Job Polarisation in India: Structural Causes and Policy Implications

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STRUCTURAL CAUSES AND POLICY IMPLICATIONS

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Abstract

Automation impacts employment and wage levels at the micro-level, and the structure of employment-shift at the macro-level. Job polarisation is defined as the automation of 'middle-skill' jobs that require routine cognitive and manual applications while high and low-skill occupations are preserved. This paper examines the nature of job polarisation in India during the period 1983-2012 when Indian manufacturing was being gradually automated. The research uses disaggregated data from National Sample Survey Office and examines supply-side factors such as nature of employment growth in manufacture and presence of educated labour force which have not been adequately analysed before. The study has three observations. First, only the increased demand for high-skilled workers in the formal sector is due to skill-bias of technology conforming to theoretical expectation. Second, the transition of agricultural labourers has been to low-skill manufacturing sectors such as construction and textiles signalling distress in traditional manufacturing to provide employment. Third, over-supply of secondary and tertiary educated labour force has squeezed out middle-skilled workers from middle-skill jobs to relatively low-skill manufacturing and service occupations, explaining the persistence of routine occupations. The study concludes that increased demand for high and low-skill jobs has co-existed with the persistence of middle-skill jobs in India.

Keywords: Automation, Job Polarisation, Supply-Side Factors, Manufacturing, India

I. INTRODUCTION

We live in the age of artificial intelligence (AI) that has provided us with immense processing power, storage capacity and access to information. The World Economic Forum termed the advent of artificial intelligence 'the fourth industrial revolution'[1] (Schwab, 2017). Automation impacts both employment and wage levels. For example, a study by Frey and Osbourne (2013) shows that since 2000, only 0.5 per cent of new jobs have been created, that did not exist before. This is against 173 million jobs that would be automated in the next eight years in G7 countries, which are also the seven largest advanced economies in the world. Research also estimates that each robot per 1000 workers reduces the wage level by 0.25-0.50 per cent (Açemoglu and Restrepo, 2018).

The manner in which occupations get automated follows a pattern referred to as job polarisation. In a study examining 702 professions globally, Frey and Osborne (2013) have shown that 'middle-skill' jobs that require routine cognitive and manual applications would be automated in the short-term. As a result, they argue that India, which has 65 per cent of global IT off-shore work and 40 per cent of global business processing, will have 69 per cent of its jobs in the formal employment automated by 2030. According to the International Labour Organisation (ILO), 60 per cent of the formal employment in India relies on 'middle-skill' jobs including clerical, sales, service, skilled agricultural and trade-related work, all of which are prone to automation (ILO, 2018). The Ernst & Young Future of the Jobs report (2018) further indicates that currently only one per cent of the Indian workforce are trained in AI.

In this context, this paper examines the nature and extent of job polarisation in the Indian economy by analysing the trends of employment using disaggregated data from National Sample Survey for

[1] The term was used in the tradition of naming major technological inventions such as spinning wheel as the first industrial revolution, electricity as the second and computers as the third. For more, refer Schwab (2017).

the period 1983-2012 as given in Sarkar (2017) and Vashisht and Dubey (2018). In particular, the study is interested in understanding the persistence of routine occupations in India which contradicts theoretical expectations. We argue that the reason for persistence of routine occupations is to be found in non-technological factors such as supply of educated workforce and the divergence between output and employment generation in Indian manufacturing.

The paper is presented in the following format. In section II, theoretical overview of polarisation is given using the model proposed by Açemoglu and Autor (2011). Following this, empirical evidence of polarisation in advanced economies is examined in section III. In the next two parts IV and V, the Indian scenario is examined and the research question explored in detail. Section VI follows the analysis with a brief outline of policy implications. The final part VII concludes the arguments of the paper.

II. THEORETICAL EXPLANATION OF POLARISATION

Understanding job polarisation requires an overview of production function and how factors of production interact with each other. Production function is mathematically represented as the maximum amount of output produced by a given set of inputs using a combination of existing production techniques (Mankiw, 2012)[2]. Let a particular production technique be *i* which is defined by two parameters a_i and b_i. Using this production technique, output *Y* can be produced with capital *K* and labour *L*. Then the production function associated with technique *i* is given by

$$Y = \widetilde{F}(b_i K, a_i L) \qquad [1]$$

[2] In a given model of production function, the direction of technological change is treated as either exogenous (Solow, 1957) or endogenous (Aghion and Howitt, 1990).

Here, $\tilde{F}$ (.,.) represents a function whose elasticity of substitution between inputs is less than 1, has constant returns to scale in *K* and *L* and has positive but diminishing marginal products[3]. The set of available production techniques is characterised by the technology menu,

$$H\,(a, b) = N \qquad [2]$$

where, $H_a>0$; $H_b>0$, $N>0$ and N is the level of knowledge. Furthermore, the trade-off is that, every idea that takes a high value for *a* will take a low value for *b*.

There are two limitations to the assumptions made in the classical production function discussed here (Autor, 2013). First, technological advancement permits the substitution of labour by capital for a specific set of tasks[4]. This phenomenon is seen in labour displacement through automation. Second, capital (machines) can simultaneously complement labour in a specific set of tasks. Thus, the division of labour evolves through both substitution and complementarity between capital and labour. New tasks are first assigned to labour and then reassigned to machines once the tasks are codified and formalised. Furthermore, division of labour shapes the demand for subsequent labour that the standard production function assumes to be static.

The need for a task-based approach to production function assumes significance due to the limitations discussed so far. Açemoglu and Autor (2011) have given a tractable model of task-based approach to production function. Their model considers *task* as a unit of work activity that produces a given output. The model further defines *skill* as the worker's stock of capabilities used to perform tasks. The assignment of a factor (K, L) to a given task depends on two factors-technology and economics. Technological factor determines substitution of and complementarity

[3] The local and global variation of this production function is given by Jones (2005) whilst variation with respect to short-term and long-term substitution of elasticities is discussed in Gilchrist and Williams (2000).
[4] Substitution also occurs between domestic and foreign labour. For more, refer Markusson, Rutherford and Tarr (2005).

effects of capital *K* upon labour *L* through the availability of production techniques. The economic factor is determined by the comparative advantage of the factor (K, L) at equilibrium[5].

In this model, let *Y* be the output of a unique final good, y_i be the production level of task *i* and η be the elasticity of substitution between the tasks. Then,

$$Y = [\int_0^1 y_i \frac{\eta - 1}{\eta} d_i]^{\frac{\eta-1}{\eta}} \quad [3]$$

Here, the economy is assumed to be closed, producing a unique final good given by combining a continuum of tasks represented by unit interval [0,1]. Furthermore, technology is a constant elasticity of substitution aggregator.

1. Case a: Introducing Skill-Based Division of Labour[6]

Suppose, there are three types of labour *L, M, H* (low-skill, middle-skill and high-skill respectively) who inelastically supply units of labour such that at a given time, $I \subset [0,1]$ represents the potentially feasible tasks that can be performed. *A* is the factor augmenting technology and α is the comparative advantage of skill across tasks. In this model, $\alpha_L(i)$ is productivity of low-skill worker in task *i* and $l(i)$ is the number of low-skill workers allotted. Analogously productivity of middle and high skill level workers as well as capital *K* are defined. Then, production function can be written as

$$Y(i)= A_L\alpha_L(i)l(i) + A_M\alpha(i)m(i) + A_H\alpha_H(i)h(i)+ A_K\alpha_K(i)K(i) \quad [4]$$

[5] It is important to note that comparative advantage looks at the least-cost factor at equilibrium. This is in turn determined by the economic cost as well as the opportunity cost of the factor under consideration.
[6] The formal model was given by Açemoglu and Autor (2011). We use the version used in Autor (2013).

Set $\alpha_K = 0$, so that all work is supplied by labour. Then, at equilibrium, the least complex set of tasks, $0 \leq i \leq I_L$ is supplied by low-skill workers, intermediate set of tasks $I_L \leq i \leq I_H$ is supplied by middle-skill workers and higher set of tasks $I_H \leq i \leq I$ is supplied by high-skilled workers.

2. Case b: Introducing Capital Substitution of Labour

Suppose, there is a range of tasks $[I', I''] \subset [I_L, I_H]$ for which $\alpha_K(i)$ increases so that they are performed by *K* rather than *L*. Then, for all $i \not\subset [I', I'']$, $\alpha_K(i) = 0$.

In this case, the aggregate labour consists of human and automated components (Mitra and Das, 2018). Let L_H be the human component of labour and L_R be the automated component of labour. If automated component is considered as perfect substitute for human component, then aggregate labour is the weighted average of human and automated components, given by

$$L = L_H + L_R \qquad [5]$$

Further,

$$L_R = nr \qquad [6]$$

where, *n* is the number of human labour units equivalent to one automated labour unit and *r* is the number of machines employed.

3. Case c: Output and Wages

Suppose, for each unit of labour provided by low-skill worker *L*, the wage be w_L. Then, the wages of middle-skill and high-skill workers will analogously be w_M and w_H such that $w_L < w_M < w_H$. Then, there exists $\alpha_K(i) > \alpha_L(i)$ such that *K* replaces the task done by *L* whilst output, *Y* increases.

To sum up, in a task-approach to production function, capital can substitute or complement labour depending on the comparative advantage of each factor. A specific set of tasks is initially taken by labour which formalises and routinises the task. At the point where the task is completely formalised, comparative advantage of capital rises with respect to labour which eventually substitutes it. Simultaneously, there exists a set of tasks performed by capital in complementarity with labour. Finally, it is possible to increase the output by increasing the comparative advantage of capital such that wage level declines. Empirical evidence suggests that substitution and complementarity of capital over labour results in job and wage polarisation, which we turn to, in the next section.

III. EMPIRICAL EVIDENCE OF JOB POLARISATION

The substitution and complementarity effects between capital and labour has accelerated due to the increasing application of robotics and artificial intelligence (Ford, 2015). One of the peculiar impacts of this phenomenon on labour is job polarisation that affects the demand for specific skill-sets from workers. The concept of skill component of occupations[7] divides jobs into routine and non-routine types and further into cognitive and manual kinds. The impact of automation through complementarity and substitution effects is different for these occupational types as shown in Figure 1. Automation has substitutive effect on routine-type of occupations that require repetition because these are the type of jobs that can be easily formalised. Examples of such jobs are sales and clerical work in service sector and assembly-line and operation in manufacturing. On the other hand, automation has complementary effect on non-routine cognitive work because these are the occupations that require labour to work with machines. Managerial and creative leadership

[7] The manual of classifying occupations based on skill components widely used in empirical analysis is given by Occupational Information Network (O*Net), which was preceded by the Dictionary of Occupational Titles (DOT).

occupations come in this category. Finally, the impact of automation on non-routine manual occupations such as personalised services is limited[8].

Figure 1: Impact of Automation on Occupational Typology

Repetitiveness/Complexity	Manual	Cognitive
Routine	Assembly-line	Clerical, Sales
	Middle Skill Substitutive Effect	Middle-Skill Substitutive Effect
Non-Routine	Personal services, Security	Managerial, Creative
	Low-Skill Limited Effect	High-Skill Complementary Effect

Source: Authors' Compilation

Job polarisation refers to the hollowing out of middle-skill jobs leaving relatively higher aggregate demand for high and low-skill jobs in an economy. It is typically represented by the inverted U-shaped curve when employment evolution by skill-type is examined[9]. For example, technology-

[8] The assumption here is the abundant presence of labour supply. In a scenario where labour is in short supply, these occupations will be substituted by automation.

[9] The effect of job polarisation can be reflected in pluralistic structural patterns as reflected in the analysis of European economies with monotonic upward rising curve, U-shaped curve or mid-level U-shaped curve depending on the extent of automation. For more, refer Fernandez-Macias (2012).

biased employment polarisation was empirically observed in many economies such as the US (Autor and Dorn, 2009; Jaimovich and Siu, 2014), UK (Goos and Manning, 2007), Sweden (Adermon and Gustavsson, 2011), Columbia and Brazil (Medina and Suárez, 2010).

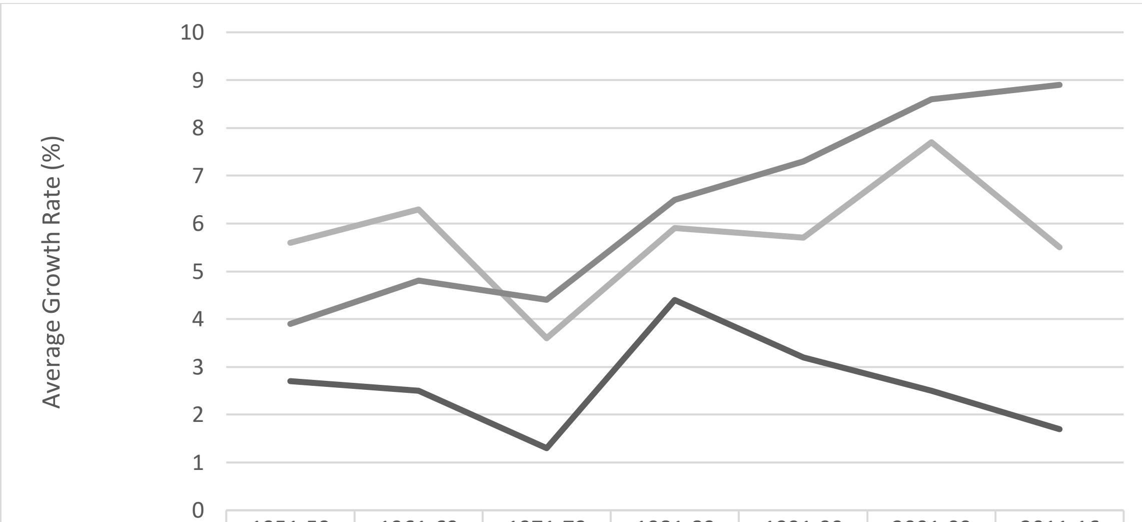
Recently, empirical studies have paid attention to other context-specific factors such as consumer preference and wage-setting institutions channelling the impact of automation on occupations. For example, in a comparative study of structural changes in the employment of 16 European economies since the 1990s, it was shown that the employment shares of high-paid professionals and low-paid service workers increased at the expense of middle-level manufacturing and routine-workers (Goos, Manning and Salomons, 2009). Furthermore, the study demonstrated that the employment impact of technology on routine jobs was higher than that of off-shoring jobs to other countries with higher labour supply. In a study of occupational change in Britain, Spain, Germany and Switzerland during 1990-2010, the authors found that wage-setting institutions were instrumental in channelling technology to replace middle-skill jobs (Oesch and Rodriguez-Menes, 2011). In the US, job polarisation was observed in conjunction with both technological impact and widening consumer preferences (Autor and Dorn, 2013). These studies reflect the impact of supply-side factors as well as institutional settings on job polarisation.

IV. JOB POLARISATION IN INDIA: GENERAL TRENDS

In this context, structural changes in Indian employment needs to be examined with care. Figure 2 shows the sectoral growth of agriculture, industry and service sectors in India from the 1950s to 2016. From the data, it is clear that whilst the share of agriculture in GDP has declined marginally in seven decades, the contribution of service sector has seen a nearly three-fold increase.

Interestingly, industry grew to an all-time high of 7.7 per cent in the 2000s before declining to an average of growth around five per cent.

Figure 2: Average Sectoral Growth in India 1950-2016



	1951-59	1961-69	1971-79	1981-89	1991-99	2001-09	2011-16
Agriculture	2.7	2.5	1.3	4.4	3.2	2.5	1.7
Industry	5.6	6.3	3.6	5.9	5.7	7.7	5.5
Services	3.9	4.8	4.4	6.5	7.3	8.6	8.9

Source: Sarkar (2017)

Note: All calculations are estimated based on Central Statistical Organisation Data (various years). Average sectoral growth is expressed in real GDP per annum (%).

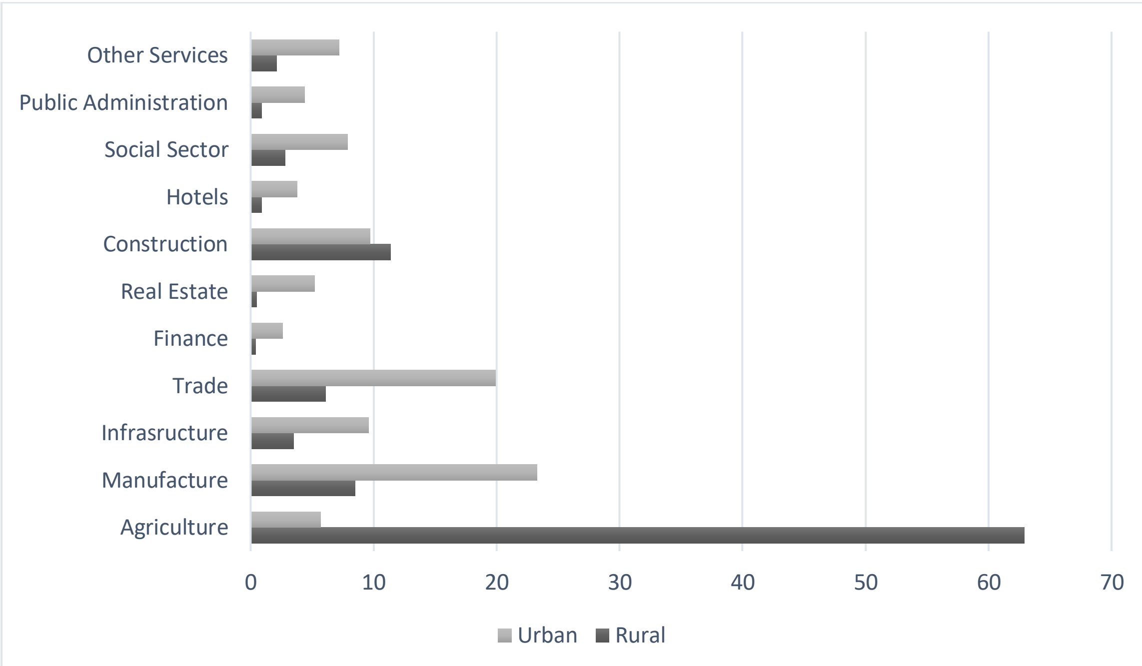
More recently, changing patterns of employment in India for the period 1980-2012[10], have been examined by two types of research- (i) those focussing on skill-biased technological change and, (ii) wage inequality studies. Industry-specific studies have demonstrated that rising demand for high-skill jobs in India was observed since the beginning of 1990s because of skill-biased

[10] This is the period relevant to the study when structural reforms in India introduced greater mechanization, computerization and automation in its economy.

technological change and increased output (Unni and Rani, 2004; Berman, Somanathan and Jan, 2005).

An increasing demand for high-skill workers has also been discussed by studies examining wage inequality in India. For example, Kijima (2006) shows that wage inequality in urban India began to rise since the late 1980s due to a skill premium associated with technological change. The urban-rural divide of India's employment typology is given in Figure 3. It is clear from the comparison that agriculture remains the source of nearly 70 per cent of all employment in rural India whilst contributing less than 2 per cent to the overall GDP. Furthermore, between 60-80 per cent of all rural labour is in the occupational category of labourers and cultivators. Urban India, on the other hand, has expanded its employment portfolio mainly through manufacturing and services (leading with real estate and construction).

Figure 3: Distribution of Labour in Rural and Urban India 2012

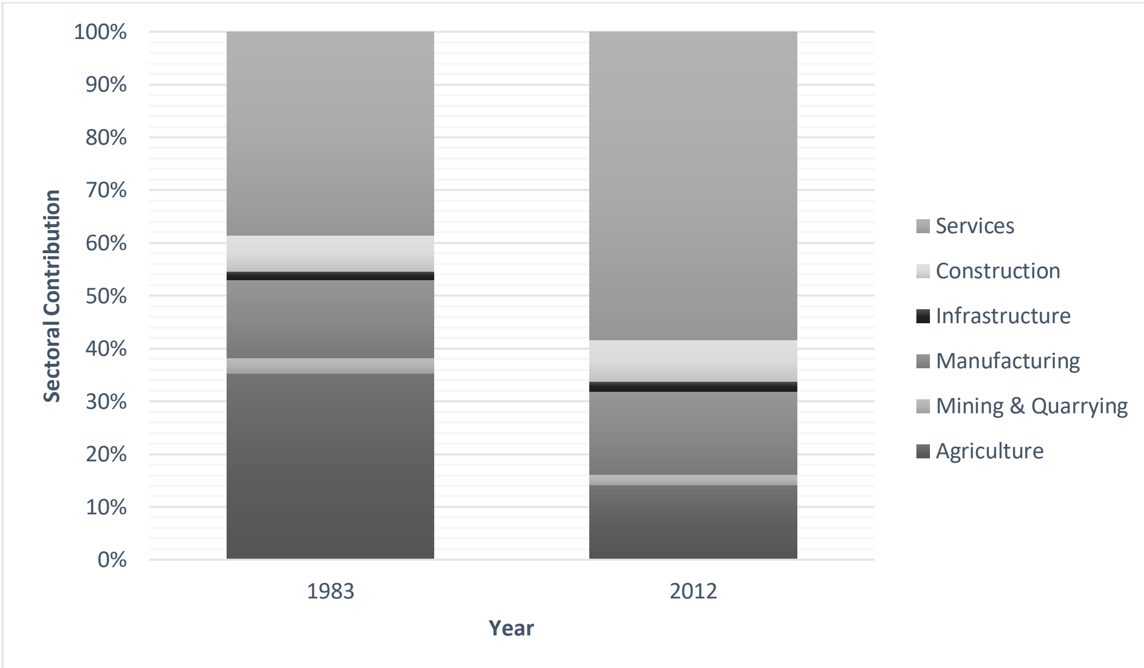


Source: Authors compilation modified from Sarkar (2017)

Note: The calculations are based on NSSO Employment and Unemployment Survey 2011-12. Agriculture includes agriculture, hunting, forestry, fishery, mining and quarrying. Infrastructure includes electricity, gas, water supply, transport and storage. Trade includes wholesale and retail trade. Social sector refers to education and health data. Hotels includes data for hotels and restaurants.

The sectoral contribution to growth should be read along with sectoral contribution to employment generation as shown in Figures 4 and 5 during the period 1983-2012. It is evident from the data that Indian economy has undergone substantial change in sector-wise contribution to GDP and employment. Most notably, the share of agriculture to employment has come down from 68 to 48 per cent whilst that of manufacturing and services increased substantially. In particular, the biggest employment generator has been construction that showed a 476 per cent increase during the three-decade period.

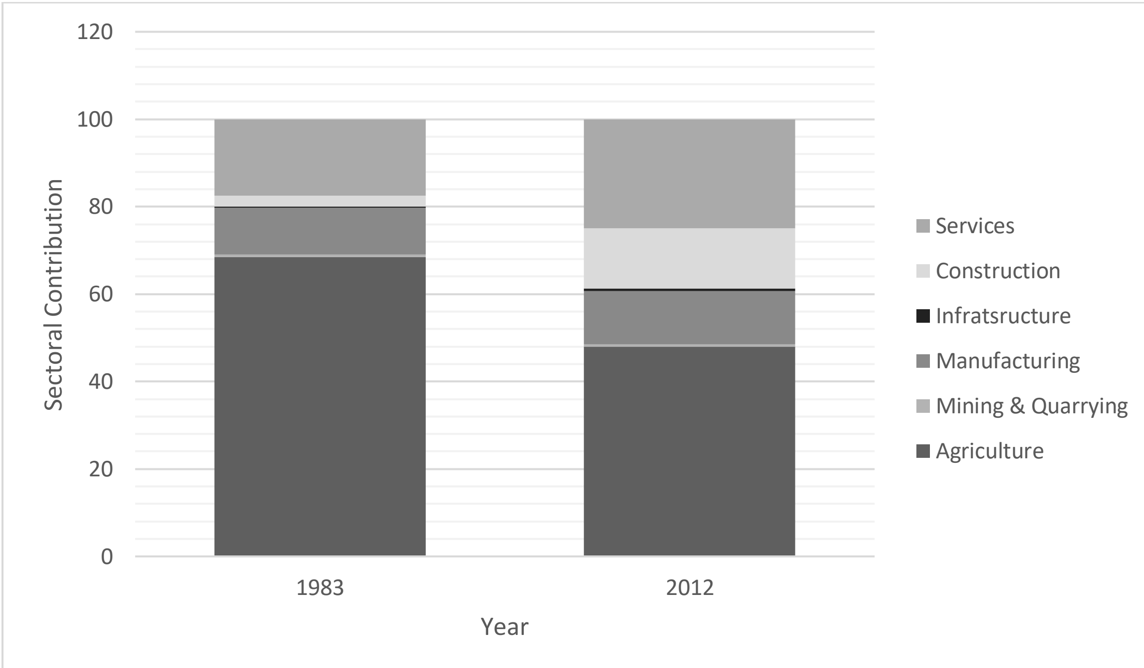
Figure 4: Sectoral Change in Contribution to GDP 1983-2012



Source: Vashisht and Dubey (2018)

Note: Infrastructure refers to electricity, water and gas supply related occupations. All calculations are based on NSSO and NAS data.

Figure 5: Sectoral Change in Contribution to Employment 1983-2012



Source: Vashisht and Dubey (2018)

Note: Infrastructure refers to electricity, water and gas supply related occupations. All calculations are based on NSSO data.

There has also been an increased interest in how relative demand has shaped up for workers based on their skills (high, medium and low) as well as type of occupation they are engaged in (routine/non-routine, manual/cognitive). In a study examining structural change in manufacturing sector of India, Nagaraj (2004) observed that there was a 15 per cent loss of routine-employment which was accompanied by a demand for non-routine low-skilled manual work in services to manufacturing such as transport, security, cleaning and catering. This phenomenon of substitution of middle-skilled work and rise in demand for low-skilled services was within the same sector that the loss of employment was not reflected at the aggregate level. The World Development Report (2016) has recently indicated a 7.8 percentage point decline in routine jobs in India during the period 1995-2012. The findings of both these studies concur with theoretical understanding of job polarisation.

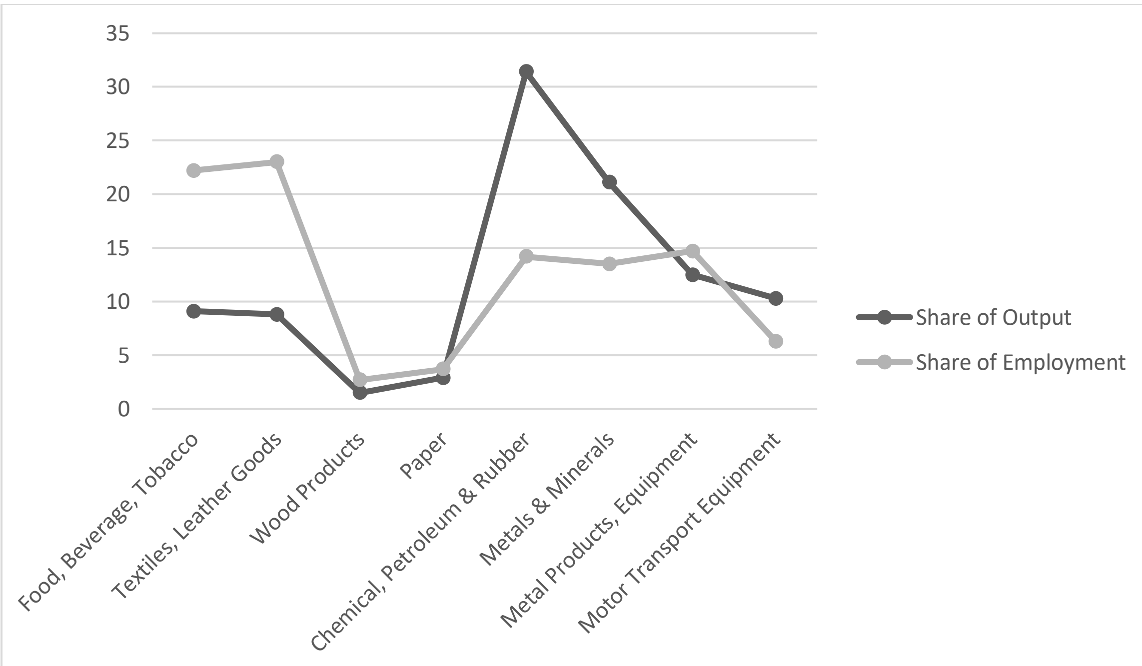
This result is also corroborated by Chamarbagwala (2006), who brings out correlation between increasing relative demand of skilled workers and the growing wage gap. More recently, Azam (2012) uses decomposition approach to wage inequality and demonstrates that in the period 1983-1994, increase in wages was observed for the higher quintiles of workers whereas in the period 1993-2004, the increase in the wages was for bottom and top end workers.

In this context, two recent studies bring out aspects of job polarisation that are anomalous with skill-biased technological change. They point to informality-driven demand for low-skill labour and persistence of routine occupations.

1. **Informality-Driven Demand for Labour**

Most recently, two studies that use disaggregated data on employment available from National Survey Sample Office (NSSO) raise some questions about the origin and nature of polarisation observed in India (Sarkar, 2017; Vashisht and Dubey, 2018). Sarkar (2017) has analysed 270 occupations from the NSSO employment data during the period 1983-2011. First, he observes that industries that provide output and employment are mutually exclusive and this has had a bearing on the relative demand of routine and non-routine occupations. The employment share of routine manual and cognitive occupations fell from 25 per cent in 1983 to well below 20 per cent in 2011 whilst that of non-routine occupations increased. The decline in routine manual occupations has been a result of mechanisation whilst that of clerical occupations have been a result of computerisation. However, the increased relative demand for high and low-skill jobs was attributed to growing self-employment in the informal sector rather than technological upgradation. This divergence between growth of output and employment in manufacturing has been discussed earlier in Thomas (2013).

Figure 6: Divergence in Output and Employment Generation in Manufacturing



Source: Thomas (2013)

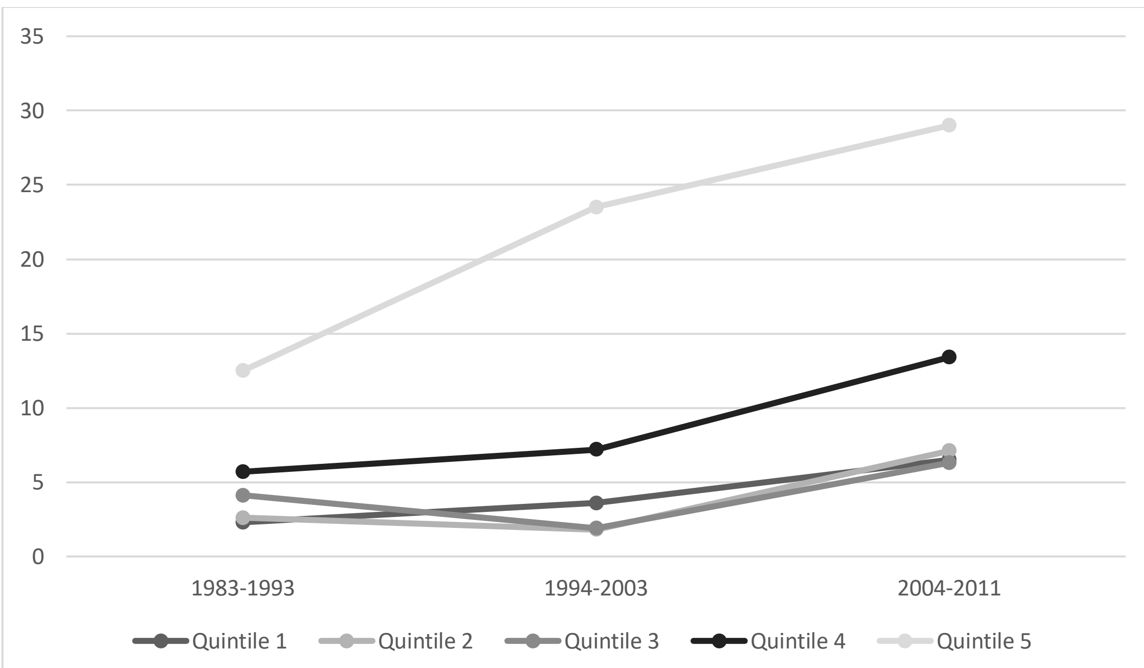
All data is for the period 2003-2006 tabulated from Annual Survey of Industries, various years

The divergence between industries that contributed to output or value-added and those that contributed to employment in manufacturing sector is shown in Figure 6. For the period 2003-2006, chemicals, rubber, plastic and petroleum products were the leading industry group in terms of factory sector output and investment. However, textiles, garments, leather goods, food products and tobacco products were the major employers. It is also important to note that the largest employment generators also had a high share of unorganized workers who were casual or contractual labourers.

2. Persistence of Routine Occupations

Second, whilst analysing the trend of real daily wage for each decile of workers, Sarkar (2017) found that the value for the highest (10th decile) and the lowest (90th decile) showed a sharp monotone increase whilst that of the median (50th decile) showed a decline, especially after 1999. This is consistent with the wage polarisation associated with the hollowing out of middle-skill occupations as a result of job polarisation. The study further compared the changes in wages across occupational tasks and skill-quintiles as shown in Figures 7 and 8.

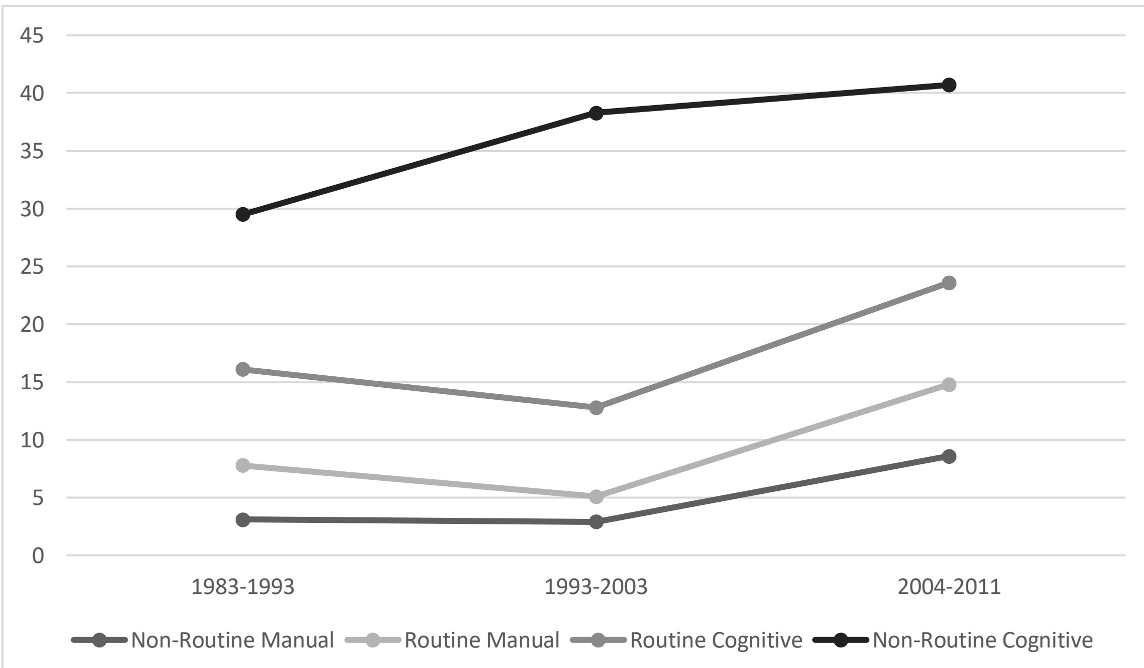
Figure 7: Changes in Real Daily Wages across Occupational Quintiles



Source: Sarkar (2017)

Growth of average earnings for occupational quintiles during the same period sheds light on wage disparities as shown in Figure 7. There are three observations of interest here. First, the average earnings of all occupational quintiles increased during the three-decade period. Second, the average earnings of the highest quintile (high-skill workers) was higher than the other groups, indicating substantial wage-differential that high-skill workers have managed to secure with respect to others. However, the third observation is that the growth of average earning of the lowest quintile (Quintiles 1 and 2) was relatively higher than that of the middle quintiles (Quintiles 3 and 4) indicating that the earnings of the low-skill workers grew at the expense of middle-skill workers.

Figure 8: Changes in Real Daily Wages across Task Groups



Source: Sarkar (2017) based on NSSO data on employment and unemployment

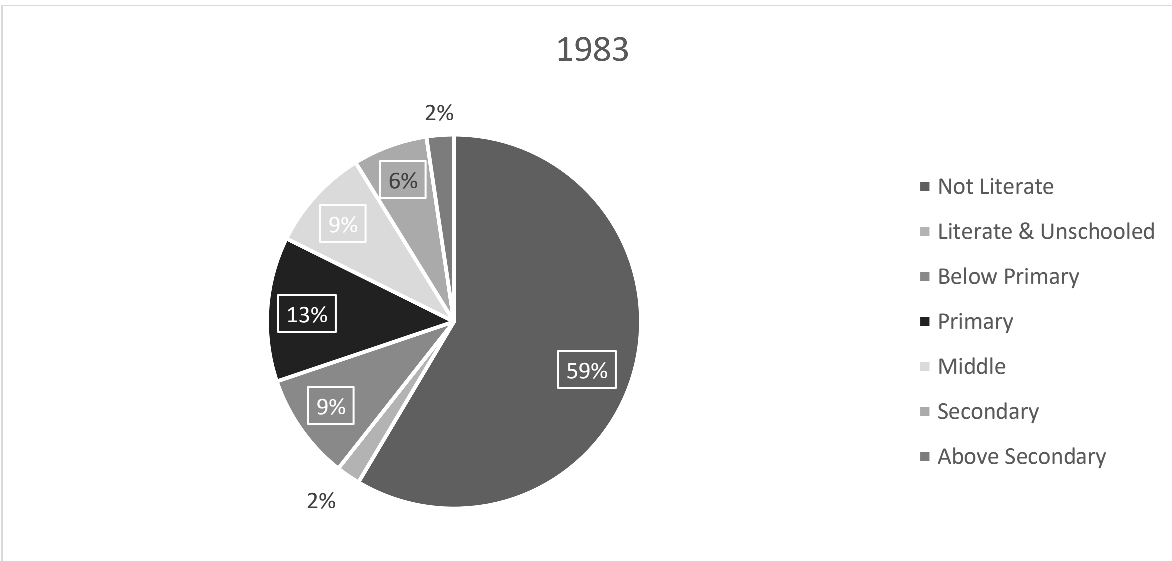
Figure 8 maps the changes in average earnings across the task-based occupational groups through the categories of routine manual, routine cognitive, non-routine manual and non-routine cognitive occupations. There are three observations of interest here. First, all occupations (routine manual, routine cognitive, non-routine manual and non-routine cognitive) received higher average earnings throughout the three-decade period. Second, the earnings growth has been highest for non-routine cognitive occupations over all the three period. In fact, the average earning doubled for this category whilst moving from the 1980s to the 1990s and has retained this wage differential to a lesser degree in the 2000s. What is of interest here is the persistent growth in average earning that the routine occupations (both manual and cognitive) have amassed, which is contradictory to theoretical expectation of the hollowing out of the middle that job polarization due to technological change presupposes.

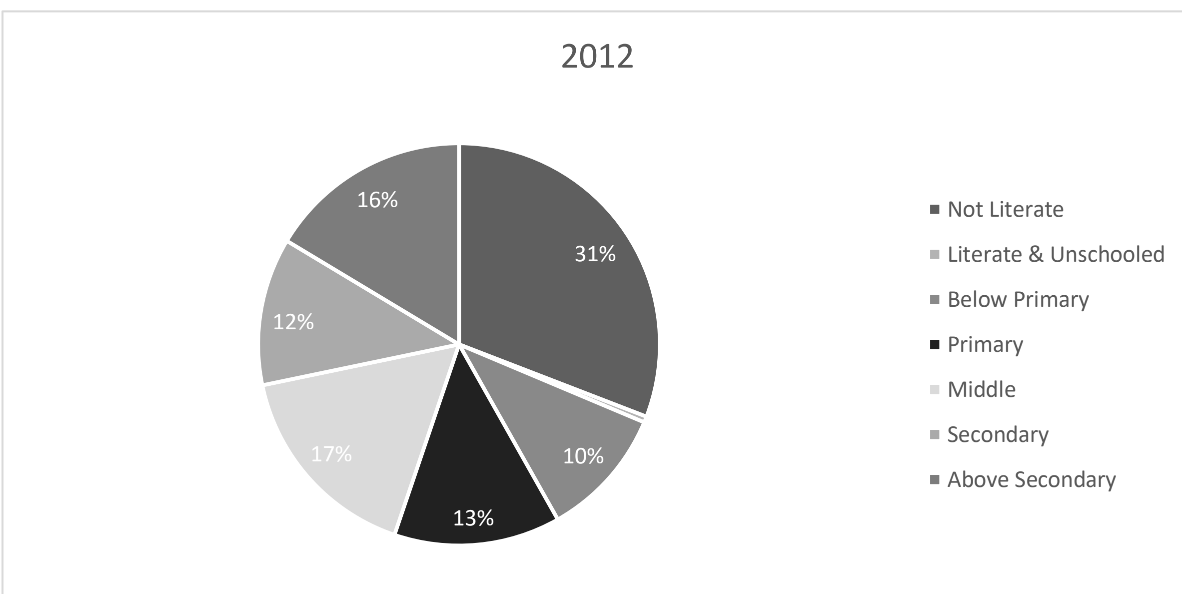
3. Supply-Side Factors

The study by Vashisht and Dubey (2018) concur with the findings of Sarkar (2017). They argue that the relative demand for non-routine cognitive tasks has increased four times since 1998 than in the period before. They also note that the demand for routine cognitive tasks have remained rather constant throughout the period. They explain that the de-routinisation of routine cognitive tasks in manufacturing is off-set by the increased demand for such tasks in services related to agriculture and manufacturing. Furthermore, they also conjecture that whilst the increased demand for non-routine cognitive tasks have been because of demand-side factors such as technological upgradation such as automation and artificial intelligence, the increased demand for non-routine cognitive and manual tasks have been due to supply-side factors such as presence of educated workforce. 57 per cent of this change in demand can be explained by the supply of tertiary educated workforce whilst secondary educated workforce explains 20 per cent of the change in demand (Vashisht and Dubey, 2018).

There was a significant quantitative and qualitative improvement in the labour force in the Indian economy based on the data from 1980-2012. For example, 286 million active workers in the Indian labour market of 1980 nearly doubled to 420 million in 2011-12 (Vashisht and Dubey, 2018). Furthermore, the level of education of workers also improved significantly as shown in Figure 9. In the period 1980-2012, the share of illiterate workers almost halved from 60 per cent to 31 per cent whilst the share of workers with primary and secondary education has increased roughly by 8 and 5 percentage points respectively. Furthermore, the supply of workers with tertiary education showed an eight-fold jump (Vashisht and Dubey, 2018).

Figure 9: Educational Profile of Indian Labour 1983-2012





Source: Vashisht and Dubey (2018)

To sum up, the empirical investigations into the occupation and task-based analyses of job polarisation in the India during the period 1983-2012 shows us that India has indeed witnessed job polarisation through the growth of high and low skill occupations at the expense of middle-skill occupations. It has also witnessed consequent wage polarisation through the growth of real daily wages of high and low skill occupations and a decline in that of middle-skill occupations. However, the disaggregated data also poses two searching questions. First, why does the routine occupation show persistence despite the evidence of polarisation? Second, how much of the relative change in demand of routine and non-routine occupations can be explained by supply-side factors such as educated workforce? Both these questions clarify where and by what degree the fourth industrial revolution with its attendant automation and artificial intelligence might impact the Indian employment context. We turn to these questions in the next section.

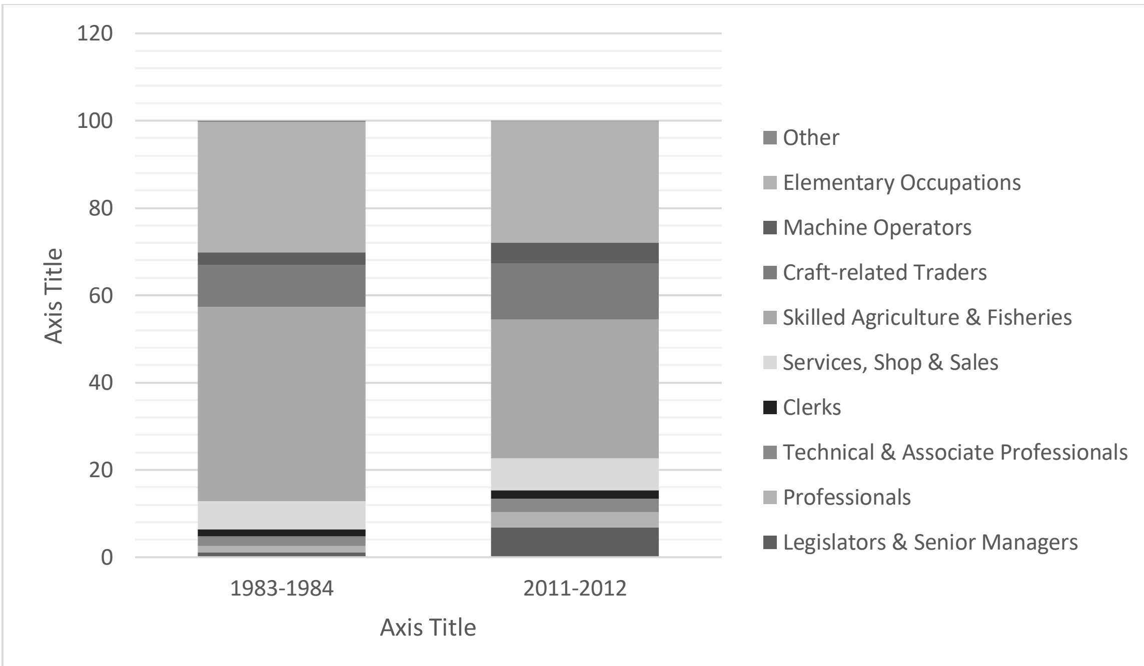
V. EXAMINING NON-TECHNOLOGICAL FACTORS

The key to answering the reason for persistence of routine occupations lie in non-technology related aspect of the Indian economy. The first among them is the supply-side factors, especially that of educated work force. Second is source of employment generation in low-skill manufacturing and service sectors through informality. Both these aspects are examined further in this section.

1. Presence of Educated Work Force

Data from India does not show the relative demand of non-routine cognitive and manual occupations at the expense of routine occupations which leads to the hollowing out of middle-skill occupations as seen in the US, UK and European economies. Rather, there is a higher demand for non-routine cognitive occupations and a constant rate of demand for routine cognitive and manual occupations belying the influence of supply-side factors. In order to understand the relationship of education returns and type of employment, we need to examine the change in occupational structure of employment given in Figure 10.

Figure 10: Change in Occupational Structure of Employment



Source: Vashisht and Dubey (2018)

The structural change in the economy has been accompanied by the demand for different skill-sets in labour as shown in Figure 10. For example, since the biggest increase in employment generation was witnessed in manufacturing and service sectors, an overall employment shift in favour of high-skill workers has taken place as shown by the rising composition of high managerial, professional, technical and associate technical workers from registering a three-fold increase in their demand. The second interesting feature from the data is that the growth of high-skilled workers has taken place at the expense of skilled agricultural and fishery workers whose share declined from 44 per cent to 32 per cent. Furthermore, the share of elementary occupations which employ low-skill workers declined to a level below that of 1983. Another noteworthy trend is that unlike the evidence in developed economies, the share of routine occupations represented by clerks, sales persons, craft traders and plant operators have marginally increased during the same period. The co-existence of these three trends, growth in demand for high-skill workers, declining demand for low-skill workers and persistence of middle-skill workers require further examination.

The returns to education, referred to as 'college premium' depends on the growth of high-skill manufacturing and servicing occupations. Figure 10 shows the shift in educational profile of Indian workers. The relationship between education and wages have explained the sectoral shift of employment in India (Kocchar *et.al*., 2006; Mehta and Mukhopadhyay, 2007; Mehta *et.al*., 2007). First, the share of aggregate employment in agriculture declined by 8.5 percentage points. Consequently, the erstwhile agricultural workers were engaged in construction, low-skill services, unemployment, low-skill manufacturing and high-skill services in the decreasing order of absorption. The main explanation for this shift is the growth of high-skill service exports which has increased demand for inputs to construction, complementary consumer goods and to a lesser degree, capital goods (Mehta and Mukhopadhyay, 2007). As a result, the new jobs in manufacturing have heavily concentrated on textiles (43.9 per cent of manufacturing jobs) and inputs to construction (25.9 per cent). It is important to note that 70 per cent of new manufacturing employment went to workers without lower secondary education (Kocchar *et. al*., 2006). In fact, less than 20 per cent of textile workers and 13 per cent of construction workers finished lower secondary school in India (Mehta and Mukhopadhyay, 2007). Additionally, a bulk of lower secondary school graduates were absorbed in sectors such as low-skill services and agriculture that did not historically hire this cohort, pulling up educational level of such workers for the first time.

On the other hand, workers with higher secondary education and college degrees who traditionally found employment in high-end services found sluggish growth in this sector (Mehta *et.al*., 2007). This in turn pushed out the less-educated workers into low-skill service jobs that historically did not employ them. Therefore, service occupations grew faster and also became menial on an average. This also explains the persistence of routine jobs in low-skill services during the period.

These dual forces- pull of agricultural workers into low-skill manufacturing and push of educated workers into low-skill service occupations- explain a part of job polarisation through supply side factors such as education. In India, middle-skill workers were squeezed out because of mechanisation in manufacturing and computerisation of clerical tasks only up to a point. The rest of the polarisation is explained by the supply of educated workforce in an environment of low-skill manufacturing and service employment generation.

2. Divergence between Output and Employment Generation

The growth of manufacturing sector in India in the last two decades through the structural change in employment is closely related to informality. Informality, as a concept used in Indian labour, can be understood either in terms of the place of work (informal sector) or nature of employment (informal occupation in formal/informal sector) (Papola, 2013). As of 2011-2012, the informal employment in India, including the formal and informal sector, is at 92 per cent (Verick, 2018). In the period 2004-2012, the share of informal employment in the unorganised sector fell from 86.3 per cent to 82.7 per cent whilst that of the organised sector rose from 15.3 per cent to 17.3 per cent, most of whom were hired on casual and contractual basis without social security and collective bargaining power (Verick, 2018).

It is in this scenario that the divergence in output and employment growth in the manufacturing industry has been observed (Thomas, 2013). Since the 2000s, the growth in value-added (output) is in the organised manufacturing sector that is capital intensive whilst the growth in employment is observed in the unorganised sector that is labour-intensive. Consequently, this growth in employment has focused on firms with more than 500 employees or those with less than 10 employees, leading to a bi-modal distribution of firms, where large and small-sized firms grow at the expense of middle-sized firms (Mazumdar and Sarkar, 2009). Many aspects of industrial policy especially availability of formal credit and implementation of labour laws permits this divergence to persist (Thomas, 2013).

The development of these dual forces - divergence of output and employment generation in manufacturing and bi-modal distribution of firms - has implications for the way jobs get polarised. First, there is a small per cent of fast-growing specialised high-skill export-oriented products and services industry which demands a small pool of high-skill workers especially those with non-routine cognitive tasks (Vashisht, 2015). Second, there has been a declining trend of female labour participation due to rising household income, declining opportunities for employment in non-farm sector and rising gross enrolment in secondary and tertiary education (Verick, 2018).

VI. POLICY IMPLICATIONS

India has seen job polarisation and subsequent wage polarisation in its employment from the 1990s as a result of which the demand for high and low skill workers have risen in comparison to the middle skill workers. On examination, India's job polarisation is unlike that found in the developed countries where polarisation is mainly driven by skill-biased technological change and trade. In the Indian case, supply-side factors, especially growth of educated workforce, and divergence between output and employment generation have been the main source of polarisation. What are the implications of the type of job polarisation in the medium term?

First, significant impact can be expected in economic growth due to slow gross capital formation and reduced GDP per capita. According to ILO estimates (2016), nine million workers are to be added every year in the next five years in India. This further affects labour productivity as the share of working age population increases as given by

$$Y/N = Y/E \; E/P \; P/N \tag{7}$$

where Y/N- GDP per capita; Y/E- output per worker/labour productivity; E/P- employment population ratio and P/N-share of working-age population.

Second, continued job polarisation of the Indian kind will allow sectoral characteristics of employment generation and labour force participation to persist. The divergence between employment and output generation in the manufacturing sector and the bi-modal distribution of firms is related to lack of sufficient competitiveness of non-export-oriented industry. This is in turn influenced by formal credit availability and lack of rigour in implementing labour laws as Thomas (2013) has pointed out. It should also be noted that the growth of high-skill entrepreneurial ventures in informal sector is a sign of distress employment rather than an indicator of entrepreneurial activity supported by policies geared towards supporting skill-building and small and medium enterprises.

Third, the Mincerian returns to education, by which each additional year of schooling should proportionally increase the wage returns at employment, faces challenge in India due to over-supply of secondary and tertiary educated workforce. The absence of college premium has led to squeezing of middle-skill workers in low-skill service jobs bringing the daily wage rate down and making service occupations menial on an average. Additionally, women's gross enrolment ratio has climbed from 48.7 per cent to 69.2 per cent in secondary education and 8.8 per cent to 23.1 per cent in tertiary education during the period 2008-2012 (Verick, 2018). This is one of the reasons for declining female labour participation among women in non-farm activities in India during this period. Furthermore, the organised sector is absorbing informal employment at an increasing rate. Only a sufficiently stimulated manufacturing sector can absorb skilled workers by retaining the wage premium.

Fourth, the pattern of job polarisation in India also has a negative impact on possible technology diffusion from the fourth industrial revolution. The decision to purchase technology and invest in research and manufacturing depends on state-led policies, industrial network, competitiveness and firm size. The absence of middle-size firms in manufacturing and services is a variable of interest in determining technological uptake.

VII. CONCLUSION

This study set out to understand the origin and nature of India's job polarisation. Technology-biased skill change argues that automation leads to the growing demand of high and low skill workers at the expense of middle-skill workers due to substitution and complementarity effects. This phenomenon has been empirically observed in advanced economies.

Recent examination of India's disaggregated data on employment patterns in the period 1983-2012 also demonstrate job polarisation and subsequent wage polarisation. But, such studies also reveal certain unique characteristics that contradicts theoretical explanation. For example, in India, there is persistence of routine occupation that corresponds to middle-skill level tasks. In order to examine this anomaly, this study examined two non-technological aspects- the reason for growth of low-skill manufacturing and service occupations in informal employment and supply-side factor such as an educated labour force.

The study has two main conclusions. First, although India shows a job-polarisation scenario, only the high demand for high-skilled workers in the formal sector is due to technology automation. The high demand for low-skill workers in manufacturing in India has been strongly led by construction and textiles. Second, over supply of secondary and tertiary educated labour force during the same period has squeezed out middle-skilled workers from routine middle-skilled jobs to relatively low-skill manufacturing and service occupations, explaining the persistence of routine occupations.

There are four-fold policy implications to this type of polarisation. First, the type of job polarisation in India potentially slows down economic growth because of its impact on gross capital formation. Second, the divergence in output and employment generation creates a bi-modal distribution of firms in manufacturing where middle-sized firms are absent. Third, returns to education especially through 'college premium' is challenged in India because of over-supply of educated labour force and sluggish growth in skilled employment in manufacturing and services. Finally, the absence of middle-sized firms in manufacturing can negatively impact the diffusion of technology, hampering further productivity.

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