	72.94	77.99	71.42	75.52	70.52	73.95	70.38	71.43	70.49	73.39
Others	60.5	65.62	51.58	51.71	59.1	63.07	60.3	66.9	56.74	64.77	59.65	66.44	60.36	66.51	55.42	61.34	59.49	65.45
All	65.63	70.55	61.36	58.83	64.85	68.15	64.44	70.62	65.09	72.47	64.56	71.05	64.86	70.6	63.82	67.52	64.66	69.92

Source: Computed from Unit Level Data of NSSO-EUS 2011-12 and PLFS 2018-19

Table 15: Regular Wage/Salaried Employees (in percent) according to the usual status (ps+ss) Not Eligible for Paid Leave

Social Group	Rural						Urban						Rural+Urban					
	Male		Female		Person		Male		Female		Person		Male		Female		Person	
	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19	2011-12	2018-19
ST	40.43	53.91	44.25	52.68	41.45	53.63	39.6	51.81	42.9	61.42	40.19	54.22	39.97	53.2	43.67	55.91	40.78	53.84
SC	56.85	63.38	49.34	62.79	55.34	63.25	52.31	55.76	57.32	62.11	53.52	57.46	54.15	59.62	54.52	62.42	54.24	60.31
OBC	55.61	60.1	49.86	45.12	54.54	57.04	54.67	56.27	53.01	55.3	54.37	56.05	55.02	57.83	51.81	51.53	54.43	56.44
Others	47.07	55.24	42.03	44.76	46.28	53.32	44.97	48.01	40.48	44.03	44.14	47.16	45.58	50.2	40.87	44.22	44.76	48.97
All	52.02	58.86	47.01	50.04	51.09	57.06	49.39	52.47	48.17	52.17	49.16	52.4	50.31	55.02	47.78	51.4	49.83	54.22

Source: Computed from Unit Level Data of NSSO-EUS 2011-12 and PLFS 2018-19

Table 15 suggests that the proportion of RWS employees without any paid leave is 55.02 for males and 51.4 percent for females in 2018-19. It has increased from 50.31 and 47.78 percent respectively for males and females for the year 2011-12. The share of RWS employee without any paid leave has increased for all groups, which is quite worrisome because it is happening simultaneously with an increase in jobs without contracts.

Further, the share of regular workers without any paid leave is larger in rural areas at 57.06 percent than in urban areas, which is at 52.4 percent. Moreover, the gender divide is more visible in rural areas with 58.86 percent of rural males working in RWS employment without any leave in comparison to 50.04 percent for the rural male regular workers. Similar to the absence of a written contract, the share of RWS employees without paid leave is more among SCs and OBCs than the FCs and STs. Thus, the worsening of quality of employment and lack of decent work is a problem that cuts across caste and gender. Still, individuals belonging from marginalised socio-economic groups are affected by a greater probability of being deprived of any written job contract or paid leave.

6. Conclusion

In this chapter, a discussion on the state of the Indian labour market, particularly recent changes that have happened between 2011-12 and 2018-19 has been undertaken. One of the major positive changes that is happening within the Indian labour market is the demographic window of opportunity that India is experiencing. In other words, the proportion of the working-age population is increasing, and it has reached to 68.19 percent. But to harness the power of the youth, the country needs to generate sufficient jobs to absorb the ever-increasing population of workers. However, this chapter finds that the rate of generating employment is so low that India has experienced a highest level of open unemployment ever. Further, the total numbers of the unemployed have increased for the first time. The chapter also finds that there is a decline in the LFPR and the WPR. Further analysis suggests that the decline is majorly caused by the decline in participation of female workers in rural areas. The chapter further finds that ST women saw the highest decline in their LFPR.

With the decline in the LFPR and a rise in the level of unemployment, it seems impossible to get the benefit of “demographic window of opportunity”. It is particularly worrisome because, unlike 2005-12, when workers moved towards educational institutions to gain access to better job opportunities, in 2018-19 the share of those in educational institutions has also declined by

one percent. Therefore, an increase in open unemployment is observed with disheartened workers leaving the labour market altogether. One such example was found in the increase in the number of those who have declared themselves as attending domestic duties.

Further, the examination of the changing employment structure of India found that there is a general trend of declining casual employment and increasing regular work. However, the share of the population employed in casual work was higher for SCs and STs and those employed in regular work was higher among FCs. It was also found that, while male workers are highly represented in Own-Account Employment, female workers were mostly employed as helpers in household enterprises. Thus, a clear gender-based and caste-based divide is observed in the status of employment for an individual.

Since the increase in regular employment was the only positive aspect of an otherwise grim labour market situation, a closer examination was done to better understand the quality of the jobs that have been created. Upon examination, it was found that the proportion of RWS employees has increased. However, mostly of the newly created jobs are without written job contracts or paid leaves. Thus, although the proportion of RWS workers has increased, jobs with low security in RWS employment has also increased. Thus, the situation here is positive only with a serious caveat, which may present the entire picture as problematic for a different set of reasons.

Chapter 4: Wage Differentials and Discrimination: Caste and Gender Identity in the Labour Market

1. Introduction

As already mentioned in the last chapter, employment and the lack of it is an important question and has been at the centre of political debate in the recent past. However, an equally important and related question is of wages as it is not just employment but also a decent and well-paying job that is required for fair distributive justice. It is therefore important to understand the method of determination of wages and the reason the prevalence of wage disparities. In the neo-classical framework, wage formation is done by the intersection of supply and demand curves. As a result, it is implicit that employees will typically earn wages equal to their marginal product. In other words, this framework suggests that the difference in wages among workers reflects the endowment difference between workers. As a result, the persistence of wage discrimination is either ignored in the neo-classical framework or an attempt is made to explain it by directing towards differences in “personal endowments”.

In this chapter we will take a closer look into the question of wage differentials and discrimination based on gender and caste identity. It is important here to distinguish between differentials and discrimination as all differentials need not be due to discrimination. Hence, our main focus of analysis shall be discrimination in the labour market amongst equally skilled workers based on their social identity. Wage differential is the indication of differences in the wage level of workers. However, these differentials can arise due to various reasons and differences in human capital and skills are one of the most important among them. A discussion on labour market discrimination refers to the wage differentiation that exists between workers with similar level of skills.

This chapter first explains the dichotomy of regular and casual work; then an empirical analysis is presented in two parts. The first part of the analysis will look into the question of wage structures and wage differentials on the basis of gender and social group while the second part focuses on analysing wage discrimination across gender and social groups in the urban areas for regular employment. Fastly, a concluding remark would be presented regarding the existence of labour market discrimination.

2. Dual Labour Market: Casual-Regular Dichotomy

The Indian labour market is highly segmented. The segmentation is based on the dichotomy of regular-casual, rural-urban, formal-informal, primary-secondary, public-private etc. The dual labour market theory proposed by Piore and Doeringer (1970) distinguishes labour market into two distinct sectors. While one sector consists of stable jobs with high pay scales, availability of social security and better working conditions, the other sector is marked by the of lack such basic amenities and social safety nets. However, duality is not just limited to these sectors, as employment is of two kinds: formal/organised and informal/unorganised. While formal employment provides high wages, stability, and availability of social security, informal employment consists of economic activities that are deprived of these amenities.

The majority of casual workers are working in the informal/unorganised sector and a majority of RWS workers are employed in the formal/organised sector. Above that, the proportion of casual employment in organised/formal sector has increased over the years (Srivastava R. , 2019). This informalisation and casualisation of a majority of wage earners have placed them at a disadvantageous position and the wage differential is substantial between the two labour market segments. Therefore, the assumption of a single wage equation for the two labour market segments would be an unfair representation of the situation. In this context, the following section will provide separate analyses for regular and casual employment with particular focus on regular labour market.

Table 16: Percentage Share of Workforce Force (ps+ss) in 2011-12 and 2018-19

	2011-12	2018-19
Self-Employed	52.22	52.06
Regular Worker	17.85	23.78
Casual Worker	29.92	24.16

Source: Computed from Unit Level Data of NSSO-EUS 2011-12 and PLFS 2018-19

The workers in the Indian labour market are mainly divided into self-employed, regular, and casual workers. The portion of self-employed, regular, and casual workers was 52.22 percent, 17.85 percent, and 29.92 percent respectively in 2011-12. The data for the year 2018-19 suggests that while the proportion of the self-employed has continued to be stable, the proportion of regular workers has increased to 23.78 percent with the share of casual labourers declining to 24.16 percent. The rise in the number of regular wage workers is a desirable

outcome. However, it has happened at a time when the informal sector has experienced massive shocks repeatedly from poorly conceived and implemented government policies ranging from demonetisation to the poor implementation of GST (Harriss-White, 2020). Therefore, the rise in the proportion of regular employment is not necessarily due to a positive impact but may point towards a decrease in the absolute number of workers employed in the informal sector.

The Current Weekly Status (CWS) has been used to calculate average monthly wage. While the CWS codes 31, 71, and 72 have been taken to calculate regular wage, only CWS code 51 has been taken to calculate casual wages. The casual work in the public sector (CWS code 41 and 42) is only limited to rural areas, and outside these regions it forms a miniscule part of the total casual work. The wages for casual workers have doubled between 2011-12 and 2018-19. However, the corresponding increase for regular workers has not been comparably significant. There has been only a 30 percent increase in wages between the two time periods for regular workers. However, the wage differential between regular and casual employment has remained substantial for both 2011-12 and 2018-19 as evident from Table 17.

Table 17: Monthly Wage (in Rupees) for Regular and Casual Workers in 2011-12 and 2018-19

	Regular	Casual
2011-12	11750.93	4258.36
2018-19	16166.99	8403.10

Source: Computed from Unit Level Data of NSSO-EUS 2011-12 and PLFS 2018-19

Moreover, the wage levels hide the real difference in earnings between casual and regular workers. While the regular workers are paid for all weekdays, the payment for casual workers is heavily reliant upon the availability of work. Thus, the nature of employment is more precarious for casual workers than regular workers. Further, the rural-urban wage divide is clear from Table 18. We see that the wages in urban areas are higher than that in rural areas. While the average monthly wage for regular workers was Rs. 8868.12 in rural areas, it was Rs. 13350.07 in urban areas in 2011-12. Similarly for the year 2018-19, the average monthly wage was Rs. 12539.31 for rural areas, it was Rs. 18558.52 for urban areas. Thus, we see that for both the time periods, the average monthly wage is higher for workers in urban areas than rural areas. A similar rural-urban divide can be found for workers employed in casual work. While the average monthly wage for casual workers in 2011-12 was Rs. 4134.03 in rural areas, it was Rs. 5006.34 in urban areas. In 2018-19, the average wages for casual workers have increased to Rs. 8026.86 in rural areas, it has increased to Rs. 10262.04 in urban areas. Thus, we find

that, while the rural-urban divide is prevalent for both casual and regular workers, the rural-urban gap is higher for regular workers in comparison to casual workers.

Table 18: Monthly Wage (in Rupees) for Regular and Casual Workers in Rural and Urban Areas in 2011-12 and 2018-19

	Regular		Casual	
	2011-12	2018-19	2011-12	2018-19
Rural	8868.12	12539.31	4134.03	8026.86
Urban	13350.07	18558.52	5006.34	10262.04

Source: Computed from Unit Level Data of NSSO-EUS 2011-12 and PLFS 2018-19

Apart from the rural-urban divide, education is significant while determining the wage level. The education category is divided into “Not Literate”, “Literate up to Primary”, “Middle”, “Secondary/Higher Secondary including Diploma”, and “Graduate and Above”. Wages rise in lockstep with educational attainment, as expected. However, the increase is much higher among regular workers. Level of education plays a much smaller role in determining wages for casual workers as shown in Table 19.

Table 19: Wage Ratio by the Levels of Education for Regular and Casual Workers in 2011-12 and 2018-19

	Regular		Casual	
	2011-12	2018-19	2011-12	2018-19
Not Literate	1.00	1.00	1.00	1.00
Literate and upto Primary	1.20	1.15	1.11	1.13
Middle	1.37	1.37	1.24	1.25
Secondary/Higher Secondary including Diploma	2.25	1.95	1.26	1.27
Graduate and Above	4.44	3.46	1.38	1.30

Source: Computed from Unit Level Data of NSSO-EUS 2011-12 and PLFS 2018-19

While wage differentials across educational categories for casual workers have been fairly stable during the two time periods, it has decreased for regular workers. Among regular workers, those who had at least a graduate degree were earning 4.44 times more those who with no formal education in 2011-12; by 2018-19 that ratio had reduced to 3.45. In other words, the gap across educational groups has decreased.

However, education has remained an important factor in determining the wage levels for RWS employment. It is generally suggested that the identity of an individual has no role to play in the determination of wages in such segments of the labour market. Further, it is also assumed that merit and talent are the only factors that determine the level of wages. Therefore, the main analysis will focus on the regular labour market, particularly in urban areas because of two reasons: one, because jobs in this segment of the labour market are assumed to be allocated on the basis of human capital and two, because it is less likely for women in this segment to under-report their participation in the market unlike other segments (Deshpande, Goel, & Khanna, 2015, p. 9).

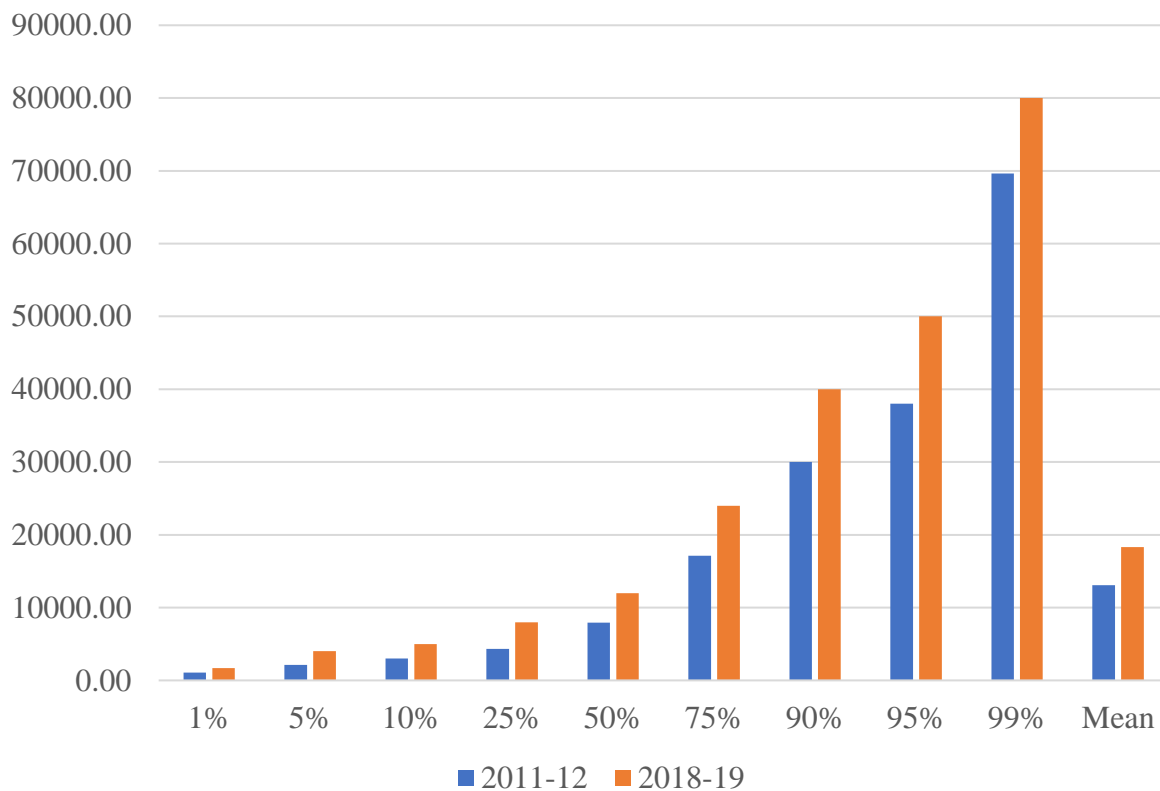
3. Wage Differential among Regular Wage/Salaried (RWS) Workers in Urban Labour Market

NSSO defines RWS workers such that it consists of those who work on farms not owned by them or non-farm enterprises and in exchange receive a salary or wages on a regular interval. We concentrate on RWS workers because they are mostly employed in the formal sector, where wages are assumed to be determined by merit and skill. The analysis in this section is limited to those parts of India outside of the North-Eastern states and the Union Territories because the historical evaluation of North-Eastern states has been different and therefore the nature of social conflict is also different with ethnic identity at the centre of it (Bijukumar, 2013). We have also excluded UTs to keep the analysis limited to the larger states of India. Therefore, when an average wage is referred, it indicates only to the average wage in regions of India excluding the North-East and the Union Territories.

The mean wage level for urban RWS workers has increased from Rs. 13099.91 in 2011-12 to Rs. 18296.56 in 2018-19. However, the measurement at mean can be misleading as there is considerable heterogeneity within regular workers at different income levels. The wage level varies considerably across percentile groups. It can be observed from Figure 1 that between the bottom 1 percentile and the top 1 percentile for regular workers for both 2011-12 and 2018-19 there exists a wage gap that is considerably enormous. In the year 2011-12, the bottom 1 percentile on average earned Rs. 1071.43 while the top 1 percentile on average earned Rs. 69642.85 per month. There is a general increase in wages across all percentile groups between 2011-12 and 2018-19. In 2018-19, the bottom 1 percentile on average earned Rs. 1700 per month while the top 1 percentile on average earned Rs. 80000 per month. Thus, even within

RWS workers in urban areas, there is a huge gap between different segments of the society. While on the one end are jobs like construction labour, manual labour, and other such low paying and labour-intensive activities, on the other end are high paying jobs like that of legislators, senior officials and managers are present. In between the two kinds of employment lies a heterogeneous spectrum of occupations that provides a wide range of incomes.

Figure 1: Average Monthly Wage (in Rupees) across percentile groups for RWS Workers in Urban Areas for 2011-12 and 2018-19

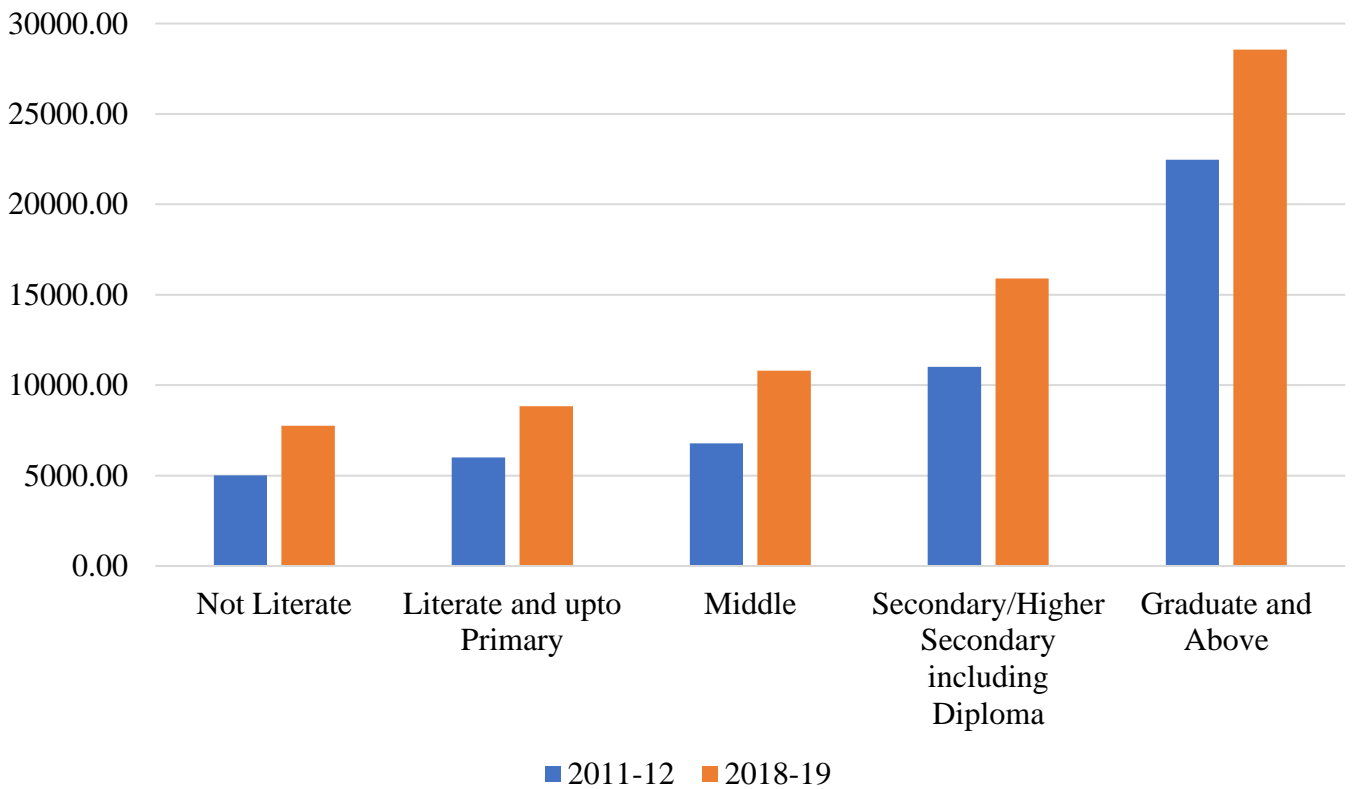


Source: Computed from Unit Level Data of NSSO-EUS 2011-12 and PLFS 2018-19

The nature of work assigned to workers is also dependent on the nature of skills and education. Based on different levels of education, workers would receive different levels of wages. Figure 2 indicates, that as expected, there is an increase in wages with an increase in educational levels for regular workers in urban areas. The increase in wages is steeper after the completion of secondary education, as being a graduate brings the largest increase in monthly wages. There has been an increase in average monthly wages for those who have no education from Rs. 5009.65 in 2011-12 to Rs. 7761.32 in 2018-19. Similarly, the monthly wage levels on average were Rs. 6009.92 and Rs. 8830.17 for those with up to a primary level of education for the

years 2011-12 and 2018-19 respectively. Even those with a middle level of education earned around the same at Rs. 6775.97 and Rs. 10804.36 for 2011-12 and 2018-19 respectively.

Figure 2: Average Monthly Wage (in Rupees) across educational groups for RWS Workers in Urban Areas for 2011-12 and 2018-19



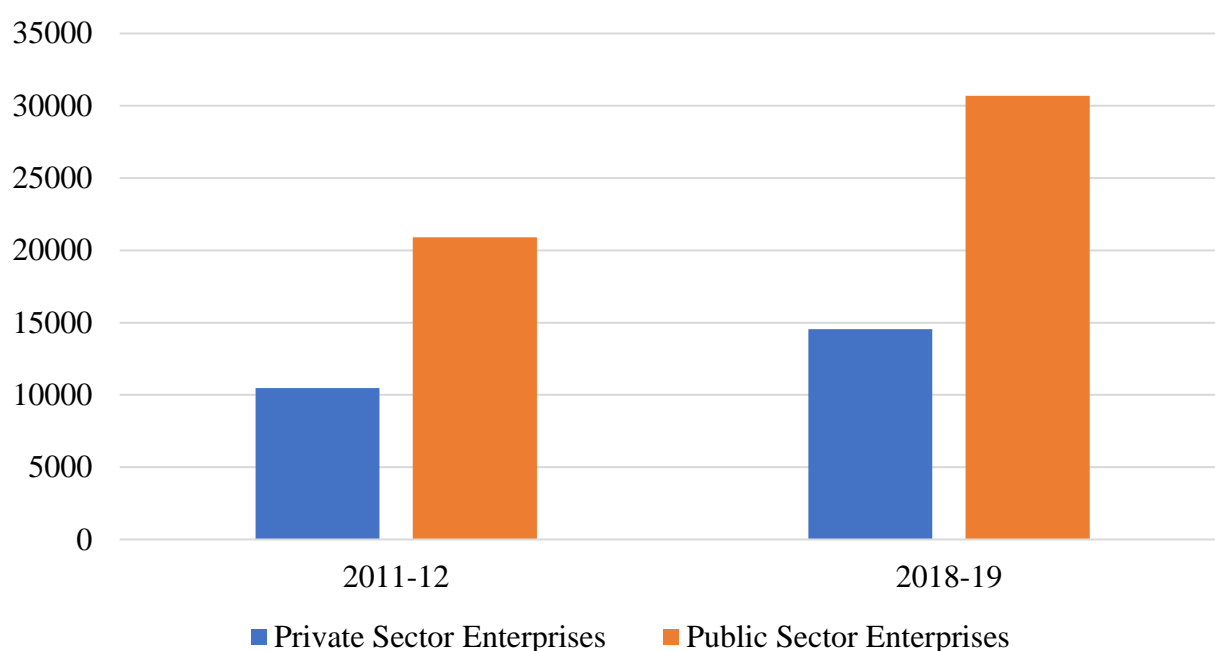
Source: Computed from Unit Level Data of NSSO-EUS 2011-12 and PLFS 2018-19

It is only with a higher secondary level of education that we see a greater rise in the wage level. While persons in this category were earning Rs. 11020.58 on average in 2011-12, they are earning Rs. 15908.61 on average in 2018-19. However, the highest increase in the level of wages is for those with at least a graduation degree, with the average wage increasing from Rs. 22469.09 in 2011-12 to Rs. 28553.27 for the year 2018-19. Thus, we see that wage levels differ drastically with the level of education.

Apart from education, the level of wages also differed based on the enterprise of work. The enterprises are clubbed into two types: one being public sector enterprises and the other being private sector ones. From Figure 3, it is clear that the level of wages for the public sector are much greater than that for the private sector. We can also observe that the level of wages has increased for both sectors over the two time periods. While the monthly wage on average for

RWS workers in the private sector was Rs. 10476.68 in 2011-12, it has increased to Rs. 14537.72 in 2018-19. Similarly, for the public sector it has increased on average from Rs. 20910.45 in 2011-12 to Rs. 30690.95 in 2018-19.

Figure 3: Average Monthly Wage (in Rupees) for RWS Workers in Urban Areas by Enterprise Type for 2011-12 and 2018-19



Source: Computed from Unit Level Data of NSSO-EUS 2011-12 and PLFS 2018-19

3.1. Wage Differentials by Gender

This section will delve into the issue of gender wage differentials that exist among RWS workers employed in urban areas. The proportion of males in the overall population in 2018-19 is 51.13 percent and that of females is 48.87 percent. However, the proportion of males among RWS workers is 76.89 percent and the share of females is only 23.11 percent.

Table 20: Percentage Share by Gender for 2011-12 and 2018-19

	2011-12		2018-19	
	Male	Female	Male	Female
Percentage share in population	51.92	48.08	51.13	48.87
Percentage share in RWS Workers	80.58	19.42	76.89	23.11

Source: Computed from Unit Level Data of NSSO-EUS 2011-12 and PLFS 2018-19

Thus, we can observe that the share of females in RWS employment is much below their proportion of the overall population. The low representation of women among RWS workers is an important concern because it reflects a lack of job opportunities available for them in the labour market as compared to their male counterparts.

Many sociological factors contribute to the low LFPR among women in India where a disproportionate burden of household work is placed upon them. Employment for women entails the need to transfer this burden upon someone else, primarily domestic workers. Hence there exists a trade-off between wages/salary of the employed woman vis-à-vis the expenditure required to employ a domestic worker. This would mean the existence of a reservation price which would have to be substantially higher than the wages of the domestic worker employed. If not, women would be compelled to remain outside the labour force whereby their work in domestic spaces would remain unpaid. Therefore, lower wages/salaries are a significant cause of lower participation of females. The wages of women workers are less than the male counterparts, as seen in Table 21. In the regular labour market, the women workers earn 76 percent that of their male counterparts in urban areas. The gender wage differential has declined between 2011-12 and 2018-19. In 2018-19, a female worker is earning on average 80 percent than that of male counterparts.

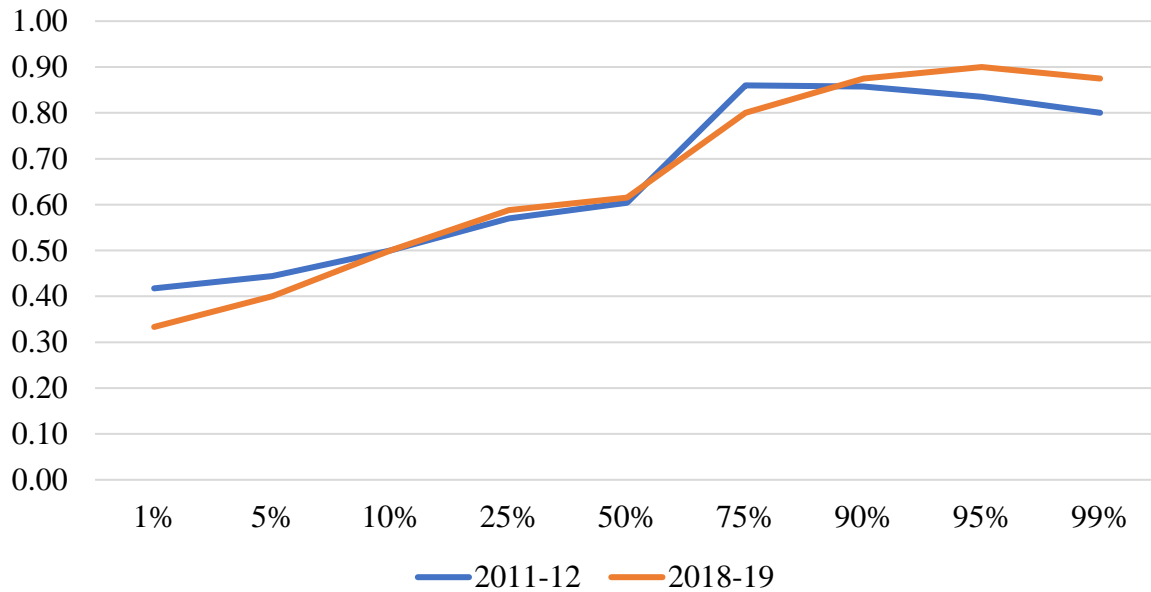
Table 21: Female-Male Wage Ratio for 2011-12 and 2018-19

	Male	Female	Female/Male
2011-12	13751.39	10396.49	0.76
2018-19	19168.35	15395.96	0.80

Source: Computed from Unit Level Data of NSSO-EUS 2011-12 and PLFS 2018-19

The average monthly wages for both males and females show an increase between 2011-12 and 2018-19. In urban areas, the percentage increase among regular workers is higher for female workers than male ones. The mean wage has increased by around 39.33 percent for males and 43.77 percent for female workers. The comparison of the gender wage gap by percentile reveals that there is a considerable heterogeneity. So, measuring the gender pay gap at mean can produce a misleading picture. The mean pay gap can hide varied gaps between high-paid workers and low-paid workers.

Figure 4: Female-Male Wage Ratio for Regular Workers in Urban Labour Market for 2011-12 and 2018-19



Source: Computed from Unit Level Data of NSSO-EUS 2011-12 and PLFS 2018-19

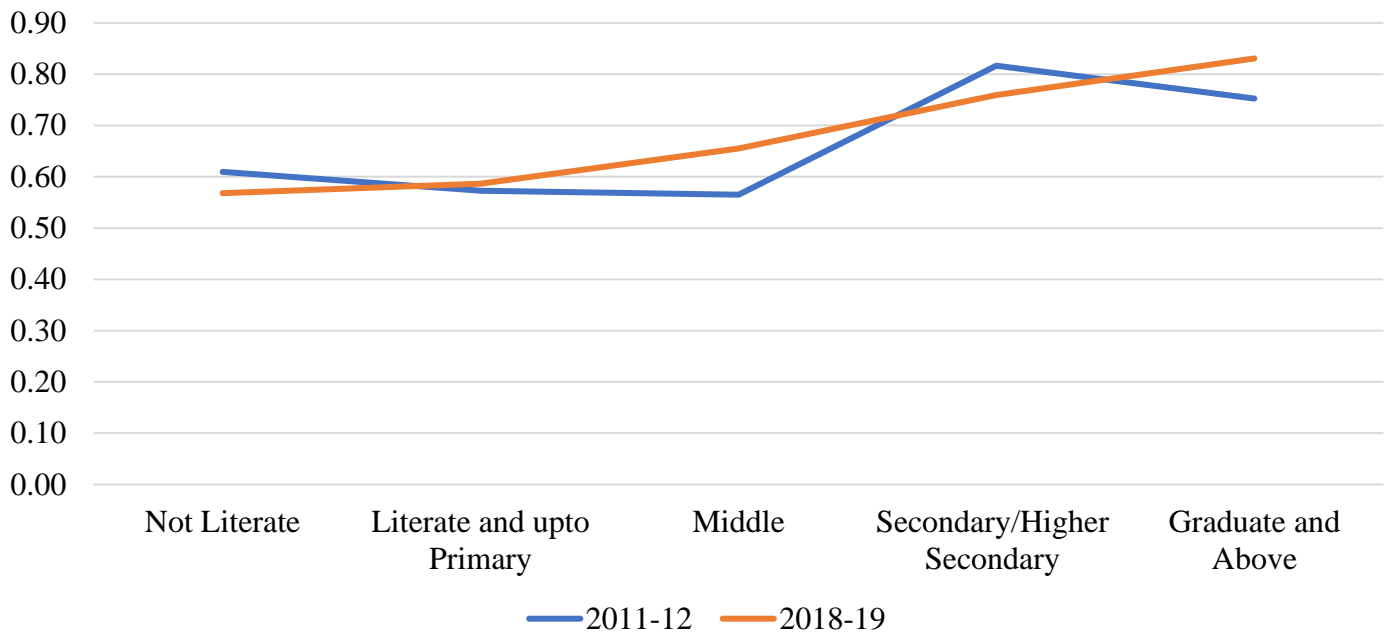
From Figure 4, it can be observed that the female-male wage ratio is lowest at lower percentiles and gradually increases as one moves up the pay ladder. The gender wage gap is smallest at the 95th percentile and it increases again at the 99th percentile. We further find that, while female-male ratio has declined at lower percentile groups between 2011-12 and 2018-19, it has increased at the higher percentile groups. This means that while the wage gap has increased at the lower percentile groups, it has declined at the higher percentile groups between the two time periods. Thus, we find an increase of wage gap between the higher and lower earning population in 2018-19.

In the regular labour market, we observe a pattern of increasing earnings with increasing levels of education. However, there is no notable wage difference between illiterate regular workers and those with primary education holders amongst both the genders. Even a middle level of education can only make a little difference in daily wages. Only after completing a secondary level of education do wage prospects improve dramatically. As a result, people with greater levels of education have fewer obstacles across various labour market segments, whereas workers with lower levels of education face more.

Therefore, the question arises: Does education help to close wages gap? It seems that it does so in regular labour market. However, the gender gap decreases only up to secondary and

higher secondary level of education and it increases for those with at least a graduate degree for the year 2011-12. It can be observed from Figure 5 that the wage gap continuously diminishes with an increase in educational qualification for the year 2018-19. Thus, we see that although the wage gap continues to exist despite a higher level of education, the gap continues to decrease.

Figure 5: Female-Male Wage Ratio for 2011-12 and 2018-19 by Level of Education



Source: Computed from Unit Level Data of NSSO-EUS 2011-12 and PLFS 2018-19

Apart from levels of education, the type of enterprise can impact the gender wage gap too. It is generally suggested that a public sector enterprise would be more equitable as the state would prevent discrimination based on workers' social identity as described in the Article 15 of the constitution.

Similar results can be observed from Table 22, where female to male ratio is higher for public sector enterprises for both years. In private sector enterprises, the female to male ratios were 0.71 and 0.78 for the year 2011-12 and 2018-19 respectively. For public sector enterprises, the ratios were 0.82 and 0.81 respectively for the year 2011-12 and 2018-19. Therefore, we see that although female-male ratio has remained higher for public sector enterprise than private sector enterprise the gender wage gap has increased over the two-time periods for public sector enterprises while it has decreased for private sector ones.

***Table 22: Female-Male Wage Ratio for Regular Workers in Urban Labour Market for 2011-12 and 2018-19
by Type of Enterprises***

	2011-12			2018-19		
	Male	Female	F/M	Male	Female	F/M
Private Sector Enterprises	11079.14	7823.29	0.71	15311.42	11907.57	0.78
Public Sector Enterprises	21726.97	17753.37	0.82	32185.72	26063.92	0.81

Source: Computed from Unit Level Data of NSSO-EUS 2011-12 and PLFS 2018-19

3.2. Wage Differentials by Social Groups

The caste system, as believed among upper middle class urban Indians, has become a relic of the past, an age-old structure with no significance in our modern life (Desai & Dubey, 2011). However, several studies have shown that caste is not only present but also plays a central role in determining the distribution of resources in India. There is also the view that Capitalism and Brahmanism are the twin enemies of the working class and are both rooted in discriminatory practices (Ambedkar B. R., 2020). In this section, we will analyse the disparity in earnings based on caste amongst workers in the regular urban labour market in India. We further analyse caste-based wage differentials by level of education, type of enterprises, and percentile groups.

As pointed out by Ambedkar, caste is a system of graded inequality that places different sections of the society at different levels of the social ladder (Ambedkar B. R., Annihilation of Caste, 2014). This is evident from Table 23, where we find that workers from SCs are at the bottom of the ladder while workers from FCs are at the top of the ladder with STs and OBCs in between these two groups. From Table 23 we can also observe huge disparities between different percentile groups across all social groups. In 2018-19, the bottom one percentile of SCs and STs earned Rs. 1100 and Rs. 1500 respectively, while bottom one percentile of OBCs and FCs earns Rs. 2000 each. However, we observe that, as we move up the ladder, the average monthly earning for the FCs increases at a higher rate than any other social group. When we look at the top one percentile group in 2018-19, we observed that the average monthly wage is lowest for STs at Rs. 70600 followed by SCs and OBCs at Rs. 72000 each. The average monthly wage at the top 1 percentile group is highest for FCs at Rs. 85000. Therefore, it can be said that while the average monthly wage for OBCs is nearer to FCs in the lowest percentile groups, it is nearer to SCs and STs at the highest percentile groups.

Table 23: Average Monthly Wage (in Rupee) across Social Groups for Regular Wage/Salaried Workers in Urban Areas for 2011-12 and 2018-19

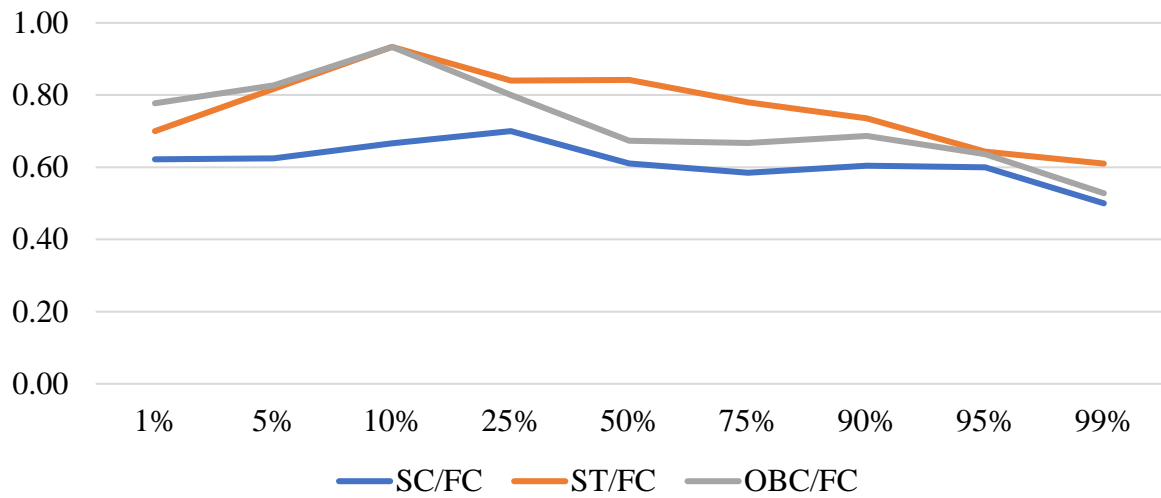
	2011-12				2018-19			
	SC	ST	OBC	FC	SC	ST	OBC	FC
1%	800.00	964.29	998.57	1285.71	1200.00	1500.00	2000.00	2000.00
5%	1607.14	2001.43	2130.00	2571.43	3000.00	3000.00	3500.00	4500.00
10%	2142.86	3000.00	3000.00	3128.57	4000.00	4000.00	5000.00	6000.00
25%	3728.57	3998.57	4285.71	5198.57	6000.00	6500.00	7500.00	9000.00
50%	6000.00	7500.00	6857.14	9998.57	9300.00	10000.00	12000.00	15000.00
75%	12857.14	16714.29	14498.57	21428.57	16000.00	21000.00	20000.00	28000.00
90%	22448.57	25714.29	24998.57	35001.43	32000.00	40000.00	35000.00	45000.00
95%	30000.00	32142.86	31800.00	48214.29	45000.00	50000.00	45000.00	52850.00
99%	42857.14	53571.43	45000.00	85714.28	72000.00	70600.00	72000.00	85000.00

Source: Computed from Unit Level Data of NSSO-EUS 2011-12 and PLFS 2018-19

The Figure 6 and Figure 7 represent the wage ratio by social group for RWS workers in urban labour market for the year 2011-12 and 2018-19 respectively. From both the figures it can be observed that the wage ratio is the least for the SCs for both the years. Figure 6 also suggests that the wage ratio is worse for workers that are at the upper percentile of wage earning for all the social groups. The wage ratio with respect to FCs was better for STs than the OBCs across all percentile levels in 2011-12; however, in 2018-19 it is better for OBCs in the first half of percentile groups and STs for later half. We also observe a convergence of wage ratio for all three groups at the top 1 percentile in 2018-19. Thus, the advantage in wage for the OBCs and STs over SCs is limited only up to a certain level of wages and at higher levels of wages all disadvantaged groups are clustered at one point. However, we also find a clear advantage for the FCs at higher levels.

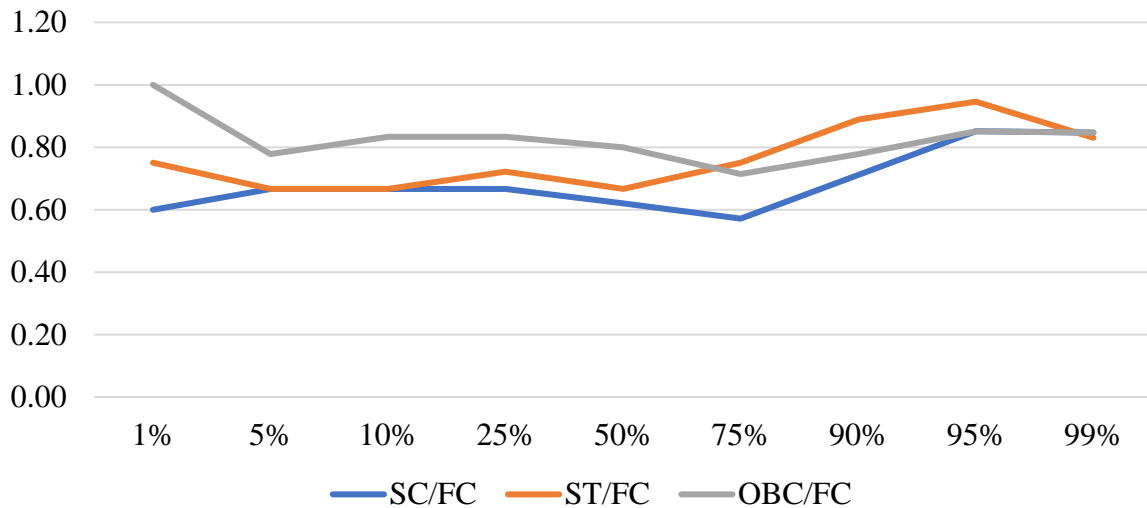
Thus, from the two figures, we observe the existence of different levels of wage gap for different social groups in comparison to FC groups. We also find that the wage gap has reduced between the two time periods i.e., between 2011-12 and 2018-19 for all three social groups. It is interesting to observe that the wages of OBC and FC individuals in lower percentile groups are, on an average, equal. This might be because of the close networking that the OBC groups have been able to form at the bottom of the ladder over the years. However, one would require a larger field study to say anything substantial about this phenomenon.

Figure 6: Wage Ratios by social group for Regular Wage/Salaried Workers in Urban Areas for 2011-12



Source: Computed from Unit Level Data of NSSO-EUS 2011-12

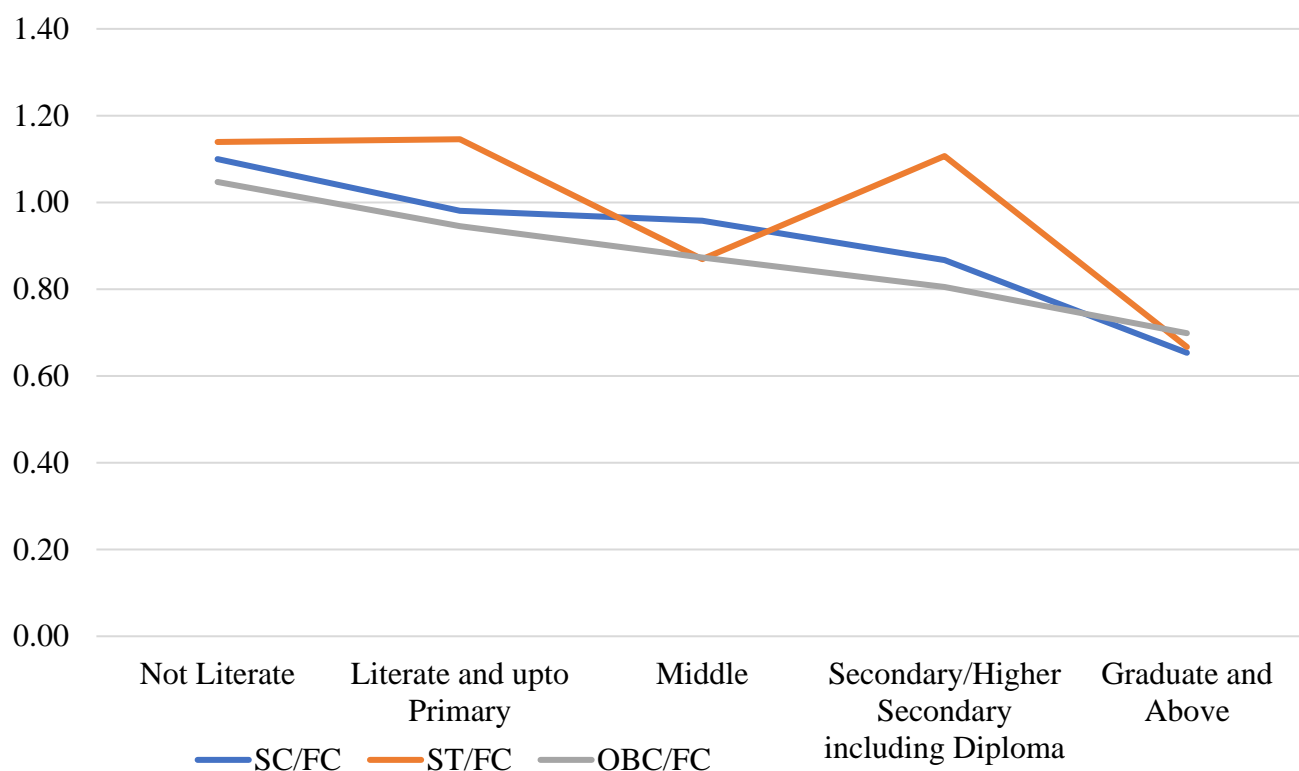
Figure 7: Wage Ratios by Social Groups for Regular Wage/Salaried Workers in Urban Areas for 2018-19



Source: Computed from Unit Level Data of PLFS 2018-19

Education is considered to be an important tool to overcome the barrier of caste that has historically prevented a majority of the population to access education. The Brahmins were considered to have a monopoly over education and SCs and OBCs were not allowed to get educated. There have been several movements in Indian history to claim a right over education; nevertheless, the fight against discrimination at educational institutions continues even today (Thorat, Shyamprasad, & Srivastava, 2007).

Figure 8: Wage Ratios by Castes for Regular Wage/Salaried Workers in Urban Areas for 2011-12 by Level of education



Source: Computed from Unit Level Data of NSSO-EUS 2011-12

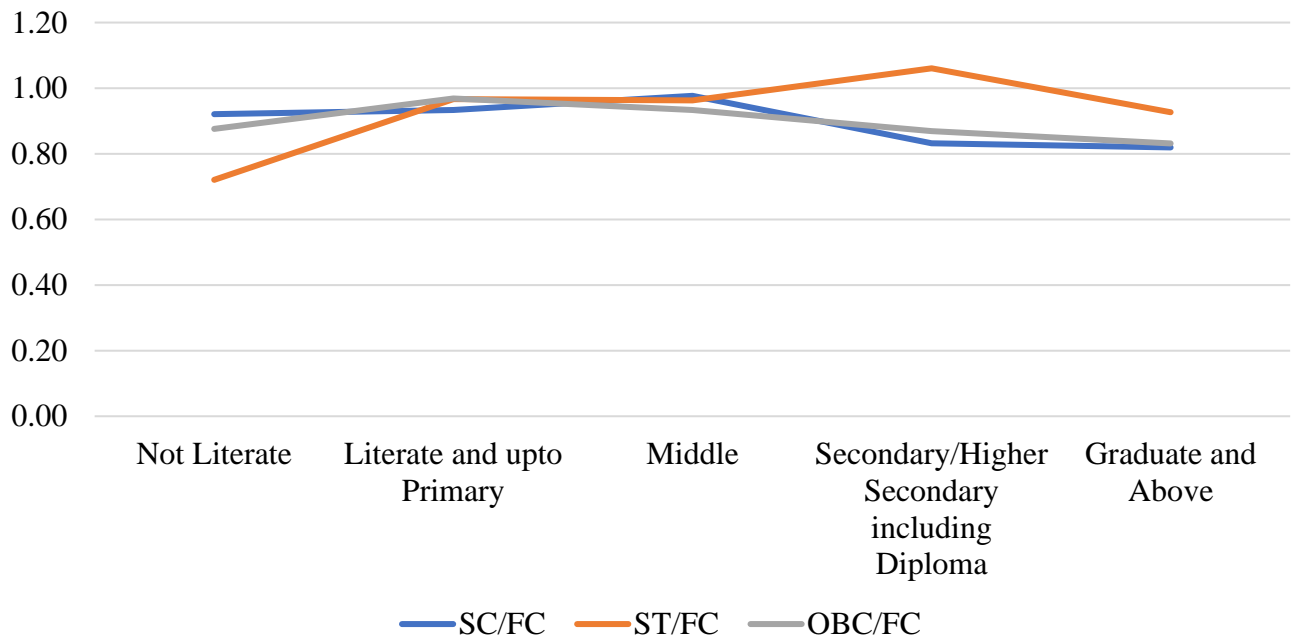
Wage differential by level of education for different social groups in the year 2011-12 is presented in Figure 8. It can be observed that the wage ratio for SCs and OBCs is continuously decreasing as one moves up the educational ladder. Illiterate SCs and OBCs earned almost as much as illiterate FCs. However, the ratio of wage kept decreasing and was lowest for SCs and OBCs with at least a graduation in comparison to FCs with the same level of education. Thus, we can observe that getting educated is more beneficial for FCs than other social groups. The wage ratio for STs is also lowest at the graduate level of education. However, for STs the wage ratio increases at other levels of education.

Even for the year 2018-19, the wage ratio is more than one for STs for workers with secondary and higher secondary level of education as observed from Figure 9. However, wage ratios for STs are less than one for illiterate workers and for workers with at least a graduate degree. The wage ratio is less than one throughout the education level for SCs and OBCs for the year 2018-19. We also find that with an increase in the level of education, wage ratio decreases for both the groups with it being lowest at the highest level of education. Similar to 2011-12 we find

that getting education has proven to be more beneficial for FC workers than other social groups leading to a wider wage gap between the social groups.

As discussed previously, the enterprise of work is equally important for wage determination. It becomes even more important for social groups as the role of the State and its enterprises are

Figure 9: Wage Ratios by Social Group for Regular Wage/Salaried Workers in Urban Areas for 2011-12 by the Types of Enterprises

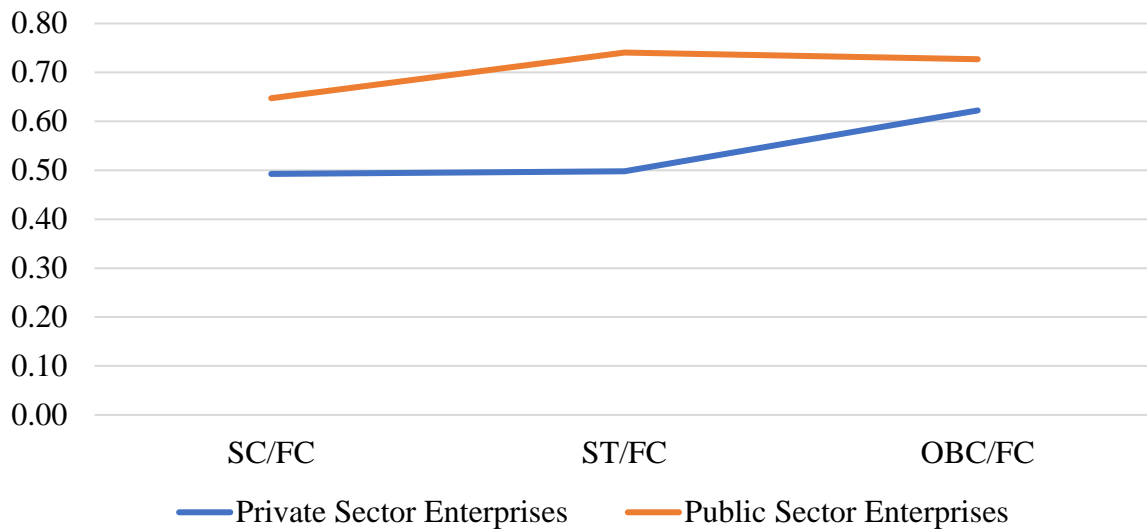


Source: Computed from Unit Level Data of PLFS 2018-19

supposed to play an important role in reducing such horizontal inequalities. From Figure 9 and Figure 11, it can be observed that the wage ratio of social groups with respect to FCs is higher for public sector enterprises than that of private sector enterprises for both the years. From Figure 9, we find that the wage ratio is highest for STs in public sector enterprises while it is lowest for STs in private sector enterprises for the year 2011-12. We can also observe that SCs in the private sector in 2011-12 earn only half that of what the FCs earn. For the public sector the wage ratio improves to 0.65. The OBCs earn around 60 percent and 70 percent of FCs for private and public sectors respectively. In 2018-19, we observe that the wage ratio is higher in

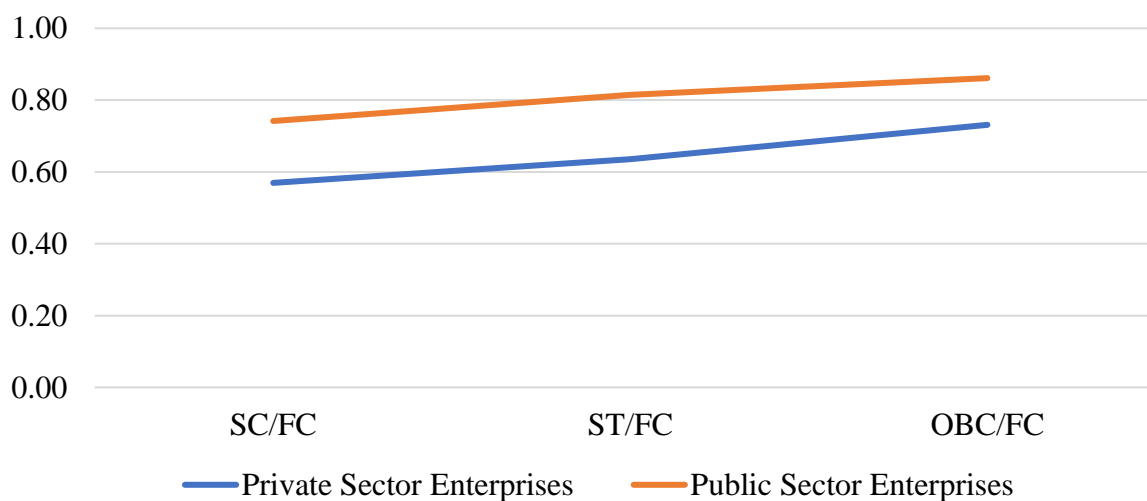
public sector enterprises than that of the private sector. The wage ratio is lowest for SCs and highest for the OBCs.

Figure 10: Wage Ratios by Social Group for Regular Wage/Salaried Workers in Urban Areas for 2011-12 by the Types of Enterprises



Source: Computed from Unit Level Data of NSSO-EUS 2011-12

Figure 11: Wage Ratios by Social Group for Regular Wage/Salaried Workers in Urban Areas for 2018-19 by the Types of Enterprises



Source: Computed from Unit Level Data of PLFS 2018-19

Thus, from Figure 9 and Figure 11, it can be said that the public sector enterprises help in reducing the wage gap among social groups. However, it is still far from ideal. It is also

important to point out here that the so-called hypothetical “invisible hand” of the market to ensure equitable distribution is also missing here as the wage gap is higher in private sector where there is no State intervention. On the other hand, we find that positive discrimination in the form of implementation of reservations in the public sector has lowered the wage gap between social groups. Therefore, unlike the neo-classical understanding that claims that the market will solve the problem of wage gap between two groups, we find that policy-level interventions are required to minimise the wage gap. Therefore, many economists have argued that reservation and similar policies be extended to the private sector (Thorat S. , 2004). However, the nature of remedies would depend on the exact nature of economic and social discrimination and exclusion faced by the marginalised groups. Hence, it is critical to understand the process of labour market discrimination.

We have discussed the process of wage disparities in the labour market; however, the average wage gap can be due to several reasons. Therefore, the existence of a wage gap can't be equated with the wage discrimination. The neo-classical framework expresses discrimination as remunerating employees differently when they have equivalent productivity and to quantify the same, the unexplained portion of the differential in wages is calculated. Therefore, in the next section, we will calculate the unexplained part of the wage differential in the urban regular labour market using different methods discussed in chapter 1.

4. Wage Discrimination among Regular Wage/Salaried (RWS) workers in Urban Labour Market

The discussions in the previous sections suggest the existence of a considerable wage differential across social groups in the RWS employment. However, the existence of wage differentials cannot be viewed discrimination, because earning differentials may partly be due human capital and productivity differences that exist between the groups. Therefore, it is important to decompose the raw wage differential into explained component which indicates differences in human capital and an unexplained component that represents discrimination. This section analyses gender and caste-based discrimination in the regular labour market in urban areas for the public separately in order to observe the effectiveness of anti-discrimination policies. Initially, we adopt the single equation method, which includes dummy variables for gender, caste, and religion. This indicates that the existence of significant wage gaps on the basis of social identity. However, this approach assumes that the wage structure of both

advantaged and disadvantaged groups is the same. In order to overcome this limitation, several decomposition methodologies have been used in this study.

4.1. Ordinary Least Square (OLS) Regression and Sample Selection Correction

As discussed in methodology section, initially, we will use Mincer's human capital wage equation, which is a single equation model (Mincer, 1974) and incorporate gender and caste dummies into the model. The results of OLS robust regression and Heckman sample selection corrected models have been provided in Table 24. For the years 2011-12 and 2018-19, the table shows the basic OLS robust regression represented in Model A and Model C as well as selectivity-corrected OLS estimates provided in Model B and Model D. As discussed in chapter 1, this study uses the human capital wage equation proposed by Mincer with log of real wage as the explained variable and education, experience, and other households and individual attributes are taken as explanatory variables along with controls. The nominal wage rates are converted into real term using price indices available for national and state levels separately with 2012 as the base year. After adjusting for selectivity bias, the size of the coefficient values and their significant level changed marginally as observed from Table 24. The selectivity-corrected model is used to analyse the data (Model II for the 2011-12 and Model IV for 2018-19).

For both the years 2011-12 and 2018-19, explanatory variables such as age and education are found to be statistically significant. The age variable's coefficients have a positive sign, but the age square has a negative sign. This means that wages increase with age and then begin to decline once you reach retirement age. The education coefficients have a positive value and increase with education levels. The coefficient of education shows that it is significant at 1% level of significance for all levels of education. We have further found out that the magnitude of the coefficients of education is less for the year 2018-19 than for 2011-12. Thus, it indicates that, as the level of education increases, the wage increases; however, this effect was stronger in 2011-12 and has weakened by 2018-19. The regression results provided in Table 24 are consistent with the findings of earlier studies on wage discrimination in the Indian labour market.

Table 24: OLS and Heckman Corrected Regression Estimates for the Year 2011-12 and 2018-19

Variables	2011-12		2018-19	
	Model 1: OLS	Model 2: Heckman	Model 3: OLS	Model 4: Heckman
Age	0.0557***	0.0472***	0.0569***	0.0485***
	0.00249	0.00255	0.00225	0.00212
Age square	-0.000541***	-0.000459***	-0.000564***	-0.000484***
	0.0000317	0.0000314	0.0000285	0.0000257
Gender (Female)	-0.411***	-0.400***	-0.426***	-0.419***
	0.0127	0.0114	0.011	0.00943
ST	-0.104***	-0.106***	-0.0987***	-0.101***
	0.023	0.0233	0.0239	0.0226
SC	-0.187***	-0.184***	-0.200***	-0.197***
	0.0136	0.014	0.012	0.0118
OBC	-0.124***	-0.124***	-0.0977***	-0.0985***
	0.0102	0.0102	0.00851	0.00855
Islam	-0.0572***	-0.0368**	-0.0928***	-0.0802***
	0.0136	0.0139	0.0114	0.0117
Christianity	0.116***	0.117***	0.0857***	0.0848***
	0.0254	0.0247	0.0232	0.022
Others	0.0777**	0.0794**	0.0576**	0.0649***
	0.0248	0.0241	0.0182	0.0194
Literate and up to primary	0.178***	0.172***	0.157***	0.147***
	0.0198	0.0204	0.0188	0.0193
Middle	0.295***	0.286***	0.287***	0.277***
	0.0197	0.0204	0.0177	0.0179
Secondary/Higher Secondary	0.567***	0.557***	0.480***	0.471***
	0.0185	0.0185	0.0174	0.0171
Graduate and Above	1.019***	1.010***	0.934***	0.928***
	0.0196	0.0188	0.0182	0.0173
Job contract Available	0.137***	0.137***	0.263***	0.261***
	0.00429	0.00397	0.01	0.0095
Private enterprise	-0.411***	-0.407***	-0.430***	-0.428***
	0.0132	0.0119	0.0112	0.0101
Mills ratio		-0.211***		-0.233***
		0.0198		0.0181
Constant	7.870***	8.374***	7.920***	8.448***
	0.0606	0.0747	0.0547	0.0654
Observations	20068	152006	22994	148304
R-squared	0.536		0.48 1	

Standard errors in parentheses

* p<0.05, ** p<0.01, *** p<0.001

Source: Computed from Unit Level Data of NSSO-EUS 2011-12 and PLFS 2018-19

The caste and gender dummies indicate that both variables are significant at 1 percent level. The sign of coefficients for caste groups SC, ST, and OBC are negative. This means that, compared to the FC reference group, the other caste groups have lower earnings. However, we find that the SCs earn the lowest of all social groups. Similarly, the gender variable indicates that women earn significantly less than males. Also, the coefficient of gender variable has increased from 2011-12 to 2018-19 indicating an increase in the gender wage difference over the two time periods. Thus, we find that caste and gender identities are important in determining wages.

In the next section, decomposition analysis will be taken up to determine the presence of discrimination. The decomposition analysis will be limited to SCs among social groups because the above analysis suggests that among other social groups their wages are the least. Further, we have also conducted a decomposition analysis for the gender category.

4.2. Blinder-Oaxaca (B-O) Decomposition

The B-O decomposition results are provided in Table 25 indicate that a larger part of gender wage difference can be attributed to discrimination in the urban regular labour market. The raw wage differential between male and female has reduced from 0.66 in 2011-12 to 0.63 in 2018-19. However, the discrimination component has increased from 89.62 percent to 96.49 percent. Endowment contribution to the raw female wage gap has decreased from 10.4 percent in 2011-12 to 3.4 percent in 2018-19. The gender wage gap has declined among regular workers in urban areas between 2011-12 and 2018-19; however, the discrimination has increased over the two-time periods.

Table 25: Oaxaca- Blinder Decomposition – Male Vs Female

	2011-12	2018-19
Raw wage Differentials	0.66	0.63
Explained (endowment)	0.07	0.02
Unexplained (Discrimination)	0.59	0.61
Endowment Difference (%)	10.41	3.49
Discrimination (%)	89.62	96.49

Source: Computed from Unit Level Data of NSSO-EUS 2011-12 and PLFS 2018-19

The wage disparity between FC and SC workers in the regular labour market in urban areas was decomposed using the B-O decomposition method. Table 26 indicates that the raw wage gap as well as the discrimination coefficients have increased between the years 2011-12 and 2018-19. The raw wage differential has increased from 0.71 in 2011-12 to 0.73 in 2018-19. The percentage contribution of discrimination component has increased from 65.22 percent in 2011-12 to 74.76 percent in 2018-19. Thus, unlike the gender wage gap where the raw wage differential has decreased between 2011-12 and 2018-19, raw wage gap between FC and SC has increased. The increase in raw wage gap has happened along with increase in discrimination component leading to a worsening situation for SCs.

Table 26: Oaxaca-Blinder Decomposition – FC Vs SC

	2011-12	2018-19
Raw wage Differentials	0.71	0.73
Explained (endowment)	0.25	0.18
Unexplained (Discrimination)	0.47	0.55
Endowment Difference (%)	34.78	25.24
Discrimination (%)	65.22	74.76

Source: Computed from Unit Level Data of NSSO-EUS 2011-12 and PLFS 2018-19

Thus, from the above two tables, we find that the unexplained component is high for both gender and caste groups. This is clear evidence for the existence of discrimination in the labour market against SCs and women. In order to solve the problems arising out of mean based decomposition method, the study will use the quantile decomposition method.

4.3. Machado, Mata, and Melly (MMM) Decomposition Results

Thus far, we have analysed the wage gap using Oaxaca-Blinder decomposition, which is a mean-based decomposition method. However, given the limitations of a mean-based decomposition method as discussed in the methodology section in Chapter 1, wage gap would be decomposed using MMM decomposition method at different wage quantiles. The wage differential is decomposed into two components using MMM decomposition method. The two components are effect of characteristics (endowment difference) and effect of coefficients (discrimination). A further disaggregation has been made for those employed in the public and private sectors. Table 27 and Table 28 present results of the MMM decomposition of raw wage

differentials between males and females. We find that both characteristic and coefficient effects differ significantly across quantiles of the wage distribution.

Table 27: MMM Decomposition Results across Quantiles: Male Vs Female

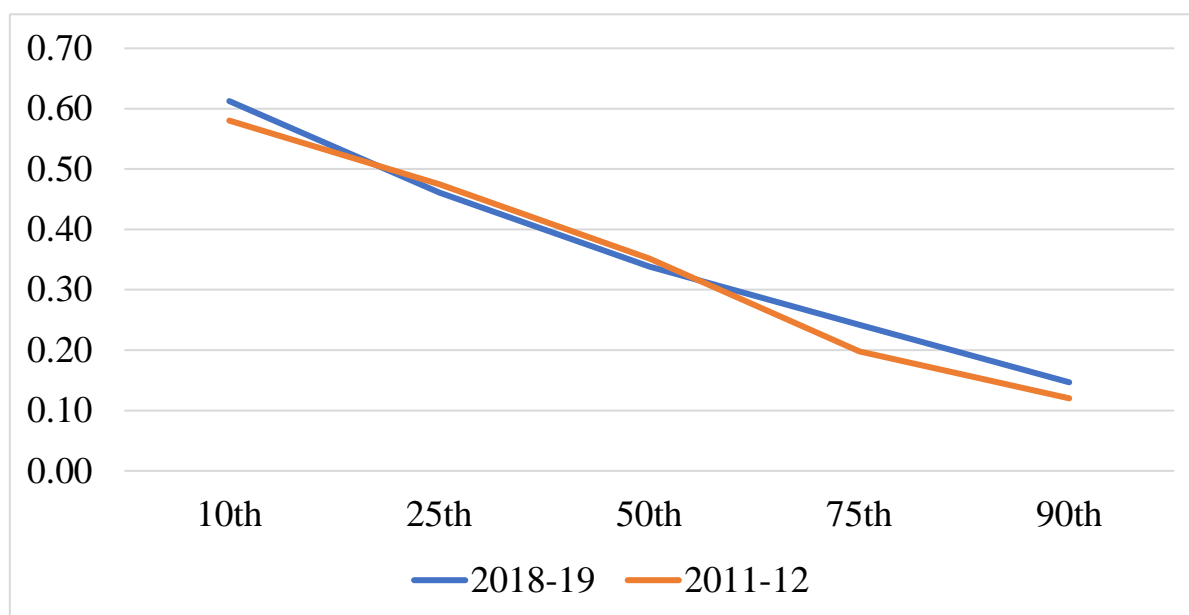
2018-19					
	10th	25th	50th	75th	90th
Raw difference	0.71	0.53	0.36	0.21	0.10
Explained/Characteristics	0.10	0.07	0.02	-0.03	-0.05
(% Explained)	13.90	12.68	5.78	-16.28	-52.27
Unexplained/Coefficients	0.61	0.46	0.34	0.24	0.15
(% Unexplained)	86.10	87.32	94.22	116.28	152.27
2011-12					
Raw difference	0.71	0.58	0.42	0.23	0.13
Explained/Characteristics	0.13	0.10	0.07	0.03	0.01
(% Explained)	18.32	17.98	17.11	12.60	9.74
Unexplained/Coefficients	0.58	0.47	0.35	0.20	0.12
(% Unexplained)	81.68	82.02	82.89	87.40	90.26

Source: Computed from Unit Level Data of NSSO-EUS 2011-12 and PLFS 2018-19

From Table 27, we find that in 2011-12, the raw gender wage differential among regular urban workers is 0.71 at the 10th percentile and it has declined to 0.58 at the 25th percentile. Similarly, for the year 2018-19, the raw wage differential is 0.71 at the 10th percentile and it is 0.53 at the 25th percentile. In other words, the gender wage differential at the 10th percentile is higher than that of the 25th percentile of wage distribution for both the years 2011-12 and 2018-19. Thus, it proves the presence of the “sticky floor effect” in the urban regular employment. This means that women at the bottom of the general wage distribution face larger wage disparities than women at the top.

The phenomenon of “sticky floor effect” is also evident in Figure 12 because the extent of gender discrimination is higher at the bottom quantiles than at the top quantiles of the wage distribution. This evidence of the “sticky floor effect” is consistent with other previous studies. Further, we examine the gender wage gap across the quantiles of wage distribution separately for public and private sector for the year 2018-19 to assess the impact of state policies against discrimination.

Figure 12: Discrimination Coefficient between Male and Female for 2011-12 and 2018-19



Source: Computed from Unit Level Data of NSSO-EUS 2011-12 and PLFS 2018-19

A similar pattern of “sticky floor effect” is observed in the public as well as private sectors where the gender wage difference is higher at the bottom quantiles than at the top ones of the wage distribution in both the sectors for the year 2018-19. In all wage quantiles, however, the gender wage disparity is larger in the private sector than in the public sector.

Table 28: MMM Decomposition Results across Quantiles: Male Vs Female – Public and Private Sector of Regular Urban LM, 2018-19

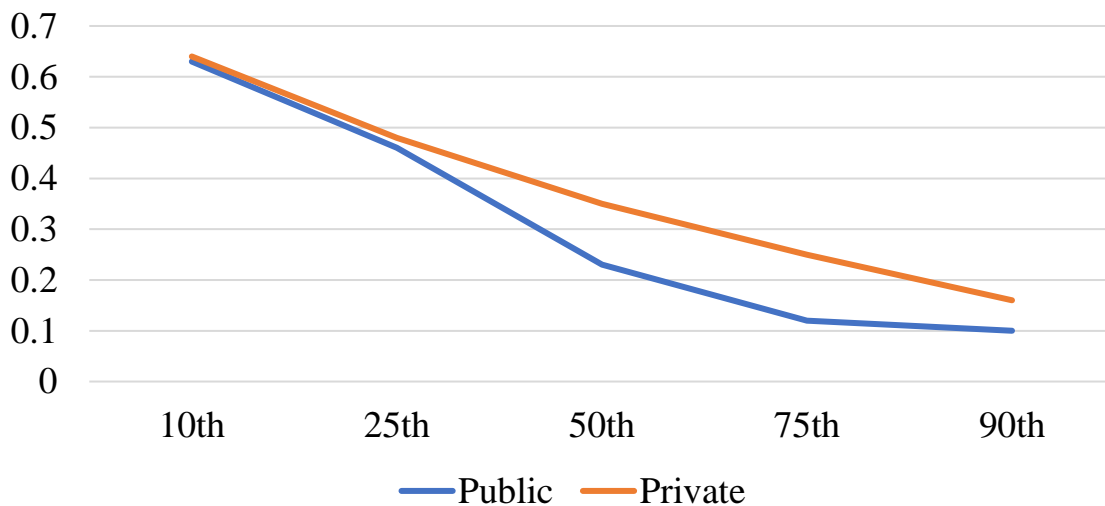
Public					
	10th	25th	50th	75th	90th
Raw difference	0.64	0.46	0.23	0.14	0.12
Explained/Characteristics	0.01	0.00	0.00	0.02	0.02
(% Explained)	1.38	-0.08	0.77	13.89	18.37
Unexplained/Coefficients	0.63	0.46	0.23	0.12	0.10
(% Unexplained)	98.62	100.08	99.23	86.11	81.63
Private					
Raw difference	0.76	0.58	0.42	0.28	0.17
Explained/Characteristics	0.12	0.11	0.08	0.03	0.00
(% Explained)	15.30	18.36	18.03	12.16	2.75
Unexplained/Coefficients	0.64	0.48	0.35	0.25	0.16
(% Unexplained)	84.70	81.64	81.97	87.84	97.25

Source: Computed from Unit Level Data of PLFS 2018-19

In the public sector, the raw gender wage gap among regular urban workers is 0.64 at the 10th percentile and declines to 0.46 at the 25th percentile. Similarly, in the private sector, it was 0.76 at the 10th percentile which declines to 0.58 at the 25th percentile. Thus, the “sticky floor effect” is observed in the private as well as public sectors. However, the unexplained component is higher for the public sector till the 75th percentile, but is higher for private sector till the 90th percentile. Nonetheless, the unexplained component remains high for both private and public sectors.

Figure 13 shows the raw wage difference between gender groups at different percentile groups in private as well as public sector. At all levels of wage distribution, we find that the value of the raw wage difference is higher for the private sector in comparison to the public sector. Thus, we discover that the wage disparity between men and women is greater in the private sector. The reason for such outcome may be due to the establishment of proper rules and regulations in determining wages in the public sector while there is an absence of the same in the private sector. Further, there are government policies that prohibits wage discrimination based on gender identity, which is either absent in the private sector or its implementation is non-existent.

Figure 13: Discrimination Coefficient between Male and Female for Public and Private Sector for 2018-19



Source: Computed from Unit Level Data of PLFS 2018-19

Therefore, we find that the gender wage gap can’t be explained by the differences in endowments between males and females. Thus, the gender discrimination is quite evident. Further, a “sticky floor effect” can be observed for both the public and the private sectors.

We will now analyse the wage difference between FCs and SCs. The findings of the MMM method of decomposition of wage differentials between FCs and SCs are given in Table 29 and Table 30. Table 29 shows that the magnitude of the social-group based wage disparity and discrimination, changes considerably throughout the quantiles of the wage distribution for both 2011-12 and 2018-19 in the regular labour market in urban areas. The wage gap that is on account of endowment difference is relatively higher at the bottom quantiles of the wage distribution than at the top ones. In other words, the wage gap that is due to discrimination is higher at the top quantiles than at bottom ones. Between the years 2011-12 and 2018-19, the wage gap attributable to discrimination has increased for all quantiles. However, we find that in 2011-12 there is no evidence of neither the “sticky floor effect” nor the “glass ceiling effect”. However, in 2018-19, we see the evidence of the “sticky floor effect” as the raw wage difference is 0.35 for the 10th percentile while it is 0.36 for the 25th percentile. Thus, the raw wage gap for the 10th percentile exceeds the raw wage gap of the 25th percentile by more than 2 percent.

Table 29: MMM Decomposition Results across Quantiles: FC and SC

2018-19					
	10th	25th	50th	75th	90th
Raw difference	0.35	0.36	0.42	0.45	0.33
Explained/Characteristics	0.22	0.18	0.17	0.15	0.13
(% Explained)	62.00	49.64	39.18	32.96	40.50
Unexplained/Coefficients	0.13	0.18	0.26	0.30	0.20
(% Unexplained)	38.00	50.36	60.82	67.04	59.50
2011-12					
Raw difference	0.38	0.43	0.53	0.50	0.39
Explained/Characteristics	0.27	0.26	0.26	0.22	0.18
(% Explained)	73.25	61.35	49.65	44.73	44.77
Unexplained/Coefficients	0.10	0.17	0.27	0.27	0.22
(% Unexplained)	26.75	38.65	50.35	55.27	55.23

Source: Computed from Unit Level Data of NSSO-EUS 2011-12 and PLFS 2018-19

Further, we decompose the wage differentials for the public and the private sector enterprises for the year 2018-19 are looked at separately. From Table 30 we observe that, while the raw wage differential is declining as one moves up the wage quantiles in the case of the public sector, it is increasing for the private sector. Besides, the wage gap at the 10th percentile is higher than the 25th percentile in the public sector. This gives evidence for the “sticky floor effect” in the case of wage discrimination in the public sector; in the private sector, the wage

differential at the 90th percentile is higher than the estimated wage differentials in other parts of the wage distribution. This proves the existence of the “glass ceiling effect” in the private sector.

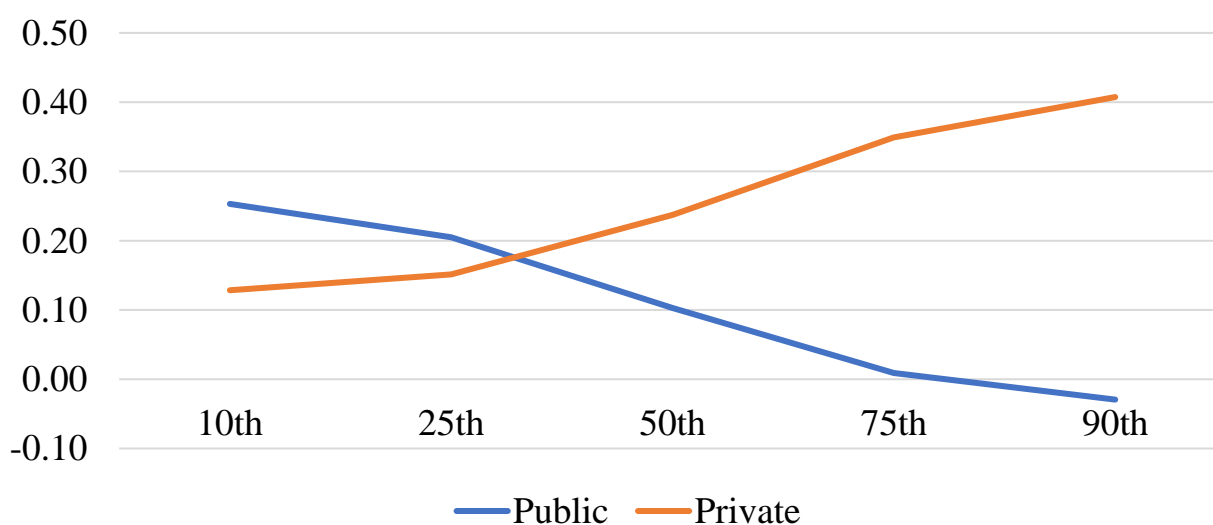
Table 30: MMM Decomposition Results across Quantiles: FC vs SC – Public and Private Sector of Regular Urban LM, 2018-19

Public					
	10th	25th	50th	75th	90th
Raw difference	0.58	0.54	0.38	0.24	0.16
Explained/Characteristics	0.33	0.33	0.28	0.23	0.19
(% Explained)	56.43	61.79	73.15	96.20	118.04
Unexplained/Coefficients	0.25	0.20	0.10	0.01	-0.03
(% Unexplained)	43.57	38.21	26.85	3.80	-18.04
Private					
Raw difference	0.34	0.32	0.39	0.51	0.59
Explained/Characteristics	0.21	0.17	0.16	0.16	0.18
(% Explained)	62.56	52.36	39.69	31.87	31.07
Unexplained/Coefficients	0.13	0.15	0.24	0.35	0.41
(% Unexplained)	37.44	47.64	60.31	68.13	68.93

Source: Computed from Unit Level Data of PLFS 2018-19

From Figure 14, we find that the value of the raw wage difference kept decreasing for the private sector as one moved higher up the wage ladder, while it kept increasing for the public sector. Thus, we find the phenomenon of the “glass ceiling effect” in the private sector and the “sticky floor effect” in the public sector.

Figure 14: Discrimination Coefficient between FC and SC for Public and Private Sector for 2018-19



Source: Computed from Unit Level Data of NSSO-EUS 2011-12 and PLFS 2018-19

Thus, the “sticky floor effect” is most important in explaining wage discrimination on the basis of gender in both types of enterprises; public as well as private sectors. However, when explaining the caste wage discrimination, we find that, while the “sticky floor effect” is prominent in the public sector, it is the “glass ceiling effect” which is more prevalent in the private sector. Hence one can conclude that both identities of caste and gender lead to labour market discrimination although how these discriminations manifest themselves differ.

In the public sector, the sticky floor effect is prominent in explaining both gender and caste wage differentials. An attempt to explain this can be made by analysing the nature of work in the public sector at both ends of the spectrum. The public sector jobs at the bottom end of the wage distribution are more ad-hoc while the payment mechanism is far more structured and rigid at the upper end of the wage spectrum. This leaves a higher possibility of wage discrimination at the lower end of the spectrum. At the upper end of the spectrum, while wage discrimination on the basis of gender is low, policies like reservation have led to negative values of discrimination against SCs. Therefore, we can argue that the government policies play an important role in protecting workers against discrimination based on social identity. Since policies like a fixed minimum wage are not adhered to properly, the scope of discrimination becomes higher at the lower end. This leads to a “sticky floor effect” in public sector enterprises.

On the other hand, while in the private sector the gender wage difference can be explained by the “sticky floor effect”, the wage differential between the SCs and the FCs is explained by the “glass ceiling effect”. The possible reason for this difference could be the unavailability of any social protection at any point in the wage spectrum. The existence of “sticky floor effect” in the private sector indicates that, just like the public sector there is a high resistance against equal pay for men and women as the wage received by the workers fall. The possible reason for such resistance could be the patriarchal notion that ‘women are not as productive as men’ and are thus assigned jobs that pay less. Also, the bargaining power for women employed at the lower end of the wage spectrum is extremely weak and they are, therefore, more likely to be trapped in an unequal power relation to their employers vis-à-vis their male counterparts. Similar reasons could explain the existence of a “glass ceiling effect” in the private sector due to the prevailing caste structure i.e. between the SCs and the FCs . The possibility of discrimination is less at the lower end of the wage spectrum in the private sector as all workers are paid equally low. However, when we move up the wage spectrum, the resistance against workers from SCs is relatively more in the private sector as there is no policy to counter the

pre-existing biases against people from marginalised groups. Therefore, the role of the state and its policies are important in reducing discrimination on the basis of caste and gender identities.

5. Conclusion

This chapter has analysed the existence of wage disparities and discrimination on the lines of gender and social identity. The chapter started with explaining the prevalence of the dichotomy of casual and regular employment. We found that while wages in regular employment are higher than the casual employment, the average wage gap between the two group of workers has declined between 2011-12 and 2018-19. However, the gap has remained substantial. Further, we found that education plays a very important role in determining wages in the regular labour market than the casual labour market. An urban-rural divide was found to exist in the distribution of wages with average wage levels much higher in urban areas than in rural areas. Since there is a popular belief that wages in the urban regular labour market are determined by merit and talent, the identity of an individual has no role in the same. Hence, this study was aimed at analysing the role of identity in the urban regular rural market.

In the first part of the empirical analysis, we looked at the wage differentials between gender and social groups in the urban labour market with regular payments. The percentage of females in RWS employment is significantly lower than their proportion in the overall population. Further, the average wage for females was observed to be less than that of males. However, the wage differential has decreased between the period 2011-12 and 2018-19. Also, the wage gap is higher at lower percentile groups than the higher percentile groups. A similar pattern was observed at different educational levels with the gender wage gap being higher among workers with lower levels of education than among workers with higher levels of education. Apart from gender identity, the social group that an individual belongs to also plays a significant role in the determination of wages for urban regular employment. We found that SCs were earning the lowest followed by STs and OBCs. We also observed that, while the average wage level for OBCs was nearer to FCs in the lowest percentile groups, it is nearer to SCs and STs at the highest percentile groups in 2018-19. Further, we found that the wage gap across genders and social groups is lower in the public sector than the private sector.

The second part of the empirical analysis focuses on the wage discrimination existing for urban employment. We first adopted a single equation model and incorporated gender and caste

dummies, upon which we found that *ceteris paribus*, female wages were half of that earned by males. Similarly, SCs were earning the lowest followed by STs and OBCs. We found that while SCs were earning almost 19 percent less than FCs, STs were earning 10 percent less than FCs and OBCs were earning 9 percent less than FCs.

We then used the Blinder-Oaxaca (B-O) decomposition and MMM methods to decompose the raw wage gap into explained and unexplained components. We limited this decomposition analysis to SCs among the social groups since they were at the bottom of the wage distribution. Through B-O decomposition analysis for gender, we found that there is a reduction wage differential on the basis of gender among regular urban workers between 2011-12 and 2018-19; however, the discrimination has increased over the two time periods. Further, an increase in absolute wage difference between the FCs and the SCs over the two time periods was observed. This has happened along with an increase in the discrimination component leading to a worsening situation for SCs. Using the MMM decomposition method, we observe that the “sticky floor effect” is most important in explaining gender wage discrimination for public as well as private sector enterprises. However, when explaining the caste wage discrimination, we find that, while the “sticky floor effect” is prominent in the public sector, it is the “glass ceiling effect” which is the prevalent form in private enterprises.

Hence, from the empirical analyses done in this chapter, we observe a persistence of wage disparities and discrimination. It was also observed that the unexplained or the discrimination component has increased for both gender and social groups. Further, we also found that discrimination is more prevalent in the private sector than the public sector. Thus, we can say that the neo-classical approach falls short in explaining the persistence discrimination in the labour market as it proposes that market forces shall correct all such disparities while our empirical analyses suggest otherwise. Therefore, in the concluding section of this dissertation, we would critically evaluate neo-classical frameworks and point out reasons for them not being able to explain the persistence of wage discrimination in the labour market. Further, we shall critically evaluate theoretical alternatives to the neo-classical framework so as to better understand the issue of wage discrimination.

Conclusion

In the previous chapters we have examined the role played by identities, both gender and caste, in the labour market. We have observed that both of them determine accessibility to employment as well as wage levels. The study is restricted to the time period between 2011-12 and 2018-19 i.e. before the onset of the COVID-19 pandemic.

The study was undertaken with an aim to comprehend the changes that the labour market has undergone in the aforementioned period. We find that the rate of generating employment is so low that India has experienced a high level of open unemployment. Further, the absolute numbers of the unemployed have increased for the first time in the history of its measurement of unemployment. We also find that the LFPR and the WPR has declined. Further analysis suggests that the decline is majorly caused by a decline in participation of female workers in rural areas. ST women saw the highest decline in their participation in the labour market.

Further, the examination of the changing employment structure of India within this time period found that there is a decline in casual employment and increase in regular work. However, the share of the population employed in casual work is higher for SCs and STs and those employed in regular work is higher among FCs. We also find that, while male workers are highly represented in Own-Account Employment, female workers are mostly employed as helpers in household enterprises. Thus, a clear gender-based and social group-based divide is observed in the status of employment for an individual.

Since the increase in regular employment is the only positive aspect of an otherwise grim labour market situation, a closer examination was done to better understand the quality of the jobs that have been created. Upon examination, it was found that the share of regular wage/salaried employees has increased. However, most of the newly created jobs are without written job contracts or paid leaves. Thus, although the share of regular workers has increased, jobs with low security in regular wage/salaried employment has also increased. This increase in RWS employment may also be because the informal sector was disproportionately impacted by policies like demonetisation and GST.

Another aim of the study was to understand the existence of a wage gap between genders and social groups. In this regard it was observed that the average wage for females is lower than males. However, the wage gap has decreased between the period 2011-12 and 2018-19. Also, the wage gap is higher at lower percentile groups than the higher percentile groups. Further, it

was observed that education is inversely related to the gender wage gap. In other words, gender wage gap is higher at lower educational levels and lower at higher educational levels. Apart from gender identity, the social group that an individual belongs to also turns out to be important for the determination of wages. We found that SCs were earning the lowest, followed by STs and OBCs. We also observed that, while the average wage level for OBCs was nearer to FCs in the lowest percentile groups, it is nearer to SCs and STs at the highest percentile groups in 2018-19. Further, we found that the wage gap is lower in the public sector than the private sector for all social groups.

While we have established wage differentials, the study also aimed at analysing discrimination based on social identities in the labour market. From the empirical analyses undertaken, we observe a persistence of wage discrimination. Further, it was observed that the discrimination component has increased for both gender and social groups. We used the Blinder-Oaxaca (B-O) decomposition and MMM methods to decompose the raw wage gap into explained and unexplained components. The decomposition analysis is limited to SCs among the social groups because they were at the bottom of the wage spectrum. Through a B-O decomposition analysis for gender, we found a reduction in the wage gap among the regular urban workers between 2011-12 and 2018-19; however, discrimination has increased over the two time periods. Further, we found that the raw wage gap between FCs and SCs has widened over the two time periods. This has happened along with an increase in the discrimination component leading to a worsening situation for SCs. Using the MMM decomposition method, we observe that the 'sticky floor effect' is most important in explaining gender wage discrimination for both public and private sectors. However, when explaining the caste wage discrimination, we find that, while the 'sticky floor effect' is prominent in the public sector, it is the 'glass ceiling effect' which is more prevalent in the private sector.

Although the neo-classical understanding of wage discrimination tries to answer the question of persistence of wage inequality by suggesting that pre-labour market discrimination consistently produces lower human capital for workers from marginalised groups which leads to lower wages, the empirical work in Chapter 4 suggests that, wage discrimination exists among equally skilled workers as well. However, it is not possible to account for all the variables that account for the differences in wages. There are several neo-classical economists that continue to assert that the residual would be negligible if the variables could be correctly specified; however, others have criticised the method for treating gender as a dummy variable rather than analysing the process of gender discrimination (Figart, 2005). Thus, the neo-

classical analysis of discrimination either ignores wage disparities as short-run aberrations or explain them by pointing to variations in schooling and other ‘personal attributes.’

As discussed in chapter 2 and 4, there have been several empirical and correspondence studies that have suggested that social discrimination is not just a residue of the past, but occurs in private enterprises and in the most dynamic modern sectors of the Indian economy, manifesting itself in different forms. A correspondence study done by Deshpande & Newman (2007) shows that the social and cultural capital are important factors impacting the labour market. Discriminatory social structures have influenced labour market results not just in terms of wage disparities, but also in terms of differential treatment by employers, differing service conditions, and discriminatory work contracts. Even the problem of sexual harassment at the workplace reflects the existence of a discriminatory work environment for women leading to their exclusion. Thus, the above analysis indicates that the labour market discrimination remains a concern particularly in the private sector.

This raises a question about the neo-classical understanding of discrimination, which assumes that the free market shall correct all discriminatory practices. It is not just that labour market discriminations exist, but that they persist even among equally skilled workers as has been ascertained by various correspondence studies. Thus, the neo-classical understanding of discrimination is unable to answer an important question of the persistence of wage discrimination. Therefore, it is critical to investigate the political economy of the persistence of the labour market discrimination. Although a comprehensive socio-economic and historical study of discrimination under capitalism in India falls beyond the purview of this dissertation, certain observations can be made on the basis of the above.

A critical understanding of discrimination relies on its historical analysis that is embedded in particular social and economic contexts. It sees discrimination as part of a historical process in a way that connects the past to the present. In the process of placing discrimination in a historical context, it is important to locate discrimination as an integral component of the caste system and patriarchy. Under capitalism, discrimination in the labour market not only leads to exploitation of the discriminated group but also helps to maintain systems of oppression that exist outside of the firm and the labour market. The ideological systems of ‘Brahmanism’ and ‘Patriarchy’ are important in understanding the process of discrimination in the labour market. However, these power relations are considered to be, both structurally and ideologically, components of a pre-capitalist system of power. It was expected that capitalist expansion would lead to a dissolution of such pre-capitalist systems. But experience has shown that, rather than

doing away with such structures, capitalism has assimilated them into itself resulting in multiple modes of inequality on the bases of class, income, gender, religion, race etc. (Basile, 2015). The current phase of capitalism is also therefore continuously engaging with pre-existing social structures and in the process of this dialogic interaction, it is moulding these structures while transforming itself. That is the reason capitalist societies across the world are diversified and in a perennial state of conflict. Thus, we can say that the urban labour market discrimination is not a result of a feudal caste system rather it is due to the interaction of caste, patriarchy, and the capitalist mode of production. Thus, the critical understanding of discrimination enunciated here is fundamentally different from the neo-classical one. Firstly, neoclassical economics believes that the discriminator often pays for discrimination, that is the discriminating party suffers losses for discriminating, as it is incompatible with the neoclassical notion that holds the primacy of the profit motive, and that such behaviour shall be corrected by the 'invisible hand' of the free market. Secondly, neoclassical economists view discrimination as an individual phenomenon, while it is clear that it is as a historical process embedded in hierarchical social relations that are at the end, group based. Thirdly, neoclassical economists believe that discrimination will have a short shelf-life in a competitive economy, while it has been seen that discrimination will persist unless there is a collective and purposeful action to oppose it.

In our case, while the social nature of production has considerably been transformed by capitalism in the last century, and caste no longer operates in exactly the same nature in the division of labour and distribution, as it did earlier, we see that there still exists a social division of labour, access to employment and the associated distribution of wages, under capitalism as well. Throughout our study, we have observed that the nature of labour, or more specifically the nature of the commodification of labour power and the exchange of labour power for wages, and the prevalence of a system of wage labour, capital, and thus developed exchange value conform to Marx's description (Marx K. , *Capital: Volume 1: A Critique of Political Economy* (Penguin Classics), 1990), and thus indicative of a developed form of capitalism. How then can we reconcile the existence of a social division of labour in employment opportunities and wages? We believe that a historical analysis of the nature of Indian capitalist class can be the first step towards such an enquiry. It has been pointed out that the Indian capitalist class is predominantly upper caste (FC) in its composition (Omvedt, 2005). As pointed out by a historical study on the development of the Indian capitalist class, the development of the Indian capitalist class under colonialism was dominated by upper castes. The study demonstrated that in the

Bengal Presidency, Brahmins and Kayasthas were the first to form the indigenous bourgeoisie (Pavlov, 2016, p. 248), and were later supplanted by British and Marwari Capital (Pavlov, 2016, p. 256). In Gujarat, the trading (Baniya) and money lending castes dominated the fledgling capitalism (Pavlov, 2016, pp. 195-197), similar to the rest of the Bombay Presidency (Pavlov, 2016, pp. 231-232), except for marginal share of the bourgeoisie being Brahmins and Marathas who also served the state apparatus (Pavlov, 2016, p. 238).

Regarding the Marwari bourgeoisie, Pavlov notes that they formed a separate community of capitalists, with close ties of caste that retarded the assimilation of the caste into the larger community, where ever they moved (Pavlov, 2016, p. 202). The Marwaris were originally small traders and moneylenders, and through moneylending and wholesale and retail dealership (the state of being intermediaries in trade) in the import of commodities and export of agricultural produce, developed to such an extent that they commonly extended loans to British firms (Pavlov, 2016, p. 209). The development of the Marwari bourgeoisie under capitalism, does not seem to be in spite of their caste ties, but was contingent upon it. It can be postulated that the development of capitalism under colonialism produced conditions where, capitalism rather than dissolving caste, produced conditions such that certain castes could use caste ties to expand their operations in the new milieu and become the insurgent bourgeoisie.

On the other hand, the social division of labour such that members of lower castes could only be employed for the most menial and physical form of labours, which also were the lowest paying jobs, which meant that the caste-based system of social division of labour and distribution continued under colonialism and the incipient capitalism. In his presidential speech to the Conference of all the 'Untouchable' workers of the 'Great Indian Peninsula' (GIP) Railways, held at Manmad on the 13th February, 1938, B.R. Ambedkar pointed out the prevalence of discrimination and exclusion within the Cotton mills in Bombay, indicative of private enterprise, and the Railways, representative of the public sector. Ambedkar noted that in the mills, untouchable workers were employed only in the spinning department and not the weaving departments, with the spinning department employment being the lowest paid jobs. The upper castes in the weaving department objected to working with untouchables, citing their caste purity and principles of untouchability. Similarly, in railway employment, untouchables were employed only as gagman, without the possibility of promotion, and not porters, who were also accorded duties in the station master's household. The station masters being generally upper caste, would object to an untouchable in their household. Similar exclusion was observed in all branches of the railway, including the bureaucracy and the workshops

(Ambedkar B. R., Dr. Babasaheb Ambedkar : Writings and Speeches Vol. 17-III, 2014, pp. 177-178). It is logical to assume from the above description that the condemnation of the untouchables to the lowest paying jobs, meant that not only were the wages of the untouchables kept low, but because of a limited number of opportunities, unemployment too would be higher among the untouchables than the caste Hindus.

Ambedkar further notes that in his view, Brahmanism, that is the ‘negation of the spirit of Liberty, Equality, and Fraternity’ and Capitalism are the two foremost enemies of the working class (Ambedkar B. R., Dr. Babasaheb Ambedkar : Writings and Speeches Vol. 17-III, 2014), and that Brahmanism was to be uprooted if a working class unity was to be achieved (Ambedkar B. R., Dr. Babasaheb Ambedkar : Writings and Speeches Vol. 17-III, 2014, p. 180).

Similar to the discrimination faced by the SCs (former untouchable castes), the STs too have faced the brunt of systemic exclusion under colonialism and incipient capitalism. On one hand many tribes were designated as ‘born criminals’ and lumped together to form the ‘Criminal’ Tribes, subjected to continual discrimination and segregation (Kapadia, 1952) that continues in post-colonial India, on the other hand through successive political and economic measures there have been attempts to forcefully integrate STs into capitalist relations of production that are based on an asymmetric power relation (Singh, 1982). The caste based nature of Indian capitalism, where certain castes within the FCs have had a hegemonic position both within the bourgeoisie and the state bureaucracy (Business Line, 2014) and judiciary (Saxena, 2021) along with the historical legacy of enforcing the caste based division of labour enforced within the framework of capitalism present a picture where the SCs and STs are sequestered within certain sectors of the labour market, which not only limits employment opportunities, but also enables employers to employ them at lower wages. Becker’s model which posits a taste for discrimination, while not wholly satisfactory in explaining the nature and reasons for discrimination, makes a similar observation as ours, that the presence of discriminating firms creates an obverse in firms that can hire negatively discriminated groups at lower wages. Marx pointed out that while a specific kind of production remains the pre-dominant mode in a given situation, in our case capitalism, other modes may subsist alongside it, but their particularity would be modified by the nature of the dominant mode (Marx K. , 1973, pp. 106-107). In our case the particularity of caste, in as much as its relation to a ‘division of labourers’ in production and distribution has been modified in accordance to the requirements of the capitalist mode.

Marx also noted that the “surplus population of workers is a necessary product of accumulation or of the development of wealth on a capitalist basis, this surplus population also becomes,

conversely, the lever of capitalist accumulation, indeed it becomes a condition for the existence of the capitalist mode of production.” (Marx K. , 1990, p. 784) This surplus population, that cannot become a part of the labour force, i.e. partially or wholly unemployed, is thus inalienable to the capitalist mode of production. As we have seen, in the Indian context, this population is not an abstract population, comprised equally of all sections of society, but primarily of socially and historically disadvantaged groups. The historical exclusion or rather the limiting the lower castes to a certain section of the labour market, creates a situation that can only lead to a stagnant population of these castes, either unemployed or with very irregular employment. In the Marxist framework of capitalism this is similar to the third category of relative surplus population, characterised by being to capital “an inexhaustible reservoir of disposable labour-power. Its conditions of life sink below the average normal level of the working class, and it is precisely this which makes it a broad foundation for special branches of capitalist exploitation. It is characterized by a maximum of working time and a minimum of wages.” (Marx K. , 1990, p. 796) It can thus be argued that the systemic requirement of capitalism to have a relative surplus population of workers has been fulfilled in the Indian context largely by the historically marginalised social groups, particularly the SCs and the STs. In this context Ambedkar’s words stand vindicated “The Out-caste is a bye-product of the Caste-system. There will be out-castes as long as there are castes. Nothing can emancipate the Out-caste except the destruction of the Caste-system.” (Ambedkar B. , 1933) The prevalence of a network at the top of the labour market, inevitably creates a hierarchy, and the systemic exclusion of the most marginalised.

It has been further pointed out that an important mechanism of safeguarding the caste system in India has been through restrictions on the mobility of upper caste women (Chakravarti, *Conceptualising Brahmanical Patriarchy in Early India: Gender, Caste, Class and State*, 1993, p. 579). Similarly, patriarchy itself has assimilated with the systemic operation of class and caste oppression, to produce patriarchies that function differently according to the class and caste position of individual women to control their productive and reproductive labour-power (Chakravarti, 1995). In this context we can see that there lies a structural explanation for the high difference in wage ratio, participation in the labour force, and high discrimination coefficient when comparing genders across social categories.

The question of social disparity within wages and employment is thus a complex issue which is influenced by the institutions of caste and gender. Ambedkar’s early theorisation of each caste being an enclosed class (Ambedkar B. R., 2014, p. 15) is particularly important here as a system of hierarchy within the working class, ensures that castes shall be allotted a particular

employ and consequently wages, while preserving the system. It must also be noted that the caste nature of the Indian bourgeoisie is also a factor in the continuation and entrenchment of the practice. The accelerated rise in inequality in India in recent years (Chancel & Piketty, 2019) along with a rapid privatisation of public sector undertakings (Gupta & Sidhartha, 2021) that ensured policies against discrimination only foretells that the situation of the socially marginalised in the labour market is going to worsen. Further, the rapid expansion of the informal sector to accommodate a vast majority of the working class only means that not only does the scope for caste and gender-based discrimination increase, but also that the nature of the employment shall be changed in a manner that is unfavourable to the working class. It seems that the spectres of caste and gender that continue to favour and bolster the current socio-economic model, weigh like a nightmare upon the possibility of a radical transformation of the current system. A first step towards a solution of this problem can be through an analysis of the methods of operation that caste and patriarchy take within the capitalist framework. However, such studies fall outside the scope of the present study. Also, the non-release of the socio-economic caste census data of 2011 and no such plans to undertake such a study on a nationwide scale further compounds the problem of understanding the mechanism of caste and patriarchy in the present day.

Bibliography

- Abraham, V. (2009). Employment Growth in Rural India: Distress-Driven? *Economic and Political Weekly*, 97-104.
- Abraham, V. (2013). Missing Labour or Consistent “De-Feminisation”? *Economic & Political Weekly*, 99-108.
- Agrawal, T. (2013). Gender and caste-based wage discrimination in India: some recent evidence. *Journal for Labour Market Research*, 47(4), 329–340.
- Agrawal, T. (2015). Occupational Segregation in the Indian Labour Market. *European Journal of Development Research*, 28(2), 330–351.
- Agrawal, T., & Agrawal, A. (2015). Trends in occupational gender segregation in India. *International Journal of Gender Studies in Developing Societies*, 1(1).
- Albrecht, J., Björklund, A., & Vroman, S. (2003). Is There a Glass Ceiling in Sweden? *Journal of Labor Economics*, 21(1), 145–177.
- Alonso-Villar, O., & del Río, C. (2010). Local versus overall segregation measures. *Mathematical Social Sciences*, 60(1), 30–38.
- Ambedkar, B. (1933, February 11). *Dr. Ambedkar & Caste*. Retrieved from The Collected Works of Mahatma Gandhi: <https://www.mk Gandhi.org/journalist/ambedkar.htm>
- Ambedkar, B. R. (2014). Annihilation of Caste. In B. R. Ambedkar, & V. Moon (Ed.), *Dr. Babasaheb Ambedkar: Writings and Speeches Vol. 1* (pp. 37-85). New Delhi: Dr Ambedkar Foundation, Ministry of Social Justice and Empowerment, GoI.
- Ambedkar, B. R. (2014). Annihilation of caste. In *Dr. Babasaheb Ambedkar : Writings and Speeches* (Vol. 1). Dr. Ambedkar Foundation, Ministry of Social Justice & Empowerment, Govt. of India.
- Ambedkar, B. R. (2014). *Dr. Babasaheb Ambedkar : Writings and Speeches Vol. 17-III*. Dr. Ambedkar Foundation, Ministry of Social Justice & Empowerment, Govt. of India.
- Ambedkar, B. R. (2014). *Dr. Babasaheb Ambedkar : Writings and Speeches Vol. I*. 2014. Dr. Ambedkar Foundation, Ministry of Social Justice & Empowerment, Govt. of India.

- Ambedkar, B. R. (2020). Trade Unions Must Enter Politics to Protect Their Interests. In B. R. Ambedkar, H. Narake, M. L. Kasare, N. G. Kamble, & A. Godghate (Eds.), *Br Babasaheb Ambedkar: Writings and Speeches Vol No. 17 Part III* (pp. 173-192). New Delhi: Dr. Ambedkar Foundation, Ministry of Social Justice and Empowerment, GoI.
- Anand, A., Sandefur, J., & Subramanian, A. (2021). *Three New Estimates of India's AllCause Excess Mortality during the COVID-19 Pandemic*. Washington, DC: Center for Global Development.
- Anand, I., & Thampi, A. (2016). Recent trends in wealth inequality in India. *Economic and Political Weekly*, 51(50), 59–67.
- Annual Estimates*. (2021). Retrieved from Ministry of Statistics and Programme Implementation: <https://www.mospi.gov.in/web/mospi/national-accounts-division>
- Arrow, K. J. (1971). The theory of discrimination. *Industrial Relations Section, Princeton University, Working Paper No. 30A*.
- Arrow, K. J. (1998). What Has Economics to Say about Racial Discrimination? *Journal of Economic Perspectives*, 12(2), 91–100.
- Banerjee, B., & Knight, J. B. (1985). Caste discrimination in the Indian urban labour market. *Journal of Development Economics*, 17(3), 277–307.
- Basile, E. (2015). A heterodox analysis of capitalism. In B. Harriss-white, & J. Heyer, *Indian Capitalism in Development* (pp. 170-189). New York : Routledge.
- Becker, G. S. (1957). *The Economics of Discrimination*. University of Chicago Press.
- Bhalla, S. S. (2019, April 13). *A statistical embarrassment*. Retrieved from The Indian Express: <https://indianexpress.com/article/opinion/columns/modi-government-opposition-congress-unemployment-jobs-data-statistical-embarrassment-5673325/>
- Bhaumik, S. K., & Chakrabarty, M. (2008). Does move to market have an impact on earnings gap across gender? Some evidence from India. *Applied Economics Letters*, 15(8), 601–605.
- Bhaumik, S. K., & Chakrabarty, M. (2009). Is education the panacea for economic deprivation of Muslims? Evidence from wage earners in India. *Journal of Asian Economics*, 20(2), 137–149.

- Bijukumar, V. (2013). Social Exclusion and Ethnicity in Northeast India. *The NEHU Journal*, 19-35.
- Bloom, D., Canning, D., & Sevilla, J. (2002). *The Demographic Divident: A New Perspective on the Economic Consequences of Population Change*. RAND.
- Borjas, G. J. (2016). *Labor Economics*. McGraw Hill Education.
- Botwinick, H. (2018). *Persistent Inequalities: Wage Disparities under Capitalist Competition*. Chicago: Haymarket Books.
- Brown, R. S., Moon, M., & Zoloth, B. S. (1980). Incorporating Occupational Attainment in Studies of Male-Female Earnings Differentials. *The Journal of Human Resources*, 15(1).
- Business Line. (2014, November 26). *SCs, STs form less than 10% of Central higher bureaucracy, says Personnel Dept*. Retrieved from Business Line: <https://www.thehindubusinessline.com/news/SCs-STs-form-less-than-10-of-Central-higher-bureaucracy-says-Personnel-Dept/article20919870.ece>
- Chakravarti, U. (1993). Conceptualising Brahmanical Patriarchy in Early India: Gender, Caste, Class and State. *Economic and Political Weekly* , 579 - 585.
- Chakravarti, U. (1995). Gender, Caste and Labour: Ideological and Material Structure of Widowhood. *Economic and Political Weekly*, 30(36), 2248-2256.
- Chamarbagwala, R. (2010). Economic liberalisation and urban-rural inequality in India: A quantile regression analysis. *Empirical Economics*, 39(2), 371–394.
- Chancel, L., & Piketty, T. (2019). Indian Income Inequality, 1922-2015: From British Raj to Billionaire Raj? *Review of Income and Wealth*, 65(S1), S33–S62.
- Coate, S., & Loury, G. (1993). Will affirmative-action policies eliminate negative stereotypes? *American Economic Review*, 83(5), 1220–1240.
- Das, M. B., & Dutta, P. V. (2007). Does Caste Matter for Wages in the Indian Labor Market? *World Bank, Washington, DC*, 91(11), 1–24.
- Deaton, A., & Dreze, J. (2002). Poverty and Inequality in India: A Re-Examination. *Economic and Political Weekly*, 37(36), 3729–3748.
- Desai, S., & Dubey, A. (2011, March 12). Caste in 21st Century: Competing Narratives. *Economic and Political Weekly*, XLVI(11), 40-49.

- Deshpande, A. (2000). Does caste still define disparity? A look at inequality in Kerala, India. *American Economic Review*, 90(2), 322–325.
- Deshpande, A. (2011). *The Grammar of Caste: Economic Discrimination in Contemporary India*. Oxford University Press.
- Deshpande, A. (2019). The Visible and Invisible Barriers to Indian Women Working. *The India Forum*.
- Deshpande, A., & Newman, K. S. (2007). Where the Path Leads: The role of Caste in post-university employment expectations. *Economic and Political Weekly*, 42(41), 4133–4140.
- Deshpande, A., & Ramachandran, R. (2014). *How Backward are the Other Backward Classes? Changing Contours of Caste Disadvantage in India*. Centre for Development Economics.
- Deshpande, A., Goel, D., & Khanna, S. (2015). *Bad Karma or Discrimination? Male–Female Wage Gaps Among Salaried Workers in India*. World Development.
- Doeringer, P. B., & Piore, M. J. (1970). *Internal Labor Markets and Manpower Analysis*.
- Dubey, A., Olsen, W., & Sen, K. (2017). The Decline in the Labour Force Participation of Rural Women in India: Taking a Long-Run View. *The Indian Journal of Labour Economics*.
- Duraisamy, M., & Duraisamy, P. (1996). Sex discrimination in Indian labor markets. *Feminist Economics*, 41–61.
- Duraisamy, M., & Duraisamy, P. (1999). Gender Bias in the Scientific and Technical Labour Market: A Comparative Study of Tamil Nadu and Kerala. *Indian Economic Review*, 34(2).
- Duraisamy, M., & Duraisamy, P. (2016). Gender wage gap across the wage distribution in different segments of the Indian labour market, 1983–2012: exploring the glass ceiling or sticky floor phenomenon. *Applied Economics*, 4098–4111.
- Duraisamy, P., & Duraisamy, M. (2017). Social identity and wage discrimination in the Indian labour market. *Economic and Political Weekly*, 52(4), 51–60.
- England, P., & Lewin, P. (1989). Economic and sociological views of discrimination in labor markets: Persistence or demise? *Sociological Spectrum*, 9(3), 239–257.

- Figart, D. M. (2005). Gender as more than a dummy variable: Feminist approaches to discrimination. *Review of Social Economy*, 509-536.
- Firpo, S., Fortin, N. M., & Lemieux, T. (2009). Unconditional Quantile Regressions. *Econometrica*, 77(3), 953–973.
- Gujarati, D. N., & Sangeetha. (2007). *Basic Econometrics*. New York: Tata McGraw-Hill.
- Gupta, S., & Sidhartha. (2021, February 8). *Over 300 PSUs may shrink to barely two dozen* . Retrieved from The Times of India: <https://timesofindia.indiatimes.com/business/india-business/300-psus-may-shrink-to-barely-two-dozen/articleshow/80740632.cms>
- Harriss-White, B. (2004). *India Working: Essays on Society and Economy*. New Delhi: Cambridge University Press.
- Harriss-White, B. (2020, May 20). *The Modi Sarkar's Project for India's Informal Economy*. Retrieved from The Wire: <https://thewire.in/political-economy/the-modi-sarkars-project-for-indias-informal-economy>
- Himanshu. (2007). Recent Trends in Poverty and Inequality: Some Preliminary Results. *Economic and Political Weekly*, 42(6), 497–508.
- Himanshu. (2011). Employment Trends in India: A Re-examination. *Economic & Political Weekly*, 43-59.
- Himanshu. (2018). *Widening Gaps: Oxfam India Inequality Report 2018*. Oxfam India.
- Himanshu. (2019). *The seriousness of the problem of unemployment in India*. Retrieved from Live Mint: <https://www.livemint.com/opinion/columns/opinion-the-seriousness-of-the-problem-of-unemployment-in-india-1564679281965.html>
- Hirway, I. (2012). Missing Labour Force: An Explanation. *Economic & Political Weekly*, 67-72.
- IHD. (2014). *India labour and employment report 2014*. New Delhi: Academic Foundation.
- ILO, & OECD. (2015). *The Labour Share in G20 Economies*. Report Prepared for the G20 Employment Working Group.
- ILO. (2018). *India Wage Report: Wage policies for decent work and inclusive growth India Wage Report*. ILO Decent Work Team for South Asia and Country Office for India.

- ILO. (2020). *ILOSTAT database*. Retrieved from The World Bank: <https://data.worldbank.org/indicator>
- IMF. (2020). A Crisis Like No Other, An Uncertain Recovery. *World Economic Outlook Update*.
- Ito, T. (2009). Caste discrimination and transaction costs in the labor market: Evidence from rural North India. *Journal of Development Economics*, 88(2), 292–300.
- Jacob, M. (2006). *Changes in the wage gap of gender and caste groups in India*. Retrieved from <http://repositorio.unan.edu.ni/2986/1/5624.pdf>
- Jajoria, D., & Jatav, M. (2020, January 18). Is Periodic Labour Force Survey, 2017–18 Comparable with Employment–Unemployment Survey, 2011–12? *Economic & Political Weekly*, pp. 12-16.
- Janyala, S. (2016). *Behind Rohit Vemula's suicide: how Hyderabad Central University showed him the door*. Retrieved from The Indian Express: <https://indianexpress.com/article/india/india-news-india/behind-dalit-student-suicide-how-his-university-campus-showed-him-the-door/>
- Jayadev, A., Motiram, S., & Vakulabharanam, V. (2007). Patterns of Wealth Disparities in India during the Liberalisation Era. *Economic and Political Weekly*, 3853-3863.
- Jodhka, S. S., & Newman, K. S. (2007). In the Name of Globalisation: Meritocracy, Productivity and the Hidden Language of Caste. *Economic and Political Weekly*, 4125–4132.
- Kannan, K. P., & Raveendran, G. (2012). Counting and Profiling the Missing Labour Force. *Economic & Political Weekly*, 77-80.
- Kannan, K. P., & Raveendran, G. (2019). From Jobless to Job-loss Growth: Gainers and Losers during 2012-18. *Economic & Political Weekly*, 38-44.
- Kant, A. (2019, February 6). *India's employment: The true picture*. Retrieved from Business Standard: https://www.business-standard.com/article/opinion/india-s-employment-the-true-picture-119020501601_1.html
- Kapadia, K. M. (1952). The Criminal Tribes of India. *Sociological Bulletin*, 1(2), 99-125.
- Kapila, U. (2017). Demography and Development. In U. Kapila, *Indian Economy: Performance and Policies* (pp. 108-146). New Delhi: Academic Foundation.

- Khan, M. I. (2016). Migrant and non-migrant wage differentials: a quintile decomposition analysis for India. *Indian Journal of Labour Economics*, 59(2), 245–273.
- Khanna, S. (2012). Gender Wage Discrimination in India: Glass Ceiling or Sticky Floor? *SSRN Electronic Journal*.
- Kijima, Y. (2006). Why did wage inequality increase? Evidence from urban India 1983-99. *Journal of Development Economics*, 81(1), 97–117.
- Kingdon, G. G. (1998). Does the labour market explain lower female schooling in India? *Journal of Development Studies*, 35(1), 39–65.
- Kingdon, G. G., & Unni, J. (2001). Education and women's labour market outcomes in India. *Education Economics*, 173–195.
- Kishore, R. (2020, September 01). *India's economy was facing worst-ever deceleration before Covid-19 hit*. Retrieved from Hindustan Times: <https://www.hindustantimes.com/business-news/india-s-economy-was-facing-worst-ever-deceleration-before-covid-19-hit/story-gOJfU86lJ64UPOjLBoypvN.html>
- Kumar, A., & Hashmi, N. I. (2020). Labour Market Discrimination in India. *Indian Journal of Labour Economics*, 63(1), 177–188.
- LRP. (1989). *Marxists Internet Archive*. Retrieved from <https://www.marxists.org/history/etol/newspape/socialistvoice/womenPR34.html>
- Machado, J. A., & Mata, J. (2005). Counterfactual decomposition of changes in wage distributions using quantile regression. *Journal of Applied Econometrics*, 20(4), 445–465.
- Madheswaran, S. (2006). Caste discrimination in the Indian urban labour market: An econometric analysis. *Internazionale Di Scienze Economiche e Commerciali*, 349–372.
- Madheswaran, S. (2010). Labour Market Discrimination in India: Methodological Developments and Empirical Evidence. *Indian Journal of Labour Economics*, 457–480.
- Madheswaran, S., & Attewell, P. (2007). Caste discrimination in the Indian urban labour market: Evidence from the national sample survey. *Economic and Political Weekly*.
- Mandal, B. P. (1980). *Backward Classes Commission*. New Delhi: Government of India.
- Marx, K. (1844). *Economic & Philosophic Manuscripts of 1844*. Retrieved from marxists.org

- Marx, K. (1973). *Grundrisse: Foundations of the Critique of Political Economy*. London: Penguin Classics.
- Marx, K. (1990). *Capital: Volume 1: A Critique of Political Economy (Penguin Classics)*. (B. Fowkes, Trans.)
- Mazumdar, I., & Neetha, N. (2011). Gender Dimensions: Employment Trends in India, 1993-94 to 2009-10. *Economic & Political Weekly*, 118-126.
- Mehrotra, S. (2016). Capitalising on the Demographic Dividend: Policies to Achieve Inclusive Growth in India. *India International Centre Quarterly*, 35-47.
- Mehrotra, S., & Parida, J. K. (2017). Why is the Labour Force Participation of Women Declining in India? *World Development*, 360-380.
- Mehrotra, S., & Parida, J. K. (2019, October). India's Employment Crisis: Rising Education Levels and Falling Non-agricultural Job Growth. Centre for Sustainable Employment, Azim Premji University.
- Mehrotra, S., Parida, J., Sinha, S., & Gandhi, A. (2014). Explaining Employment Trends in the Indian Economy: 1993-94 to 2011-12. *Economic & Political Weekly*, 49-57.
- Mincer, J. A. (1974). The Human Capital Earnings Function. *Schooling, Experience, and Earnings*. National Bureau of Economic Research.
- Morris, S., & Kumari, T. (2019, January 1). Overestimation in the Growth Rates of National Income in Recent Years? – An Analyses Based on Extending GDP04-05 through Other Indicators of Output. *IIM Ahmedabad Research and Publications*.
- Nagaraj, R., Dholakia, R. H., & Pandya, M. (2018). Manufacturing Output in New GDP Series Some Methodological Issues. *Economic and Political Weekly*, 53(35), 10–13.
- NSO. (2019). *Annual Report: Periodic Labour Force Survey 2017–18*. New Delhi: National Statistical Office, Ministry of Statistics and Programme Implementation, Government of India.
- NSO. (2019). *Annual Report: Periodic Labour Force Survey 2017–18*. New Delhi: National Statistical Office, Ministry of Statistics and Programme Implementation, Government of India.
- NSO. (2020). *Periodic Labour Force Survey 2018-19*. New Delhi: National Statistical Office, Ministry of Statistics and Programme Implementation, Government of India.

- NSSO. (2011). *Instructions to Field Staff, NSS 68th Round*. National Sample Survey Organisation, Ministry of Statistics and Programme Implementation, Government of India.
- NSSO. (2014). *Employment and unemployment situation in India, NSS Report No. 554 (68/10/1)*. New Delhi, India: NSSO (National Sample Survey Office).
- NSSO. (2016). *Design, Concepts, Definitions and Procedures, Instructions to Field Staff – Volume 1*. Periodic Labour Force Survey, National Sample Survey Office, National Statistical Organisation, Ministry of Statistics and Programme Implementation, Government of India.
- NSSO. (2016). *Schedules of Enquiry, Instructions to Field Staff, Volume – II*. Periodic Labour Force Survey, National Sample Survey Office, National Statistical Organisation, Ministry of Statistics and Programme Implementation, Government of India.
- NSSO. (n.d.). *Schedule 10: Employment and Unemployment*. National Statistical Office, Ministry of Statistics and Programme Implementation, Government of India,.
- Omvedt, G. (2005). Capitalism and Globalisation, Dalits and Adivasis. *Economic and Political Weekly*, 4881-4885.
- Padhi, B., Mishra, U. S., & Pattanayak, U. (2019). Gender-Based Wage Discrimination in Indian Urban Labour Market: An Assessment. *Indian Journal of Labour Economics*, 62(3), 361–388.
- Panagariya, A. (2017, July). *Report of the Task Force on Improving Employment Data*. Retrieved from <https://niti.gov.in/https://niti.gov.in/writereaddata/files/Task%20Force%20on%20Improving%20Employment%20Data%20-%20Report%20for%20Public%20Comments.pdf>
- Papola, T. S. (2014). *An Assessment of the Labour Statistics System in India*. New Delhi, India: International Labour Organization (ILO).
- Papola, T. S., & Kannan, K. P. (2017). *Towards an India wage report*. International Labour Organization (ILO).
- Pavlov, V. I. (2016). *The Indian capitalist class: A historical study*. Aakar Books.
- Phelps, E. S. (1972). The Statistical theory of Racism and Sexism. *American Economic Review*, 62(4), 659–661.

- Rajan, S. I. (2020). COVID-19-led Migrant Crisis: A Critique of Policies. *Economic and Political Weekly*.
- Ramakumar, R. (2019, April 15). *Unemployment: Why Amitabh Kant and Surjit Bhalla are Wrong*. Retrieved from Newsclick: <https://www.newsclick.in/>
- RBI. (2021). *Reserve Bank of India Annual Report 2020-21*. New Delhi: Reserve Bank of India .
- Sachar, R., Hamid, S., Oommen, T. K., Basith, M. A., Basant, R., Majeed, A., & Shariff, A. (2007). *Social, Economic and Educational Status of the Muslim Community of India*. Prime Minister's High Level Committee Cabinet Secretariat, GoI.
- Sanghi, S., Srija, A., & Vijay, S. S. (2015). Decline in Rural Female Labour Force Participation in India: A Relook into the Causes. *The Journal for Decision Makers*, 255-268.
- Saxena, N. (2021, May 23). *Disproportionate representation at the Supreme Court: A perspective based on Caste and Religion of judges*. Retrieved from Bar and Bench: <https://www.barandbench.com/columns/disproportionate-representation-supreme-court-caste-and-religion-of-judges>
- Sen, A. (2000). Social Exclusion Concept, Application, and Scrutiny. Philippines: Working Paper, Asian Development Bank.
- Siddique, Z. (2008). Caste Based Discrimination: Evidence and Policy. *SSRN Electronic Journal*.
- Singh, K. S. (1982). Transformation of Tribal Society: Integration vs Assimilation. *Economic and Political Weekly*, 17(33), 1318-1325.
- Srivastava, R. (2019). Emerging Dynamics of Labour Market Inequality in India: Migration, Informality, Segmentation and Social Discrimination. *Indian Journal of Labour Economics*, 62(2), 147–171.
- Srivastava, R., & Padhi, B. (2020). *Collapse in Wage/Salary Income Growth in India, 2011-12 to 2017-18*. New Delhi: Institute for Human Development.
- Stewart, F. (2005). *Horizontal Inequalities: A Neglected Dimension of Development*. Centre for Research on Inequality, Human Security and Ethnicity, CRISE.
- Subramanian, A. (2019a, June). India's GDP Mis-estimation: Likelihood, Magnitudes, Mechanisms, and Implications. *CID Faculty Working Paper No. 354*.

- Subramanian, A. (2019b, July). Validating India's GDP Growth Estimates. *CID Faculty Working Paper No. 357*.
- Tagade, N., Naik, A. K., & Thorat, S. (2018). Wealth Ownership and Inequality in India: A Socio-religious Analysis. *Journal of Social Inclusion Studies*, 4(2), 196–213.
- Thomas, J. J. (2012). India's Labour Market during the 2000s: Surveying the Changes. *Economic & Political Weekly*, 39-51.
- Thomas, J. J. (2020). Labour Market Changes in India, 2005-18: Missing the Demographic Window of Opportunity? *Economic & Political Weekly*, 57-63.
- Thorat, S. (2004). On Reservation Policy for Private Sector. *Economic and Political Weekly* , 2560-2563.
- Thorat, S. (2008). Labour Market Discrimination: Concept, Forms and Remedies in the Indian Situation. *The Indian Journal of Labour Economics*, 31-52.
- Thorat, S. (2012). Caste Identity and Economics. *Economic and Political Weekly*, 47(19), 32–34.
- Thorat, S., & Attewell, P. (2007). The Legacy of Social Exclusion: A correspondence study of job discrimination in India. *Economic and Political Weekly*, 42(41), 4141–4145.
- Thorat, S., & Newman, K. S. (2007). Caste and economic discrimination: causes, consequences and remedies. *Economic and Political Weekly*, 42(41), 4121–4124.
- Thorat, S., Shyamprasad, K., & Srivastava, R. (2007). *Report of the Committee to Enquire into the Allegation of Differential Treatment of SC/ST Students in AIIMS*.
- Torres-Reyna, O. (2007). *Linear Regression using Stata*. Princeton University.
- Vaid, D. (2014). Caste in contemporary India: Flexibility and persistence. *Annual Review of Sociology*, 40, 391–410.
- Velaskar, P. (2016). Theorising the interaction of caste, class and gender: A feminist sociological approach. *Contributions to Indian Sociology* , 389–414.
- Zacharias, A., & Vakulabharanam, V. (2011). Caste Stratification and Wealth Inequality in India. *World Development*, 39(10), 1820–1833.