Polarisation or Jobless Growth

Structural Changes and Employment Trends in the Indian Labour Market: Evidence from the National Sample Survey

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Abstract

This paper is a descriptive analysis of the role of education, occupation, intersectoral movement of workers and wages on the evolving demand for tasks and skills in the Indian labour market. To examine the trends in these four factors separately, we draw data from NSS 1999-00, 2004-05 and 2011-12 Employment and Unemployment Surveys and the 2017-18 Periodic Labour Force Survey (PLFS). The primary focus of this paper is to test two hypotheses: first, if the increase in share of high-skill and low-skill jobs is seen alongside a consequent decline in the middle-skilled jobs, a phenomenon known as 'job polarisation'. And if this change has had any unfavourable consequences on the low-skilled workers. The secondary objective of this paper is to build a 'Skill and Tasks Comparability Conceptual Framework' that relates skills, tasks, occupations, and educational level. The framework is a useful tool in understanding the type of activities, degree of task routinisation, core work skill and educational attainment corresponding to each occupational division. Few findings are important: first, the demand for high- and low-skill workers has well increased, however such increase in the informal sector is attributed to self-employed workers. Second, the proportion of middle-skill occupations have remained consistent for urban areas while reduced considerably for rural areas from 2000 - 2018 and the supply of workers with middle and secondary education are large and have remained so. Finally, a clear distress in agriculture is seen by fall in value add and movement of labour into low skill sectors such as construction and despite visible increase in employment share of low-skill occupations, the overall conditions of low-skill workers remains unfavourable. (268 words)

Key words: Job Polarisation; tasks and skills; structural changes; conceptual framework; wages; education; intersectoral movement of labour; NSSO 55th, 61st and 68th rounds; LFPS 2017-18; NCO 2004; NIC 2008.

JEL Classification: E24, J21, J24, J31

1. Introduction

Following liberalisation reforms, the Indian economy has grown strongly since the 1990s, reaching growth rates of 8 percent or more until the crisis of 2008-09. Over about 25 years after liberalisation the "real GDP grew at a compounded annual rate of over 5.5%" (Dasgupta and Kar). However, this growth has neither been equal or equitable across sectors and skill levels. The 2009-10 NSSO figures revealed that in the five years between 2004-05 and 2009-10, the net "increase in employment was only 1.1 million", whilst the total Indian workforce being around 450 million (ILO Wage report). Further, wages increased rapidly for high-skilled labourers in the service sector, while for informal labourers, constituting roughly up to 90 percent of the economy, wage-growth was flat. A high rate of youth unemployment coupled with falling women participation, that fell relative to male participation by around 10%. In common parlance, this is seen as evidence of 'jobless growth'.

Largely, the phenomenon of 'jobless growth' has been attributed to increasing digitalisation. The main discourse being the correlation between adoption of Information and Communication Technology (ICT) and emerging disparities in earnings. Furthermore, the debate acknowledges that incorporating ICT has led to increasing inter-sectoral inequality in both employment and wage distribution (Bound and Johnson, 1992; Levy and Murnane, 1992). Having said that, on looking scrupulously at the disaggregated data, there seem to be evidence of increasing employment shares in occupations that are highly-skilled or are highly paid and simultaneously growing share of occupations that require low-skilled as well as low paid workforce, and this comes with a consequent decline in "middle-skilled" jobs. Thus the argument goes: since technology adoption has been skill biased and has impacted the labour market for "routine jobs", it has raised demand simultaneously for both "high-skilled non-routine" work and "low-skilled non-routine" work, leading to a 'U-shaped' distribution of labour across skill-levels also referred to as job polarisation.

The term job polarisation encompasses both employment and income polarisation. It is the process where both the low and high-skilled labour market witness an increase in employment and wages, while the market for middle-skilled labour declines. Frey and Osborne (2013) conducted a global study on 702 professions, they find that by 2030, about 69 % of India's formal employment jobs will be automated. That said, given that "about 65% of global IT off-shore work and 40% of global business processing" is done in India (Frey and Osborne, 2013), this figure has significant implications. This means that about 60% of the labourforce; those part of middle-skilled occupations like clerks, sales, agriculture, trade-related work etc., face automation (ILO, 2018).

In this context, the main objective of this paper is to provide a descriptive analysis of the contribution of education, occupation, intersectoral movement of labour and wages on evolving demand for tasks and skills. In order to understand the role of these four factors separately, we look into the structural composition of the Indian labour market and how the changes in demand and supply factors have impacted high- , low- and middle skill jobs. We use NSS data over four rounds: 55th round (1999-00), 61st round (2004-05), 68th round (2011-12) and 2017-18 using the Period Labour Force Survey (PLFS). Our paper covers trends in distribution of labour across sectors (formal/ informal), type of work (regular/ casual), region (rural/ urban) and gender (female/ male) over these years.

This paper is divided as follows: **Section 2** presents literature review. An overview of data sources and methodology is discussed in **Section 3**. **Section 4** gives a brief overview on trends in employment conditions and distribution of workers. These two are documented across sectors, type of worker, regions and gender. **In Section 5**, we develop our case by considering demand and supply factors causing such changes. We consider that distribution of workers by occupation and industry provide insight into demand-side factors, and levels of educational attainment as the main supply-side determinant. In **Section 6** we also discuss the transition of agriculture workers to low-skilled manufacturing occupations like construction. Job polarisation not only replaces middle skilled jobs but also leads to negative effects on wages (Böhm, 2014) driving inequalities higher. **Section 7** discusses the effect such structural change has on earnings distribution which is "one of the ways of depicting polarisation" (Schran and Böhm, 2019).

In **Section 8**, we build a 'Skill and Tasks Comparability Conceptual Framework'. NCO 2004 does not classify occupations according to skill and task intensities, nor provides comparability guidelines for corresponding educational attainment (ISCO-88 educational requirements). The framework therefore, is a useful tool in broadly understanding what types of activities, degree of task routinisation, type and extent of core work related skills and education attainment are required at each occupational division. **Section 9** discusses inequalities. Inequalities in the Indian labour market are rising and it is important to examine the portion of inequality stemming from the rise of high- and low-skill occupations. Findings are mentioned in **Section 10**, and Discussion: managerial and policy implications follows.

2. Literature Review

Over the past decades one of the most important trends in the western labour market is job polarisation. Job polarisation is looked at in literature in different ways. Whether it is the change in distribution of jobs or change in (more recent discourse) nature of work, polarisation can be a change in employment or wages in different occupations (Case and Deaton, 2015). Such changes are also an underlying cause of greater inequalities in earnings (Acemoglu and Autor, 2011; Boehm et al., 2019). Polarisation is also looked into as the "presence or disappearance of certain groups" (Chakravarty 2009), in other times, interestingly it is used to suggest how certain people individually or as "groups feel toward each other" (Duclos, Esteban, and Ray 2004), more commonly as Zhang and Kanbur (2001) describes, polarisation as "diminishing middle class" and "divided society". Sassen (1991) finds in favour of economic restructuring such as increase in financial services in the western cities as causing a "social polarisation". In any case, the trend of polarisation is definitely reconstructing the labour market all over the world.

Autor, Levy and Murnane (2003) studied how computerisation had altered the demand for job skills using data from 1960 to 1998, and found that computerisation was linked to a fall in the demand for "routine manual and routine cognitive" jobs and an increase in "non routine cognitive" jobs. This meant that a shift in demand for certain skills will cause shifts in education demand as well. The first to give the name "job polarisation" to literature were Goos and Manning (2007) in their pioneering study that over a three decade period in the United Kingdom, the share of employment and occupation for the workers with "highest and lowest wages" had gone up, along with a simultaneous decline in those with "middle- wage occupations" (Boehm, 2019). In other advanced countries, such studies found more ground. However, the 'codifiable task' approach known as "routines" that can be coded by programmers, repetitive with clear rules such as assembly, record-keeping and calculation tasks, show risks of automation as shown by Autor, Levy and Murnane (2003) is most widely documented. Few studies agree on links between "routine tasks and negative premium" as opposed to "positive premium on abstract tasks" (Borghan et al., 2014; Demning 2016).

For the Countries of the US and Europe, other studies have also shown the decline in middle-skill occupations Autor, Katz and Kearney (2006); Goos and Manning 2007); Spitz-Oener (2006); Green and Sand (2015). The concept of "skill-biased technical change" (SBTC) is commonly discussed, the idea simply stating that technical changes cause a rise in demand for skill that complements it and simultaneously also causes a fall in unskilled-worker demand. Another way of looking at this is that technological advances make certain workers more productive in existing occupations (Johnson, 1997). He explains it as "intensive" and "extensive" SBTC and "skills neutral" technical change, or even "unskilled-biased" technical change like the production assembly line increases worker productivity proportionately.

Although empirical studies suggest movement of demand in favour of the skilled in the western labour markets since the 1980s (Nickell, Bell 1995 and 1996). And this can be attributed to SBTC, however a statistical relationship, between skill-biased technical change and income inequality, cannot be established within the parameters of a particular model. Overarching trends, such as globalization or skill-biased technological change can broadly account for inequality dynamics, but country-specific situations, policies, and institutions also matter.

There has been considerable research on the effect of skill-biased technical change on skill premium. As the demand for low-skilled workers has sharply declined in developed countries during the 1980s, studies have highlighted the role of SBTC in this decline. Breman, Bound and Machin (1998), finds that the real earnings of workers at the lower or lower middle spectrum of educational levels not only decreased by about a quarter (26 %) between 1979 and 1993, they did not "recover since". This period also corresponds with high unemployment levels and falling wages that were mostly "concentrated among the un-skilled". During the 1990s when the earnings inequality was stable, despite the advancement of computerisation, some studies questioned the relevance of SBTC that did not well explain the wage inequality, gender pay gaps and other discriminatory gaps (Card and DiNardo, 2002; Vieira, 2017).

Despite the SBTC as a dominant factor (Acemoglu and Autor, 2011), there exist other factors causing overall earnings inequalities. (Feenstra and Hanson, 1999: Autor et.al 2013). Moving away from the traditional view where technological change is “factor-neutral”, a recent technical change is seen as favouring the high skilled “at least in their adoption phase” (Violante, 2016; Benzell, 2019) and “factor-bias” is relevant to the “income distribution debate”. Of course empirical evidence that technology does contribute to the rise in top income shares (the 1% share of income) and this has been witnessed across industries (Kaplan and Rauh, 2013). Benzell et al., (2019) divides occupations on the basis of eight (statistically) different skills such as “leadership intensive”, “physically intensive”, “cooperation intensive”, and so on, and uses exploratory factor analysis to explore the role of such factors in growth in earnings and employment. They find that physically intensive jobs witnessed major decline in wages while on the other hand, leadership intensive and cooperation intensive jobs saw growth in wage and employment and increase in employment respectively. Increase in wages of leadership intensive jobs were mostly in IT related capital intensive occupations.

AI is studied for analysing its impact on employment and wages and AI’s role in replacing human workers, finds that in the westen markets, AI intensive industries are lowering their hiring even in the non-AI roles and increasing the AI hirings. Largely, a small substitution effect is witnessed in certain tasks, but definite impacts on labour markets on aggregate levels are not implied (Acemoglu et al., 2021).

For Indian sector, Nambiar and Tadas (1994), Mangekar and Tadas (1999), Rashmi Banga (2005) estimates the impact of technological progress on productivity of workers and earnings inequality in the manufacturing sector. Capital intensity and its role in changing wage and incomes in the Indian context is studied by Kapoor (2016), finding that due to a large pool of workers present, there is less evidence that the domestic technological growth can “outpace supply of educated workforce. Azam (2009) analyses the origin of wage premium for the tertiary and secondary educated workers during the 1990s. Studies on changes in occupations in the urban regions with its impacts on earnings inequalities concur to standard literature where a rising share of high- and low-skill workers are attributed to increase in self-employment especially in the informal sector (Sarkar, S. 2017).

The rising capital intensity of production has recently received some attention. Das and Kalita (2010), Goldar (2000) and Hasan (et. al. 2013) highlights the increasing capital intensive production methods adopted by manufacturing and shows that factors like market imperfections push firms towards greater capital intensity. However, over time the increasing capital intensity can be because of the relative lower price of capital, or higher wages as a proportion of rental price, easier access to foreign technology (Sen and Das, 2014; Hasan 2013). The impact of ICT and automation on the labour market is described with the lens of job polarisation during the covid recession time, finds that the health crisis has paced the process of automation and this can have an increasing effect on polarisation of jobs (Nippani, A. 2021).

Recently, a few studies have looked into structural causes, looking into supply and demand determinants. Kuriakose and Iyer (2018), finds that over a period of 1983 to 2012, there has been a rise in demand for high- and low skilled occupations while simultaneously the middle-skills have persisted. Similar to such finds, studies have also recently documented increase in low-skilled jobs linked to specialisation in routine tasks (Brunetti et al., 2020).

Most studies on job polarisation in India have either focussed on explaining employment trends in the manufacturing sector (Kuriakose and Iyer, 2018; Das and Kalita, 2010), or providing overall evidence of increasing de-routinisation of jobs (Vashisht and Dubey, 2018). However, few have looked at the consequences of job polarisation on both demand and supply-side factors.

This paper looks into sectoral trends in 1). distribution of workers by occupations and industry, 2). nature of the workforce (regular versus casual), 3). type of employment (formal - informal and organised - unorganised) and 4). regions (rural - urban). We cover demand and supply side determinants of polarisation. Thus, this paper fills the gap in literature by presenting by far a more comprehensive analysis of the structural changes in the post-liberalised Indian labour market from 1999-00 to 2017-18. Finally, we also try to provide a tasks and skills compatibility tool with the lens of routinisation of tasks thereby building a “Skill and Tasks Comparability Conceptual Framework”.

3. Data Sources, Data Description and Methodology

This paper primarily draws from the Quinquennial Employment & Unemployment: National Sample Surveys (NSS rounds) of 1999-00 (55th round), 2004-05 (61st round) and 2011-12 (68th round), for 2017-18 (75th round) we use data from the more recent annual report of the Period Labour Force Survey (PLFS) 2018. This paper covers data approximately from 2000 to 2018 to form a sample of ‘workers’[1] belonging to the ‘usual principal activity status’ (ps+ss) codes assigned 11 - 51. We consider individuals in the age group of 15 to 59 years and present data for rural and urban areas. We also consider ‘ps+ss’ i.e., usual status which is “determined on the basis of the activities pursued preceding 365 days of survey date” (PLFS, 2018), since it is comparable across rural and urban regions[2] and also over different survey rounds (NSS and PLFS). We exclude self-employed and unemployed individuals from this study.

[1] Workers are defined differently from those ‘unemployed’, ‘seeking or available for work’, and ‘labour force' in the NSS report. For our analysis we consider ‘worker’ i.e., those employed or “engaged in economic activity assigned on eor more activity status”.
[2] The key economic indicators such as the “Worker Population Ratio” or “Labour Force Participation” and unemployment are documented in ‘current weekly status (CWS)’ only for urban regions, while the ps+ss status covers both rural and urban regions.

Employment conditions vary significantly between types of work and workers are also discriminated against on the basis of gender. For examining employment conditions and distribution of workers, we segregate workers based on type of work (i.e., regular - casual and formal - informal)[3] and gender (male - female), and convert figures to percentages to maintain uniformity and allow compatibility in our approach.

Next, for analysing trends in supply side, educational attainment of workers can be considered as satisfactory in absence of availability of any other large sampled data across rural-urban regions that classifies labour force on their skill-sets[4]. Assuming educational level as a proxy for skill, supply of educated labour force is one of the non-technological factors that can explain whether routine occupations have declined or remained stable over time. On the other hand, how the distribution trend has developed in occupations, skill-sets and industry are discussed under demand side factors. We take the National Classification of Occupations (NCO 2004) by 'One digit Code No.' excluding armed forces. For industry division we consider National Industrial Classification (NIC 2008) by '2-Digit Numeric Code'.

The building of Skills and Tasks Compatibility Conceptual Framework required us to collate diverse data sets. Divisions of occupations are drawn from NCO 2004, and educational requirements from ISCO. We calculate the mean years of schooling (MYS) using an approach by Barro and Lee (1993, 2010) as given in Unesco Institute of Statistics (UIS, 2012). Detailed description of Framework is given subsequently in Section 6. Wage ratios are calculated as female average daily wage as a proportion of male average daily wage for occupations.

4. General Trends: Distribution of workers in the Indian Labour Market

Over 90% of the workers in the Indian labour market are in the informal sector and around 85 % of the workers in the non-agricultural sector can also be classified as informal. Simply put, these are workers without any social insurance. Although India has been one of the fastest growing large economies in the world, employment is still largely characterised by informality, and this has been a persistent feature notwithstanding "growing positive development" (ILO 2019). Establishing trends in the nature of employment can shed some light on the emergence of polarisation. Recently studies have found that the demand for routine and non-routine tasks are linked to industries providing employment and involving either mechanisation or computerisation, and the share of non-routine jobs have risen while that of routine manual and cognitive have decreased from 1983 to 2011 (Sarkar 2017; Vashist and Dubey, 2018). Such findings do argue in favour of polarising due to increase in high- and low-skill jobs, however

[3] Please see notes for description of regular- casual, formal- informal work as per NSS.
[4] The skill level as defined under NCO 2004 are based on International Standard Classification of Education (ISCED) divided to suit indian conditions considering informal skills- are based on level of education in four groups: primary, secondary, first university degree and postgraduate university degree.

such growth in the informal sector is not attributable to SBTC, rather an increase in self-employed people.

Table 1, shows trends in employment shares within the organised and unorganised[5] sectors; along with formal and informal division. The prominent presence of the unorganised and the informal sectors is apparent from the table. Few factors can largely contribute to the large absorption of labour in the informal and unorganised sector. First from the very beginning of Indian economic planning process, the development of the small scale sector was emphasised (Ahluwalia 1997). As surplus migration happened from the agri-sectors, they "were inevitably absorbed in traditional services" (Mehrotra, 2019). Second, policies and labour laws that were either pro- small industries or were not applied to them, helped increase the share through reservations in manufacturing, and this trend grew strongly till the 1990s, by then India had a large share of the small and medium sector at the cost of of course economies of scale. Education and skill level of workers is also attributed to a large informal sector. As many as 30% of the workers in 2012 were illiterate, of the remaining about half had a maximum of secondary level education, and within this a quarter had less than eight years of formal schooling. The workers with technical education was around 3%. Even by 2017-18, workers with any vocational education or training is a mere 2.4% of the total workforce (NSS, 2011- 12; LPFS 2018-19)

It is interesting to note that those industries in manufacturing contribute differently to output and employment. Industries such as garments and textile, food industry, tobacco and leather goods are highly informal with a large part of workers employed as casual labourers. Importantly, it must be noted that the rate at which non-agricultural jobs grow must be at least at par with the rate of increase in labour force. That said, the quality of jobs remains questionable since that depends on the skill levels so that they are capable enough of adapting to the rapidly industrialising labour market conditions and the steadfast incorporation of the advances in technical knowledge to drive economic growth. This shall ensure that the people engaged in such occupations that are at a higher risk of getting automated in near future do not succumb to structural unemployment and its deleterious ramifications on the workers' income and overall quality of life.

Table 1: Trends in Employment share in non-farm sectors (type of employment: organised & unorganised, formal & informal)

	Share of employment (%)			
	Organized	Unorganized	Formal	Informal

[5] Organisations employing less than 10 workers.

	2004-05	2011-12	2017-18	2004-05	2011-12	2017-18	2004-05	2011-12	2017-18	2004-05	2011-12	2017-18
Manufacturing	28.4	34.6	32.0	71.6	65.4	68.0	10.4	10.9	15.4	89.6	89.1	84.6
Non-Manufacturing	31.2	40.4	26.2	68.8	59.6	73.8	7.2	5.3	5.2	92.8	94.7	94.8
Service Sector	27.5	31.7	29.9	72.5	68.3	70.1	19.2	19.9	21.5	80.8	80	78.5
Non-farm Total	28.3	34.4	29.5	71.7	65.6	70.5	14.8	14.4	16.5	85.2	85.6	83.5

Source: Mehrotra (2019) Employment Working Paper 254, pp.15, ILO

Table 2, allows us to look into employment shares by the nature of work as defined in the NSS broadly in three types. Most of the agriculture workers are either self-employed or work as casual labourers, however a large share of self-employed, almost half of the workers (53% to 42%) are employed in the manufacturing and service sectors. Education levels of the workers have implications. Like discussed earlier, for Table 1, we see that since about half of the workers are middle educated (secondary level) and half of these are self-employed and a third are casual workers without any social coverage or scope of formal and quality training. It is important to see that technical education increases the chance of getting a regular salaried employment (Mehrotra, 2015). That said, if most of the workers have low or middle level educations, this trend is reflected in a large unorganised, informal manufacturing, construction or agriculture sector.

Table 2: Trends in Employment based on Sector and Type of Employment (2005 - 2018)

	Share of overall employment (in %)														
Nature of work	**Agriculture and Allied**			**Manufacturing**			**Non-manufacturing**			**Services**			**Total**		
	2004-05	2011-12	2017-18	2004-05	2011-12	2017-18	2004-05	2011-12	2017-18	2004-05	2011-12	2017-18	2004-05	2011-12	2017-18
Self-employed	64.2	65.1	73.2	53.2	49.1	42.2	16.3	10.3	10.9	51.7	48.3	43.1	56.9	52.2	52.2
Regular/Salaried	1.1	0.8	1.2	29.6	34.4	41.5	10.2	9.5	10.3	40.6	44.7	51.4	14.3	17.8	22.8
Casual	34.8	34	25.5	17.2	16.6	16.3	73.4	80.2	78.8	7.7	6.9	5.5	28.9	29.9	24.9

Total	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Source: Mehrotra (2019) Employment Working Paper 254, pp.15, ILO

Looking into the type of activity as regular and casual segregation, Table 3 represents data on distribution of workers by household type from 1999-00 to 2018-19. For all years, the proportion of households with household type 'regular' is higher in urban areas, while the households with type 'casual' are higher in rural areas. Self-employment constitutes the highest proportion of households and has steadily increased over time. Between 1999-00 and 2018-19, the number of households identified as 'self-employed' has increased from 562 to 618 per thousand in rural regions, and from 434 to 462 per thousand in urban regions. Households identified as 'regular' have also increased between 1999-00 to 2018-19 over time: from 60 to 131 in rural regions, and from 375 per 1000 to 428 per 1000 in urban regions.

On the other hand, households identified as 'casual' have reduced over time, and this is true for both urban and rural regions. Between 1999-00 and 2018-19, the number of households identified as 'casual' decreased from 379 to 251 per thousand in rural regions, and from 191 to 110 per thousand in urban regions. Broadly speaking, both self-employed and casual workers fall into the informal workforce which receive no benefits or job security. Thus, despite programs such as MGNREGA, we find a significantly greater incidence of informal workers in rural areas compared to urban regions, ie.86.9% in rural versus 57.2% in urban areas .

Table 3: Trends in Distribution of workers by typeof employment 1999-00 to 2018-19

Employment type	1999-00		2004-05		2011-12		2018-19	
	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
Regular	60	375	64	382	96	417	131	428
Casual	379	191	328	157	345	118	251	110
Self Employed	562	434	609	463	559	465	618	462

Source: Own estimation based on NSS rounds (1999-00, 2004-05, 2011-12) and PLFS (2018-19). Figures in 1000.

In Table 3, For the rural and urban divide, we find that the labour force participation rate (LFPR) has followed a similar trend. Between 1999-00 and 2004-05, LFPR increased from 43.4% to

45.6% for rural areas and from 35.1% to 38.2% for urban areas. In general, 2004-05 recorded the highest LFPR. Since then, the LFPR has gradually declined, and this is more significant in rural areas. Between 2004-05 and 2018-19, LFPR declined from 45.6% to 38.1% in rural regions, and from 38.2% to 36.6% in urban regions. Overall, LFPR for rural areas is higher than for urban areas, though this gap has reduced over time. This change can be better understood once LFPR is broken down by gender.

Over time, LFPR for rural males has changed only slightly from 54.5% in 1999-2000 to 55.7% in 2018-19. For urban males, LFPR increased substantially from 53.2% to 56.3% between 1999-00 and 2004-05, and has since stabilised at around 56%. For rural females, LFPR rose from 32.5% in 1999-00 to 35.3% in 2004-05 before declining significantly to 27% and 20.1% in 2011-12 and 2018-19 respectively. Several reasons have been proposed to explain this change. First, women are increasingly choosing education over work. The Gross Enrolment Ratio of women in higher education has increased from 17.9% in 2010-11 to 25.4% in 2017-8. Chaudhury and Verick (2014) found that between 1995 and 2012, absolute increase in female employment was witnessed only in low growth sectors such as textiles and garments, agriculture and handicrafts, sectors characterised by low wages and low productivity. This is a major reason why, having invested considerably into tertiary education, women wanted to wait for a job in the higher-paying organised sector rather than entering the lower-paying, low-skilled industries.

Part of this decline may also be attributed to the lack of appropriate jobs outside of low-paying sectors. Between 2004-05 and 2018-19, labour-intensive industries such as manufacturing and agriculture have witnessed a decrease in total employment. Increase in urban incomes have corresponded with a decline in female labour participation rates, suggesting that some degree of conservatism may play a role in women being 'allowed' to work. Further, measurement problems and underreporting of women's work are also contributing to declining LFPR. By focusing on cash, PLFS/NHFS/etc. may be ignoring women who are paid in kind or not salaried at all[6].

Worker Population Ratio (WPR), which refers to the percentage of employed persons in the population, follows roughly the same trends as LFPR. WPR increased from 42.8% to 44.8% for rural areas and from 33.7% to 33.6% for urban areas. WPR was highest in 2004-05 and has witnessed a decline since then, and this decline has been steeper in rural areas. Between 2004-05 and 2018-19, WPR declined from 44.8% to 36.3% in rural areas, and from 36.6% to

[6] The economic census 2013-14, shows that over 70% of businesses in India did not even have one hired worker. A women worker working in a household enterprisemight not be recorded in the PLFS/NFHS estimates of working women earning cash.

33.4% in urban areas. WPR for rural areas is significantly greater than for urban areas, though this gap has reduced over time.

We next look into Gender discrimination that is strongly evident in the urban region, while discrimination against females is less strongly noticed in rural areas. However, the bias against women is evident in both urban and rural regions as low female participation over the years of women in the labour force. Prior to 2004-05, we see that the participation of both men and women in the labour force witnessed a rising pattern; a steady rise by an average of about 2 percent in rural regions and a slightly higher rate in the urban regions. Post 2004-05 a decline in the total labour force is persistent and has emerged into a non-reversing pattern of continued falling female labour force participation.

We see sizable variations looking from region divide: the female participation in rural regions fell from 26.7 to 20% between the period of 2011- 12 and 2018- 19. While the rate of urban women fell from 16.1 to 15.1% during the same period. Considering the trends it would not be false to say that the female LFPR is heading south with a more strong downward trend in the rural regions. Interestingly, this downward trend of women's participation has been witnessed alongside strong economic growth , rising output and wages output in both services and industry for the nation. Overall, the average participation of workers is at an all time low, and according to the PLFS (2017-18) a fall in 7 percent in rural women's participation reflects an absolute drop of close to 25 million rural workers since the 68th round and a drop of about 47 million rural workers since 66th round.

A declining WPR has direct ramifications on macroeconomic indicators such as total income or output. WPR in rural areas has declined at a faster rate than urban areas, and this is due to movement of labour from agricultural activities and into other low-skilled activities. Rural-to-urban migration may also play a role where workers migrate to urban areas in search of better employment opportunities, thereby reducing the WPR of rural areas.

Unemployment

Between 1999-00 and 2004-05, unemployment rates were stable at around 1.5% for rural areas and around 5% for urban areas. Between 2004-05 and 2011-12, UR increased only marginally to 1.7% for rural areas while reducing considerably to 4.1% for urban areas (from 5.4% in 2004-05). Both urban and rural areas saw a significant increase in UR in 2018-19 (from 1.7% to 4.5% for rural areas, and from 4.1% to 8.5% for urban areas). Urban unemployment has been consistently higher, and although the urban-rural UR gap shrunk in 2011-12, it increased again 2018-19. Data from PLFS 2018-19 shows a sharp increase in UR among higher educated classes, and this may be why UR has fared worse in urban regions.

Urban females have consistently witnessed the highest rates of unemployment (9.9% in 2018-19) among all social groups. For both males and females, we see a higher unemployment in urban regions in comparison to rural ones, and all of them peak in the years 2018-19. In urban areas, females face higher unemployment than males while the reverse is true in rural regions. Between 1999-00 and 2011-12, unemployment rates have been more or less steady and fluctuated within a 1-1.5% margin. The lower unemployment rates for rural areas may be a consequence of improved rural growth owing to programs such as MGNREGA. Looking more closely at the data, we find that the spike in unemployment in 2018-19 is largely a consequence of increased unemployment among the higher educated groups. As of 2018-19, those who have a higher degree of education and those who are completely not-literate have witnessed almost the same level of unemployment. This points toward the growing shortage of supply of high-skilled jobs in India (ILO Wage Report 2018).

5.1. Supply Side Factors and Trends in Education

When looking at the dynamics of job polarisation, it becomes imperative to look at the supply side dimensions of the kind of jobs available to the masses. Table 4 illustrates trends in worker population ratio from 1999-00 to 2017-18, across the various educational classifications. We see a considerably large proportion of workers in the middle, secondary and higher secondary levels of education exist. This can be taken to imply the persistence of routine occupations which do not require a high level of skills and education. Table 4 also sheds light on the share of illiterate workers decreased from 70.4 per cent to 53.9 percent in rural areas, while dropping from 55.5 to 48.9 per cent in urban regions. The share of those with educational levels of graduate and above and post graduate and above has roughly been the same. This does point towards a declining trend in the supply of illiterate and uneducated workers, accompanied by an increase in supply of skilled and educated workers. Vashisht and Dubey (2018) attribute the rising demand for non-routine cognitive and manual jobs to supply-side factors (as documented in this paper) including a large educated workforce, as depicted by the table above.

Table 4: Trends in Worker Population Ratio based onEducational Classification 1999-00 to 2017-18

Educational Level	1999-00		2004-05		2011-12		2017-18	
	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
Not literate	70.4	55.5	72.1	56.75	64.9	53.6	53.9	48.9
Literate upto primary	64.15	50.35	67.2	54.45	62.65	53.5	55.55	50.95
Middle	52.9	43.05	58.65	46.05	52.3	46.15	45.8	43.8
Secondary	49.7	39.6	51.85	39.8	44.5	38.05	38.3	36.35
Higher secondary	45.95	36.6	48.05	36.85	39.7	34.55	33.45	30.7

Diploma	-	-	67.2	64.2	57.8	51.75	47.3	51.3
Graduate	57.3	53.95	58.25	52.35	51.8	50.4	42.4	46.95
Post Graduate and above	-	-	65.7	60.3	62.2	61.95	53.5	56.65

Source: Own estimation based on NSS rounds (1999-00, 2004-05, 2011-12) and PLFS (2018-19). Figures in percentage.

However, what often goes unnoticed is that although the expanse of higher education has increased, the quality of learning outcomes and the ability of graduates is not always the same. Moreover, there exists a very evident gender divide between the males and the females, in terms of educational attainment and workforce participation. Thus, despite there being a noticeable increase in graduate and post graduate education in the country, routine middle level jobs still persist and as automation takes over them, the people employed in such tasks face unemployment, thereby left to either upskill themselves for accommodating to higher level jobs or take up lower level tasks with a lesser pay, hence explaining the phenomenon of job polarisation in the country.

5. 2. Demand Side Factors and Trends in Employment

5.2.a. Occupation

To understand the nature of job polarisation in India, it is essential to first investigate the existing trends in the labour market. Table 5 below shows the distribution of workers by occupational division. We find that high-skilled occupations like Legislators, Senior officials and Professionals occupy a greater share of total employment in urban areas, while occupations like Agriculture and Fishery dominate rural employment. However, these concentrations have become less severe as the proportion of Senior officials, Legislators and Professionals share of employment in rural regions have increased over time.

Elementary occupations mostly require routine tasks involving some physical work or even use of tools and hands. Those belonging to sales or elementary occupations or workers belonging to agriculture, fishery, mining, construction, manufacturing and transport— occupied a greater share in urban areas until 2011-12 when the trend reversed dramatically: from 7.1 percent in 2004-05 to 32.4 percent in 2011-12. Interestingly, during the same time, the share of employment in 'skilled agriculture and fishery' (Div. 6) experienced a decline from 72.5 percent to 43.4 percent. Table 5 documents this dramatic change is largely a consequence of MGNREGA. The Indian agricultural sector has been typically characterised by low and unpredictable wages (due to low productivity of the sector) and disguised unemployment. With the adoption of MGNREGA, low-paid underemployed workers in agriculture shifted to other activities (low-skilled) that were covered under the scheme, and this is reflected in the data described above.

Table 5: Trends in Distribution of Workers by Broad Occupational Division (NCO 2004) by Rural and Urban, 1999-00 to 2017-18

Classification of Occupations	1999-2000		2004-2005		2011-2012		2017-2018	
	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
Legislators & Senior officials	2.1	8.88	2.23	9.23	3.1	13.9	4.6	14.3
Professionals	1.4	8.38	1.58	9.15	1.5	9.85	2	9.4
Technicians & Associate professionals	1.5	9.18	1.15	7.62	1.85	7.75	2.5	7.7
Clerks	4.1	16.67	4.72	17.64	0.65	4.95	1	4.3
Service workers & shop workers	2.5	9.68	2.28	10.06	4.15	13.45	6.3	16.3
Skilled agri & fishery workers	74.2	8.28	72.48	8.78	43.35	5.25	42.1	4
Craft & selected trade	2.9	7.88	3.05	9.08	10.5	19.45	9.2	18.4
Plant and machine operators	2	8.28	1.89	7.38	2.35	6.75	4.4	9.2
Elementary occupations	6.3	14.87	7.1	13.02	32.35	18.5	28	16.5

Source: Own estimation based on NSS rounds 1999-00, 2004-05, 2011-12, and PLFS 2017-18 data. All Figures in %

Next, we classify occupations on the basis of their skill-levels. In Table 6, Div. 1, 2 and 3 occupations have been categorised as ‘high-skilled’; Div. 4 to 8 as ‘medium-skilled’; and Div. 9 as ‘low-skilled’. We find that the employment share of both low-skilled and high-skilled workers have increased over time: for rural areas, high-skilled occupations’ contribution increased from 5% in 1999-00 to 9.1% in 2017-19, while low-skilled occupations increased from 6.3% to 28%. In urban areas, the contribution of high-skilled occupations increased from 26.4 % in 1999-00 to 31.4 percent in 2017-19, while low-skilled occupations increased from 14.9% to 16.5%. The change in the distribution of workers by skill-level is greater in rural areas.

Middle-skilled occupations have declined significantly in rural areas while remaining stable for urban areas. This is largely due to the aforementioned impact of MGNREGA: since agriculture is defined as a ‘middle-skilled’ occupation, movement of labour from agriculture to non-agriculture jobs covered under MGNREGA are reflected as movement from ‘middle-skilled’ to ‘low-skilled’ labour.

Table 6 depicts how within each skill category, there is considerable variation in the way distribution of workers has changed over time. Within high-skilled occupations, 'Legislators and Senior Officials' (NCO Div. 1) has witnessed the greatest increase in the share of employment for both urban and rural areas. In urban areas, 'Technicians and Associate Professionals' (Div. 3) has witnessed a decline from 9.2 percent in 1999-00 to 7.7 percent in 2017-18.

Table 6: Trends in Share of Employment (Rural - Urban) by Occupational Skill Level 1999-00 to 2017-18

Skill Level	1999-2000		2004-2005		2011-2012		2017-2018	
	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
High Skilled	5.0	26.4	5.0	26.0	6.5	31.5	9.1	31.4
Medium-Skilled	85.7	50.8	84.4	52.9	61.0	49.9	63.0	52.2
Low-Skilled	6.3	14.9	7.1	13.0	32.4	18.5	28.0	16.5

Source: Own estimation based on NSS rounds 1999-00, 2004-05, 2011-12, and PLFS 2017-18 data. All Figures in %

Within middle-skilled occupations, the share of workers in 'Clerks' (Div. 4) saw a dramatic decline in urban areas: from 16.6 percent in 1999-00 to 4.3 percent in 2017-18. While the reduction in the share of workers 'Skilled Agriculture and Fishery' overshadows other developments in the middle-skilled labour market, 'Craft & Selected Trade' (Div. 7) and 'Plant and Machine Operators' (Div. 8) actually saw a rise in their share of employment from 1999-00 to 2017-18, both in urban and rural areas. 'Craft and Selected Trade', which is the division which saw the highest increment in its share of employment in the middle skilled category, belongs to the services sector, and this is reflective of the structural changes in the Indian economy which has generally favoured the service sector[7].

5.2.b. Industry

Table 7 represents the distribution of workers by broad industry division (NIC 2008). Here, change in employment levels between different sectors can help us gain insight into broader structural changes in the economy, thereby helping us understand the nature of job polarisation in India. First, agriculture's share of employment has reduced significantly. In 1999-00, it accounted for 78.4% of total employment in rural regions, but this number fell to 64.1% by 2017-18.

[7] See also Himanshu, 2011.

Despite economic reforms and initiatives such as ‘Make in India’ by the government, manufacturing’s share of employment has been stabilised at around 7.5% in rural and 23% in urban regions. Similarly, sectors such as mining and quarrying and electricity, water,etc. have also remained stable and not seen significant changes in proportion of workers. As discussed later, it is the construction sector in both urban and rural regions which has seen a large rise in its share of employment over time. Table 7 shows that in 1999-00, it’s share of total employment was 2.8% in rural and 6.8% in urban regions, but by 2017-18, the figures had increased to 9.9% and 7.9% respectively.

Aside from construction, services and allied sectors such as ‘trade, hotel and restaurant’ and ‘transport, storage and communications’ have also witnessed growing share of employment. “Other services” typically include high-skilled sub-sectors such as banking and finance. Thus, over time, labour has shifted from agriculture and into two major sectors: construction, which has predominantly attracted low and middle-skilled workers, and services, which attracts middle and high-skilled labour. In part, this shift in labour is motivated by wage differentials (discussed later), and partly by structural changes in the economy (i.e. increase in demand for labour in construction and services). On the demand side, the movement of labour away from agriculture has been due to: (a) increasing rural wages (due to reducing LFPR); and (b) increasing mechanisation in agriculture (Mehrotra et al., 2014).

Table 7 : Trends in Share of Employment (Rural - Urban) by Broad Industry Division (NIC 2008), 1999-00 to 2017-18

National Industrial Classification	1999-00		2004-05		2011-12		2017-18	
	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
Agriculture	78.4	12.15	74.9	12.1	67.15	8.25	64.1	7.25
Mining & Quarrying	0.45	0.65	0.45	0.55	0.4	0.6	0.35	0.4
Manufacturing	7.45	23.2	8.15	25.85	8.95	25.55	7.9	23.8
Electricity, Water etc	0.2	0.5	0.1	0.5	0.2	1.2	0.25	0.95
Construction	2.8	6.75	4.15	6.5	9.8	7.35	9.9	7.9
Trade, Hotel & Restaurant	4.4	23.15	5.4	20.1	5.5	19.4	6.6	18.75
Transport, storage & communications	1.65	6.1	2	6.05	2.2	7.2	2.75	8
Other Services	4.9	27.6	4.9	28.35	5.8	30.5	8.25	32.95

Source: Own estimation based on NSS rounds 1999-00, 2004-05, 2011-12, and PLFS 2017-18 data. All Figures in %.

6. Transition of Agricultural Labour to Low Skilled Manufacturing Sectors

Accounting for the trends in sectoral changes in agriculture, industry and service from 1999-00 to 2011-12, we see that the sectoral growth rate of agriculture has witnessed a steady decline since the 1990s, whereas that of services have consistently increased in the last 50 years to roughly 8.9% per annum in 2011-16. In comparison, while the growth rate of industry has been more staggered over these years, they have still been consistently higher when compared to agriculture.

First, we see the contribution of agriculture to total output (as understood through GVA) has reduced significantly over time. Table 8 below shows the changes in shares of gross value added (GVA) across major sectors. Between 1999-00 and 2011-12, the share of agriculture to total output fell from 29.4% to 18.5%. In the same time frame, the share of services in total GVA increased from 36.9% to 49%. Service sector's growth in GVA (CAGR) was also significantly higher than other sectors (9.9%). Manufacturing, as we find, has stabilised at around 17% of total GVA. It is expected that as a country develops, agriculture's share of value added will decline in proportion to other sectors owing to its relatively low productivity.

Table 8: Trends in Sectoral Gross Value Added (inpercentage), 1999-00 to 2011-12

	Agriculture	Manufacturing	Construction	Services	Other Industries	Economy
1999-00	29.4	17.1	8.9	36.9	7.9	100
2004-05	24.7	17.8	10.3	39.6	7.6	100
2009-10	19	17.8	9.8	47.2	6.1	100
2011-12	18.5	17.4	9.6	49	5.5	100

Source: Papola and Kanan, 2017 (Towards an IndianWage Report), pg 45.

This fall in the value added share of agriculture in proportion to the other sectors, should be accompanied by a cross-sector movement of labour. However, the manner in which these movements in value-added and labour have occurred is heavily unbalanced, as documented in Table 9.

We find in Table 9, that while changes in sectoral employment follow the same general direction as change in value-added, it is the magnitude of change that differs greatly. Between 1999-00 and 2011-12, agriculture's contribution to total employment fell from 59.6% to 47%, while services rose from 24% to 28.5%. Manufacturing rose slightly from 10.7% to 12.67% in the same time frame while construction's contribution to employment increased significantly from 4.6% to 10.7%. with regards to agriculture, it has variously been argued that low "public investment in agriculture development, inadequate access to institutional credit, and frequent droughts and floods are reasons for this declining trend" (Chowdhury et al. 2020) .

Table 9: Trends in Sectoral Employment as percentage of Total Employment, 1999-00 to 2011-12

	Agriculture	Manufacturing	Construction	Services	Other Industries	Economy
1999-00	59.64	10.73	4.68	24.04	0.91	100
2004-05	56	11.77	6.11	25.2	0.92	100
2009-10	51.52	11.09	9.74	26.68	0.97	100
2011-12	47	12.67	10.74	28.52	1.06	100

Source: Own estimations based on NSS rounds 1999-00, 2004-05, 2011-12. All figures in %

However, the lopsided nature of India's structural shift away from agriculture becomes clear once data on employment and value-added are compared. By 2011-12, agriculture's share of total output was only 18.5% while its share of employment was 47%. Between 1999-00 and 2011-12, construction's share of output increased from 8.9% to 9.6%, a minimal rise, compared to its share of employment which rose from 4.6% to 10.7%. Services, which experienced the fastest growth among all sectors, contributed 49% of total output while only comprising 28.5% of total employment in 2011-12.

Table 10: Share of various sectors in GDP and Employment (in %)

Sectors	Share in GDP (%)	Share in Employment (%)
Agriculture	14.1	48.9
Manufacturing	15.7	12.8
Construction	7.9	10.6
Secondary	27.5	24.4
Tertiary	58.4	26.7
Non-Agriculture	85.9	51.1
Total	100	100

Source: Own estimations based on NSS survey report, 2011-12

Table 10 depicts how the agriculture sector, still employing almost half the working population contributes only 15.4% to the nation's GDP, thereby pointing towards the poor productivity levels of India's agrarian sector and also the existence of disguised unemployment in the field. All non-agricultural sectors, employing the other half of the population, contribute around 85.9% to the country's GDP, with the tertiary (service) sector dominating in the same.

Thus, while services have witnessed the highest growth in value-added, this has not corresponded with movement of labour into the sector. Instead, as agriculture value-added has declined, labour from agriculture has moved into low-skilled sectors such as construction. This is despite the fact that average wages and labour productivity are highest in the services sector. This phenomenon is referred to as 'jobless growth' where macroeconomic growth—led primarily by the services sector—is not followed by a corresponding growth in employment[8]

7. Wages

Available studies on earnings and employment suggest that India has witnessed an impressive growth in wage rates following the 1991 reforms (Bhalla and Das, 2005; Sundaram and Tendulkar, 2006). Unlike in recent years where benefits of wage growth have been disproportionately experienced by high-skilled regular, in fact during the 1990s, the low-wage low-skill workers in rural and urban regions experienced a steady rise in real daily wages and male-female earnings differentials also decreased (Sundaram and Tendulkar, 2006). However,

[8] Also see Kannan, 2019

the reported data is at an aggregate level, and little is known about sectoral differences in wage rate growth before 2004-05.

However, studies conducted upon disaggregated data suggest that post-liberalisation, wage rate growth in agriculture has been higher than in non-agricultural sectors (Jose, 2016). In part, this is due to the implementation of MGNREGA (2005) which established minimum wages and equal pay for men and women, both of which had a net positive impact on wage rates at the macroeconomic level. Table 11 below supports this claim as we find that growth rates for wages of rural workers have been consistently higher than urban workers. Despite this, wages for urban workers (Rs. 384) are more than twice that of rural workers (Rs. 175). Nevertheless, this data indicates a reduction in earnings differentials between rural and urban workers over time, in contradiction to Unni (2005) who suggested that one of the consequences of 1991 reforms were a widening of the urban-rural wage gap. We also find that wages have risen faster between 2004-05 and 2011-12 (5.6%) when compared to between 1993-94 and 2004-05 (2.6%).

Aside from MGNREGA, growth in the construction sector, especially within urban regions, may be indirectly causing an increase in rural wages: Increasing demand for construction labour has led to out-migration from rural areas, creating a shortage of labour for agriculture and thereby raising average wages of the sector (Gulati et al., 2013).

Table 11 also sheds light on wage trends for regular and casual workers between 1993-94 and 2011-12. Overall, casual workers have registered a higher wage growth (3.7%) when compared to regular workers. This trend was especially pronounced between 2004-05 to 2011-12 when casual workers wages grew by 6.8% per annum compared to only 4.2% for regular workers. Wages for regular workers grew at 2.3% between 1993-4 to 2004-5 largely due to the fifth pay commission which increased wages across IT, banking and finance sectors. Despite increasing casual wages, as of 2011-12, the average wage for a regular worker is over 2.7 times that of a casual worker, though the wage differential between them has declined since 2004-05. The increase in wage differential between casual and regular workers during 1993-94 and 2004-05 is a consequence of liberalisation reforms which increased the demand for high-skills in India, particularly within the services sector.

Table 11: Trends in real average daily wages and Averagewage growth by Location and Type of worker, 1993-94 to 2011-12

Workers	Real Daily wages (INR) Base year 2011-12			Compound average annual growth (in %)		
	1993-94	2004-05	2011-12	1993–94 to 2004–05	2004–05 to 2011–12	1993–94 to 2011–12
Rural	86	122	175	3.2	5.3	4
Urban	218	282	384	2.4	4.5	3.2
Regular	231	297	396	2.3	4.2	3
Casual	75	90	143	1.8	6.8	3.7
All	128	169	247	2.6	5.6	3.7

Source: ILO Wage Report 2018, pp. 15-17

Wage differentials between different sectors of the economy can help us understand cross-sector movement of labour i.e., movement away from agriculture and toward service sector jobs (Chand and Srivastava, 2014). Following the 1991 liberalisation reforms, growth is driven primarily attributed to the service sector, though few informal sectors like heavy machinery, automobiles and chemical products experienced fast-paced growth in labour productivity, which translated into higher earnings per worker (Unni, 2005).

Average daily wages vary significantly with respect to the occupational sector. The Primary sector comprises agriculture and allied activities; Secondary sector comprises manufacturing, construction, mining, etc; and the Tertiary sector essentially encompasses the service sector. We find that wages are lowest in the primary sector, higher for the secondary sector and highest for the tertiary sector. Across sectors, wages for casual workers vary much less than regular workers. Average daily earnings for casual sector varies between rupees 122 in the primary sector to rupees 168 in secondary and tertiary sectors (a range of INR 46) while for regular workers, it ranges from INR 192 in the primary sector to INR 424 in the tertiary sector (a range of INR 232).

Table 12 documents real wage growth rates across sectors and compares two time periods: between 1993-94 to 2004-05 and between 2004-05 to 2011-12. Across all sectors, for both casual and regular workers, real wage growth accelerated in the time period between 2004-05 and 2011-12. We find, wages have grown fastest in the primary sector relative to other sectors for both casual and regular workers. The difference between average daily wages of regular and casual workers is most pronounced for the tertiary sector.

Surprisingly, however, the most extreme case of regular-casual wage differential is found in the mining and quarrying sector. It might be instructive to know that in some cases, casual workers have seen a faster rate of wage growth compared to regular workers. However, as seen in the graph above, as of 2011-12, wages of casual workers across all sectors of the economy are significantly lesser than regular workers. We see that wages have varied substantially within each sector. Within the secondary sector, mining and quarrying has witnessed the fastest wage growth (5.9% between 1993-94 to 2011-12), followed by electricity, gas and water, and manufacturing. In the tertiary sector, real estate and business services witnessed a 6.2% growth rate in earnings between 1993-94 to 2011-12, more than twice the sector average.

Table 12: Trends in Sectoral Real Wage Growth Rates,1993-94 to 2011-12

	1993–94 to 2004–05		2004–05 to 2011–12		1993-94 to 2011-12	
	Regular	Casual	Regular	Casual	Regular	Casual
Primary	3.4	2.2	6.6	6.5	4.6	3.9
Secondary	1.4	1.5	4.4	4.6	2.6	2.7
Tertiary	2.3	1.5	4	5.6	3.0	3.1

Source: Construction based on ILO Estimates. Figures in percentage

Between 2004-05 to 2011-12, trade, and hotel and restaurants experienced an acceleration in growth, especially for casual workers (6.7% and 7.5% respectively). Banking and finance witnessed significant growth between 1993-94 and 2011-12 (3.7% and 6.7% for regular and casual workers respectively). However, it is worth noting that in sectors such as banking and finance and public administration, casual workers have seen a decline in daily wages.

8. Persistence of Routine Occupation

In this section, we create a framework for evaluating how the occupational divisions as given in the National Classification of Occupation (NCO 2004) corresponds to different sets of workforce skills and job tasks, it is to be noted that these are not synonyms. It is commonly understood that routine intensive tasks are attributed to low-skill levels but it is possible that workers with higher skill levels associated with routine jobs can be affected by automation and offshoring).

We then create a parallel between these classification of occupations with skill classifications (ie., type of skills commonly perceived to be required at the level or division of occupational classification); and task classification (i.e., indicators that capture what workers do on the job and in what sequence, which is different from the skills that they are endowed). Both the skill and task classifications are based on the framework developed by Autor 2014 and 2015 respectively. He mainly classified the task content into five components: Cognitive; Non-routine; Analytical; Routine and Manual.

The framework tries to sync the level of skills required with the corresponding educational requirement and the amount of formal schooling or formal education required using the International Standard Classification of Occupations (ISCO-88). We calculate the mean years of schooling (MYS) using an approach by Barro and Lee (1993, 2010) as given in Unesco Institute of Statistics (UIS, 2012). Towards the last column, we present corresponding years to formal schooling and formal education with the previously documented educational requirement. Since there will be variations within one corresponding level of education, we mention the maximum and minimum years of schooling or formal education.

Routine occupations are defined in literature as those that follow a set of easily identifiable and codifiable patterns rules. A different approach for identifying and categorising routine tasks looks at the role that skills and tasks have in the labour market (Marcolin et al., 2016). Accordingly, at times high skilled tasks may be subject to automation when jobs require repeated work that follows a defined set of rules. Interestingly, it is also observed that even though there is indeed a negative correlation between skill content and routine intensity, it is not necessarily very strong. Even though SBTC affects routine jobs more than non-routine, as in case of a skilled worker carrying out routine jobs such as that of a medical imaging technician, high-skilled worker subject to automation and relocation in a manner similar to that of a low skill routine worker (Autor, 2013, 2015).

Routine Intensity Indicator (RII) are based on OECD study and it subdivides jobs as follows:

1. “Non-routine (NR) (Senior legislators, managers and professionals)”
2. “Low routine - intensive (LR) (secondary education teachers and hairdressers)”
3. “Medium routine - intensive (MR) (machinery mechanics and shop salespersons)”
4. “High routine - intensive (HR) (assembly line workers and food preparation assistants)”

We classify the occupations based on the routine intensity indicator. However, the framework is limited in its approach due to the fact that task intensities of occupations vary across sectors and industries shaped by technology and innovation capabilities and workforce skills. During the early 2000s, different groups of routine intensive occupations have shown changes in the share of employment. Factors such as skill endowment of the workers, composition and structure of industry are crucial in determining such changes. For example, OECD work finds that non-routine, low-routine and medium-routine tasks have a considerable share in the services sector (28%), while about a half (41%) of the high-routine workers are employed in the manufacturing sector. Therefore, no clear patterns emerge unless any country’s industry structure and stage of development is taken into consideration. High skilled jobs specialize in cognitive non-routine tasks, certain low-skill services exist simultaneously to complement the high-skill jobs, such as cleaning and personal care services, lift operators and janitors etc. Thus moving the demand for high- and low-skilled workers simultaneously.

Skills and Tasks Comparability Conceptual Framework

NCO 2004/ RII*	National Classification of Occupations 2004	Skill classification based on Autor (2015)	"Core work related skill" based on "O*NET content model" and WEF 2016	Activity and Skill description based on WEF 2016	Task classification based on Autor (2014)	ISCO education requirement	Corresponding Average Years of schooling to the corresponding level of education	Corresponding minimum/ maximum years of schooling or formal education
1/NR	Legislators, Senior officials, and Managers	High skill	Cross-functional skills, Cognitive Abilities, Systems Skills and Complex Problem Solving skills / Other Basic Skills and Abilities	Judgement and Decision Making/ Systems Analysis/ Cognitive Flexibility/ Creativity/ Logical Reasoning/ Problem Sensitivity/ Mathematical Reasoning/ Visualization / Emotional Intelligence/ Complex Problem Solving	Non-routine cognitive analytical	Post Graduation and Postgraduate Professional / Technical Diploma / Degree	Average: 17. 11 years of formal education and professional training	Minimum 15 to maximum 20 years of formal education
2/NR	Technicians and Professionals	High skill	Cross-functional Skills. Cognitive Abilities, Systems Skills and Process Skills / Other Basic Skills and Abilities	Cognitive Flexibility/ Creativity/ Logical Reasoning/ Problem Sensitivity/ Mathematical Reasoning/ Active Listening/ Monitoring Self and Others	Non-routine cognitive	Post Graduation and above	Average: 17. 11 years of formal education and professional training	Minimum 15 to maximum 20 years of formal education
3/LR	Associate Professionals	High skills	Cross-functional Skills Cognitive Abilities, Resource Management Skills and Social Skills / Other Basic Skills and Abilities	Coordinating with Others/ Emotional Intelligence/ Negotiation, Persuasion, Service Orientation,/ People and Time Management/ Financial and Material Resource Management/ Cognitive Abilities	Non-routine cognitive interactive	Graduation and Professional/ Technical Diploma/ Certificate Course	Average: 15.99 years of formal education and formal skills	Minimum 13 to maximum 18 years of formal education
4/HR	Clerks	Middle skill	Basic Content Skills and Process Skills	ICT Literacy/ Written Expression/ Reading comprehension/ Other Basic Skills	Routine cognitive	Graduation/ Higher Secondary/ Certificate Course	Average: 14 years of formal education and some training	Minimum 12 to maximum 17 years of formal education

5/MR	Service Workers, Shop and Market Sales Workers	Low skill	Basic Content Skills/ and Process Skills Cognitive Abilities and Social skills	Creativity/ Visualization/ Logical Reasoning/ Coordinating with Others/ Emotional Intelligence/ Negotiation and Persuasion/ Service Orientation	Routine cognitive	Secondary Education/ Middle	Average: 11.49 years of formal schooling	Minimum 9 to maximum 11 years of formal schooling
6/MR	Craft and Related Trade Workers	Middle skill	Physical Abilities and Process Skills	Manual Dexterity and Precision/ Physical Strength/ Critical Thinking/ Creativity/ Visualization	Routine manual	Upper Primary Education / Primary Education	Average: 6.77 years of formal Schooling	Minimum 5 to maximum 10 years of formal schooling
7/MR	Skilled Agricultural and Fishery workers	Low skill	Physical Abilities and some Technical Skills	Equipment Maintenance and Repair, Operation and Control/ Manual Dexterity and Precision	Non-routine manual	Below Primary Education upto Primary/ Middle School Education	Average: 6.77 years of formal schooling	Minimum 5 to maximum 10 years of formal schooling
8/HR	Plant and Machine Operators and Assemblers	Middle skill	Content Skills/ Technical Skills and Physical Ability	Reading and Comprehension/ ICT Literacy/ Physical Strength and Manual Dexterity/ Equipment Maintenance and Repair	Routine manual	Primary upto Middle or HSC Education/ Some Informal Training	Average: 9.48 years of formal schooling	Minimum 5 to maximum 13 years of formal schooling
9/LR	Elementary Occupations	Low skill	Physical Abilities/ Social Skills	Physical Strength/ Manual Dexterity and Precision/ Negotiation and Persuasion/ Service Orientation/ Emotional Intelligence	Non-routine manual	No Formal Schooling/ Some Training/ Primary education	Average: 2.75	Minimum 0 to maximum 5 years of formal schooling

Source: Author's own compilation based on NSSO 68th round, NCO-2004 and ISCO educational requirements, RII OECD, Autor 2014, 2015 and WEF 2016.

*Note: Routine task intensive occupations are categorised as those mentioned under level 4,7 and 8 of NCO 2004 classification (3 digit classification). RII: Routine Intensity Indicator developed by the OECD (Marcolin et al., 2016) Programme for the International Assessment of Adult Competencies (PIAAC). ISCO-88: International Standard Classification of Occupation. *This is based on the idea that all occupations have a varied degree of involvement in routine tasks*

9. Inequalities in the Indian Labour market

Structural change is characterized by movement of labour from agriculture and even recently manufacturing towards the service industry, underlying either an "uneven productivity growth" causing variations in prices (Nagai and Pissarides, 2007), or any form of technological change that reallocates consumption" (Boppart 2014) We discuss the effect such structural change has on earnings distribution, which is "one of the ways of depicting polarisation" (Schran and Boehm 2019). Inequalities in the Indian labour market are rising and the persistence of sectoral inequality in India is undeniable.

Studies have pointed towards the dominant presence of the gender wage gap regardless of the industry or sector (Lama & Majumder, 2018). The sticky phenomenon of gender based wage differentials (Deshpande & Deshpande 1999; Madheswaran & Shroff 2000) bring to light that women are persistently underpaid and face discrimination in wages. The Sustainable Development Goal 8 states creation and sustenance of "productive employment and decent work for all women and men", the labour market in India remains burdened with vast inequalities.

We calculate the gender wage ratios (female to male), across various occupational divisions, finding that almost across all the sectors, a very significant gender wage gap exists. Table 13 depicts the gender wage ratios across all the occupational divisions. Even amongst the people engaged in senior managerial level jobs, wage rates exhibit considerable disparities between men and women. Notwithstanding, the scenario has gradually been improving over the years, it is also noticeable that such improvement is not particularly seen amongst occupations in the informal or unorganised sector, such as workers in shops/markets, craftsmen, skilled agri fishery works etc, where the gender wage disparity is significantly higher.

Table 13: Gender Wage Ratio based on Educational Classification(1999-00 to 2011-12)

Occupation Type	1999-2000	2004-05	2011-12
Legislators, Senior Officials & Managers	0.64	0.8	0.92
Professionals	1.01	0.73	0.75
Technicians & Associate Professionals	0.82	0.64	0.62
Clerks	0.7	0.95	0.88

Service workers & Workers in Shops/Markets	0.47	0.57	0.52
Plant & Machine Workers	0.47	0.41	0.48
Craft & related trades	0.68	0.49	0.53
Skilled Agri Fishery Workers	0.64	0.54	0.6
Elementary occupation	0.61	0.65	0.69
All occupations	0.36	0.55	0.66

Source: Compiled from own estimates based on NSS rounds & India Wage Report ILO (2018)

In urban regions wage differentials started increasing during the late 1980s and this was mostly due to skill premium associated with technology (Kijima, 2006). The key source of inequality at the global level has been technological change favouring higher skills. The coming of what is known as the fourth industrial revolution- the rise of technology and the gradual shift to a machine intensive production system- has led to what economists now claim to be the phenomenon of 'job polarisation', that is, the loss of jobs requiring medium level of skills/education and the subsequent movement of people employed in such tasks either to jobs requiring higher proficiency or to lower level jobs which pay them less.

Findings

In this paper, we present a descriptive analysis of trends in structural composition of the Indian labour market. We tested the hypothesis if the share of middle-skill workers has declined in the context of an increasing share of high- and low skill workers. Then we examined, in this context- if there is any negative effect on low-skill workers. First, we note that since the demand for high-and low-skill jobs have risen, such an increase in the informal sector is attributed to an increase in self-employed workers. We find that between 1999-00 and 2004-05 the LFPR increased for both rural and urban areas, however since then (2004-05 and 2017-18) it has gradually declined, more rapidly in rural areas. Two factors: the role of increasing GER and females opting for higher education, discrimination, migration to urban areas in search oif better opportunities, and lack of opportunities outside of low-paying sectors are possible reasons behind this fall in LFPR post 2005. Overall, we find that since 2011, female participation has fallen in both rural and urban areas. A fall from 26.7% to 20% for rural areas alone reflects an absolute drop of about 25 million since 2011.

We find that on the supply-side, the proportion of workers with middle levels of educational attainment i.e., middle school, secondary, and senior secondary, are highest in absolute terms, and have remained so consistently over the years from 1999-00 to 2017-18. Although the share of graduate workers (46.95%) show an increasing trend recently, their dominance is subdued in presence of those with middle-level (43.8%), secondary (36.35%) and higher secondary (30.7%). Although we find that the expanse of higher education has increased, the quality of learning outcomes and the ability of graduates is not always the same. Thus, despite there being a noticeable increase in graduate and post graduate education in the country, routine middle level jobs still persist and as automation takes over them, the people employed in such tasks face unemployment, thereby left to either upskill themselves for accommodating to higher level jobs or take up lower level tasks with a lesser pay, hence explaining the phenomenon of job polarisation in the country.

From a demand-side perspective, we find an increase in share of employment in the high-skilled jobs such as senior officials, managers and professionals over time (from 8.8% in 1999-00 to 14.3% in 2017-18 in urban areas and 2.1% to 4.6% in rural areas) . We also show that labour has steadily moved out of agriculture and into elementary occupations, and that mostly can be attributed to demand driven policies such as MGNREGA. This has resulted in rapid wage growth in rural areas. With respect to skill-level, we find that the share of employment of both high- and low-skilled labour has increased over time, while middle-skilled jobs have remained largely steady for urban areas while reducing considerably in rural areas (middle skill workers were around 50.8% in 1999-00 and are 52.2% in 2017-18 in urban areas; for rural areas, the share of workers have reduced from 85.7% in 1999-00 to 63.0% in 2018-19).

We find that construction and service sectors have increased in their share of total employment, although the reduction in share of agriculture is greater (from 78.4 % in 1999-00 to 64.1 % in 2017 -18). On the demand side, the movement of labour away from agriculture has been due to: (a) increasing rural wages (due to reducing LFPR); and (b) increasing mechanisation in agriculture. “Other services” typically include high-skilled sub-sectors such as banking and finance have witnessed a growing trend (from 28.3% in 1999-00 to 32.9% in 2017-18).

In the section on wages, we find that despite wages for urban workers (Rs. 384) being more than twice that of rural workers (Rs. 175), growth rates for wages of rural workers have been consistently higher than urban workers. Nevertheless, our analysis indicated a reduction in earnings differentials between rural and urban workers over time, in contradiction to Unni (2005) who suggested that one of the consequences of 1991 reforms were a widening of the urban-rural wage gap. We also find that wages have risen faster between 2004-05 and 2011-12 (5.6%) when compared to between 1993-94 and 2004-05 (2.6%). We also find an increase in wage differential between casual and regular workers during 1993-94 and 2004-05 and can attribute is a consequence of liberalisation reforms, largely due to the fifth pay commission which increased wages across IT, banking and finance sectors; which increased the demand for high-skills in India, particularly within the services sector.

Although India has experienced strong wage growth following liberalisation, we observe that increase in earnings have been disproportionate across sectors and skill levels. Wage growth has been the highest in the tertiary sector, while wages for regular workers have increased at a faster rate than casual workers. Although rural wages have witnessed rapid growth in the 2000s, urban wages remain significantly higher. Wage differentials between occupations and skill-levels increased over time largely as a consequence of the success of the service sector in India. Overall, sectors of mass employment have witnessed slower growth in wages, while sectors of low employment have witnessed rapid wage growth.

The lopsided nature of India's structural shift away from agriculture became clear once data on employment and value-added were compared. We observe that while services have witnessed the highest growth in value-added, this has not corresponded with movement of labour into the sector. Instead, as agriculture value-added has declined, labour from agriculture has moved into low-skilled sectors such as construction. This is despite the fact that average wages and labour productivity are highest in the services sector. This phenomenon is referred to as 'jobless growth' where macroeconomic growth—led primarily by the services sector—is not followed by a corresponding growth in employment.

10. Discussion: Managerial and Policy Implications

Technological change and advancement is inevitable and will continue to cause disruptions in ways we work and the ways work is rewarded. **Instead of creating a bleak scenario about the extent to which automation will substitute human labour, policy implications undeniably call for upskilling existing workers using education and training so that they can adapt to manage new tasks, or carry on with existing ones with better efficiency**. Findings from this paper mandates adequate measures to **improve the quality of education imparted through schools and institutes while equally prioritising the spread of skill based vocational training (including training of both "abstract and manual skills" is the key (**Saunders, 2018)**.** Alongside these measures, it is also essential to **provide such pathways for mid-career professionals and workers that allow them to upskill themselves while retaining their jobs,** so as to keep pace with the rising advancements in their respective fields of work.

As discussed in this paper previously, automation and such technologies are quick to be adopted by industries and for tasks that require "expensive training requirements for workers" (Böhm, M. 2019). In this context, policy and managerial implications are important. **Certain good intentioned measures such as substantially increasing the minimum wage through public policy or through presence of unionisation can cause replacements or automation.** That said, certain sectors such as insurance and health, finance are highly sensitive to technological changes.

It is more important to consider whether in the future newer opportunities will be created for the workers in context of rapid economic transformations. And also whether occupations in the high- and low-skill segments will see any disruptions. Of course factors such as regulation and adoption of technologies leads to outsourcing of certain jobs from one industry to another specialised ones which may not provide any social coverage for its workers. **Thus the effects of regulation on the low-skill and manual workers is of concern and requires attention. Notwithstanding that in the western markets the most high skilled jobs are also the most regulated.** Changes in domestic demographic situations and changing global environment

An important aspect where policy needs attention is the increasing share of temporary workers. With a rapid change in modern labour markets including new technologies, regulations and even unemployment (Katz and Krueger 2017), gig workers, freelancers and contract workers are increasing and more so because it is proven to be cost-effective for employers to employ workers on contracts. India at present has around 15 million freelance workers engaged in projects in sectors like IT, HR, and designing, with the gig economy now becoming one of the largest in the world (The Economic Survey of 2020-21). **This change is inevitable[9] and it thus remains in the best interest of the economy to recognise it and take relevant measures to accommodate the labour market to it. The regularisation of contract and gig work, systematised assurance of certain basic rights** for the labourers even within this scheme shall protect the labourers engaging in the gig economy for survival.

The Indian labour market is complex and the trends discussed in this paper capture only to a certain extent the determinants of 'jobless growth' or 'job polarisation'. Our findings call for a crucial responsibility for policymakers in improving outcomes in the Indian labour market. Further research in demand supply mismatch and returns to tasks is required in the context of changing tasks content within occupations. **The increasing mismatch between educational attainment and labour demand warrants a need to enhance the skill sets of Indian workers, both through a revision of academic curriculums and greater skill enhancement programs initiated by employers and industries and even funded by the government.** At the same time, some protection can be provided to lower-level jobs that are at risk of becoming obsolete. While **better income security schemes and improved regulation of the informal workforce may reduce the social cost of increasing job polarisation**, a deeper problem of skill shortage in India requires conscious handling.

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