Changing Task Content of Jobs in India: Implications and Way Forward

Abstract

In this paper, we analyse the evolution of the task content of jobs in India between 1983 and 2011. Following standard literature, we calculated five task intensities by combining NSS data with O-Net data at the 3-digit level of occupational classification. We find that, in line with global trend, non-routine cognitive analytical as well as non-routine cognitive interactive task intensity of jobs has increased in India, while manual task intensities have declined. However, unlike in the US and Europe, the routine cognitive task content has not declined. Our analysis further shows that technology seems to be a major factor behind the evolution of non-routine cognitive analytical and interactive tasks in India whereas structural change and change in the supply of labour has shaped manual task contents.

Key Words: *Task content of jobs, routinisation, job polarisation*
JeL classification: J23, J24, I25

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Changing Task Content of Jobs in India: Implications and Way Forward

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1. Introduction

World has been going through a phase of digital revolution. Starting from early 1970s, digital technology has invaded all aspects of human life. From communication to finance to manufacturing to social interaction, the use of digital technology is visible everywhere. This enormous increase in the use of digital technology has also coincided with occupational upgrading and a sharp increase in wage disparity. Starting from mid-1980s, there has been an increase in wage disparities between skilled and unskilled workers in countries across the globe. A large number of theoretical as well as empirical studies conducted during the 1990s argued that rising wage disparity and the adoption of ICT technology were linked and that the adoption of ICT technology was the reason for rising wage disparities (Bound and Johnson, 1992; Levy and Murnane, 1992; Katz and Murphy, 1992). Propounding the hypothesis of Skill Biased Technological Progress (SBTP), these studies argued that digital technology has been skill biased and therefore, has increased the demand for highly skilled workers, leading to the increase in wage inequality. The SBTP hypothesis proved empirically very successful and dominated the debate on wage disparity until the late 1990s. However, it started receiving a lot of criticism towards the end of the 1990s for treating the relation between technology and skill demand as a black box. Moreover, it also failed to explain the growing polarisation of labour markets in many countries. The polarisation of the labour market suggests that the demand for both highly skilled and unskilled workers was increasing simultaneously which is clearly at odds with the SBTP hypothesis.

In response to the criticism, some scholars provided a more nuanced version of the SBTP hypothesis (Autor et al 2004). Instead of dividing labour into the skilled and unskilled categories, these models tried to understand the skill requirement of different jobs through a task based framework. These models categorise the tasks performed by labour into two broad groups – routine and non-routine – which are imperfect substitutes for each other. The routine tasks are those that can be codified and therefore, can be easily performed by machines. In contrast, non-routine tasks require human interaction and hence, cannot be mechanised easily. Non-routine tasks are further divided into two sub groups – non-routine cognitive and non-routine manual

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tasks. These models indicate that recent improvements in ICT and the consequent decline in the price of ICT capital have reduced the demand for labour to carry out routine tasks. In contrast, it has increased labour demand for non-routine cognitive tasks. Since non-routine task intensive occupations are concentrated at the top and bottom of the wage pyramid, it has led to a polarisation of labour market. In short, these models suggest that the recent surge in the use of digital technology has changed the skill demand by de-routinising jobs.

Since 2003, a number of studies have reported the de-routinisation of jobs in many countries. However, these studies differ in their explanation of the trend. One set of studies have attributed the change in the task content of jobs to changes in technology. In their pioneering work, Autor et al (2004) reported that between 1960 and 1980, use of ICT in USA was negatively associated with routine manual and cognitive task content while it was positively associated with non-routine cognitive task contents. Michaels et al (2014) and De la Rica and Gortaazar (2016) reported similar results for selected OECD countries. However, a few other studies have attributed the de-routinisation of jobs to supply side factors. Examining the employment structure in the United Kingdom (UK), Salvatori (2015) reported polarisation of jobs in the UK between 1979 and 2012. However, unlike other studies, he concluded that the change in the employment structure in the UK was purely driven by a decline in supply of non-graduates rather than technology. Hardy et al (2015, 2016) reported similar results for central and East European countries. Yet another strand of literature has attributed the change in task content or job polarisation to structural change. Barany and Siegel (2015) argued that the process of job polarisation in US started in the early 1950s and it was closely linked to the shift in employment from manufacturing to services.

The Indian economy is not isolated from the ongoing wave of technological change. Moreover, the structure of the Indian economy has also changed substantially since it opened up to international trade and technology in the early 1980s. The share of agriculture in total GDP has declined from more than 35 per cent in 1983-84 to less than 15 per cent in 2011-12, while that of services has gone up by from 38.6 per cent to 58.3 per cent during same period. These changes in the Indian economy have also coincided with a growing concern regarding skill shortage (Vashisht 2017). In response, the Government of India has started an ambitious Skill India programme. However, little is known about the evolution of skill demand and its determinants in India. Against this backdrop, following a task based framework, this paper attempts to quantify the evolution of skill demand in India. In particular, this paper examines the evolution of task content of jobs in India since 1983 and tries to identify the demand and supply side factors that have shaped the task content of jobs. The paper shows that the demand for cognitive skills has indeed increased in India and technology has played a big role in this. However, unlike in developed countries, India has not observed a complete de-routinisation of jobs as routine cognitive task intensity has not decline. The paper argues that government initiatives for skill development are steps in the right direction. However, to overcome the challenges that arise from the changing nature of jobs, the government should work on the Indian education system to improve the quality of education at all levels.

The rest of this paper is organised in four sections. Section 2 provides an overview of labour demand and supply in India. Section 3 deals with data sources and methodology for the estimation of task contents, while finding are reported in section 4. Section 5 concludes the paper with a recapitulation of the main findings and their policy implications.

2. Evolution of demand and supply Labour in India

After following inward looking economic policies for nearly three decades, India opened up to international trade and technology in the early 1980s. Since then, there has been a substantial acceleration in the growth rate of the Indian economy. The major contributors to the acceleration in the growth rate have been the manufacturing and services sectors. Consequently, the employment structure of the Indian economy has changed substantially. In 1983, the share of agriculture in total employment was more than 68 per cent; this fell to below 48 per cent in 2011-12. During same period, the share of the services sector in total employment went from less than 18 per cent to around 25 per cent, while the share of manufacturing in total employment increased from 10.63 per cent to 12.19 per cent. Notably, the share of the construction sector has registered the biggest increase in total employment. In 1983, only 2.39 per cent of the total Indian workforce was employed in the construction sector. However, this figure increased to 13.79 per cent in 2011-12.

Table 1: Changing Structure of the Indian Economy

	Share in GDP		**Share in Employment**	
	1983	**2012**	**1983**	**2012**
Agriculture, Forestry & Fishing	35.29	14.10	68.44	47.93
Mining & Quarrying	2.95	2.06	0.64	0.59
Manufacturing	14.79	15.70	10.63	12.19
Electricity, Gas & Water Supply	1.59	1.88	0.38	0.59
Construction	6.77	7.87	2.39	13.79
Services	38.61	58.39	17.52	24.91
Total	100	100	100	100

Source: *Compiled from NSS and NAS data*

The change in the structure of economy has influenced the demand for skilled labour. Since services as well as manufacturing employ more skilled workers, the employment shift in favour of these sectors increased the overall demand for skilled workers in India. An analysis of employment by occupation suggests that the share of highly skilled occupations such as managers, professionals and technical associates in total employment has increased substantially.

In 1983, the combined share of highly skilled occupations (managers, professionals and associate professionals) in total employment was only 4.78 per cent; this increased to 13.41 per cent in 2011-12. Among highly skilled workers, the most staggering increase has been in the share of managers. The share of managers in total employment went up from just 1.13 per cent in 1983 to 6.76 per cent in 2011-12, registering a growth of roughly 500 per cent. The share of highly skilled workers in total employment has increased at the cost of skilled agricultural and fishery workers as their share in total employment has declined from more than 44 per cent to below 32 per cent. Notably, unlike developed countries, the share of routine task intensive occupations such as clerks, plant and machine operators and craft related workers has not declined in India. In fact, the share of these occupations in total employment has increased marginally (Table 2). There was a marginal increase in the employment share of elementary occupations between 1983-84 and 1993-94. However, the trend reversed thereafter and the share of elementary occupations in total employment declined to 27.78 per cent in 2011-12, which is lower than what it was in 1983-84.

Table 2: Occupational Structure of Employment

	1983-84	**1993-94**	**2009-10**	**2011-12**
Legislator, Senior Officers and Managers	1.13	1.95	5.17	6.76
Professionals	1.45	1.69	3.51	3.54
Technical and Associate Professionals	2.20	2.42	2.76	3.11
Clerks	1.66	1.72	1.77	1.88
Services, Shop and Market Sales Workers	6.37	7.28	6.65	7.36
Skilled Agriculture and Fishery Workers	44.54	40.05	34.33	31.77
Craft Related Trade Workers	9.50	10.27	11.23	12.96
Plant and Machine Operator	2.97	3.26	3.49	4.64
Elementary Occupations	29.82	30.92	30.60	27.78
Missing NCO Code	0.34	0.42	0.36	0.10

Source: *Author's compilation from NSS unit level data*

The supply of labour in India has increased substantially over the last three decades. In 1983-84, 286 million workers were active in the Indian labour market; this increased to 420 million in 2011-12. The quantitative increase in labour force also coincided with a significant qualitative improvement. In 1983-84, the Indian workforce was largely dominated by illiterate workers, while the share of workers with secondary and tertiary education was very low (Table 3). However, the educational profile of workers has changed substantially over last three decades. The share of illiterate workers in the total workforce has declined from more than 60 per cent in 1983-84 to 31 per cent in 2011-12. During same period, the share of workers with primary and secondary education has increased roughly by 8 and 5 percentage points respectively. The supply of labour with tertiary education has increased the most. The number of workers with tertiary education increased from 6.7 million in 1983 to 70.6 million in 2011-12. In line with this, the share of workers with tertiary education in the total workforce increased from 2.3 per cent to 16.3 per cent.

Table 3: Education profile of Indian Labour Force

	1983-84		2011-12	
	No. in Million	**% Share**	**No. in Million**	**% Share**
Not Literate	167.11	58.33	129.07	30.70
Literate Without Formal Schooling	5.98	2.09	2.01	0.48
Below Primary	26.50	9.25	43.84	10.43
Primary	36.02	12.57	56.05	13.33
Middle	25.48	8.90	69.16	16.45
Secondary	18.57	6.49	49.64	11.81
Above Secondary	6.79	2.37	70.66	16.31
Higher Secondary			27.75	6.60
Diploma/Certificate Course			5.95	1.41
Graduate			26.88	6.39
Postgraduate And Above			10.08	2.40
Total	286.487		420.42	

Source: *Author's Compilation from NSSO Data, Various Rounds*

3. Data Sources and Methodology

3.1 Data Sources

Data needed for the estimation of task content of jobs has been drawn from two different sources. Following the standard literature, we have used the Occupational Information Network (O-Net) database as a source of information on task intensities[i] of different occupations. Two editions of O-Net dataset, O-Net 2003 and O-Net 2014, are available. However, in this paper, we use only O-Net 2003. The information about various task intensities in O-Net data is tabulated according to the Standard Occupation Classification (SOC). In order to make it comparable with Indian data, we prepared a crosswalk between SOC and NCO 2004[ii] at 3-digit level of disaggregation.

Detailed information on employment in Indian economy has been taken from several rounds of the Employment and Unemployment Survey (EUS)[iii] conducted by the National Sample Survey Office (NSSO). During the period 1983-84 to 2009-10, six rounds of survey have been conducted, at an interval of five years. However, in order to check the impact of the global financial crisis on employment, another major survey, with broad coverage, was conducted in 2011-12. In this paper, we use data from all seven rounds. Apart from providing statistics on labour conditions and employment and unemployment, the EUS also identifies the industry affiliation and occupation of individual workers. However, the industrial as well as the occupational classification used in different rounds is not the same. The National Classification of Occupations (NCO) 1968 was used in the 38th (1983-84), 43rd (1987-88), 50th (1993-94), 55th (1999-2000) and 61st (2004-05) rounds of EUS, while NCO 2004 has been used in the remaining two rounds. In order to make the data comparable, we work out a crosswalk between NCO 1968 and NCO 2004 at the three-digit level, using the official concordance table. Similarly, we work out a concordance between different National Industrial Classifications (NIC) at the one-digit level to make the sectors comparable.

3.2 Methodology

After sorting out comparability issues, we pooled the data from all seven rounds and assigned the sixteen task items to each individual according to their occupation code (Figure 1). Having assigned the task items to NSS data, we followed the standard procedure to calculate the task content of jobs. Following Hardy et al (2015), first we standardised each task item to make the data comparable using the following formula.

$$\bigwedge i \bigwedge j \in J \; t^{std} = \frac{t_{ij} - \mu_j}{\delta_j}, \quad ..1$$

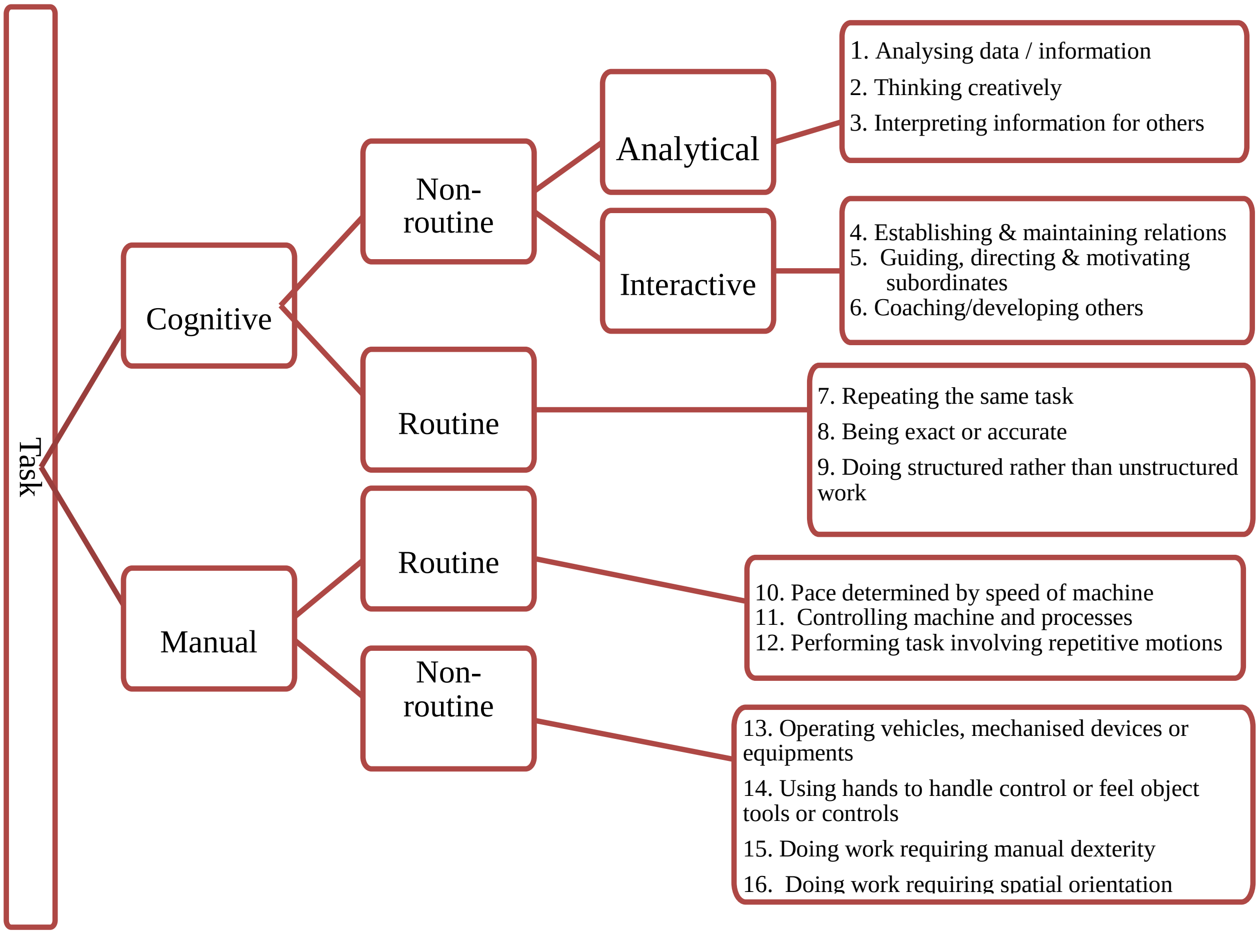
Where; j is the set of 16 task items, μ is weighted average of j^{th} task item and δ is the standard deviation of j^{th} task item, i is the i^{th} observation in EUS data and w is weight assigned to i^{th} observation in EUS data. The weighted average and standard deviation of the task item is calculated as follow.

$$\bigwedge j \in J \; \mu_j = \frac{\sum_{i=1}^{N} t_{ij} w_i}{\sum_{i=1}^{N} w_i} \quad ..2$$

$$\bigwedge j \in J \; \delta_j = \sqrt{\left(\frac{\sum_{i=1}^{N} w_i (t_{ij} - \mu_j}{\sum_{i=1}^{N} w_i}\right)^2} \quad ..3$$

After standardising the task items, we calculated the five main task content measures: non-routine cognitive analytical, non-routine cognitive interactive, routine cognitive, routine manual and non-routine manual, by adding up the appropriate task items as depicted in Figure 1 and subsequently standardising the five task contents. In order to make the results comparable, we also rescale the five task contents so that the initial value of all five task contents become 0.

Figure 1: Task Content Measures



Source: *prepared based on Acemoglu and Autor (2011)*

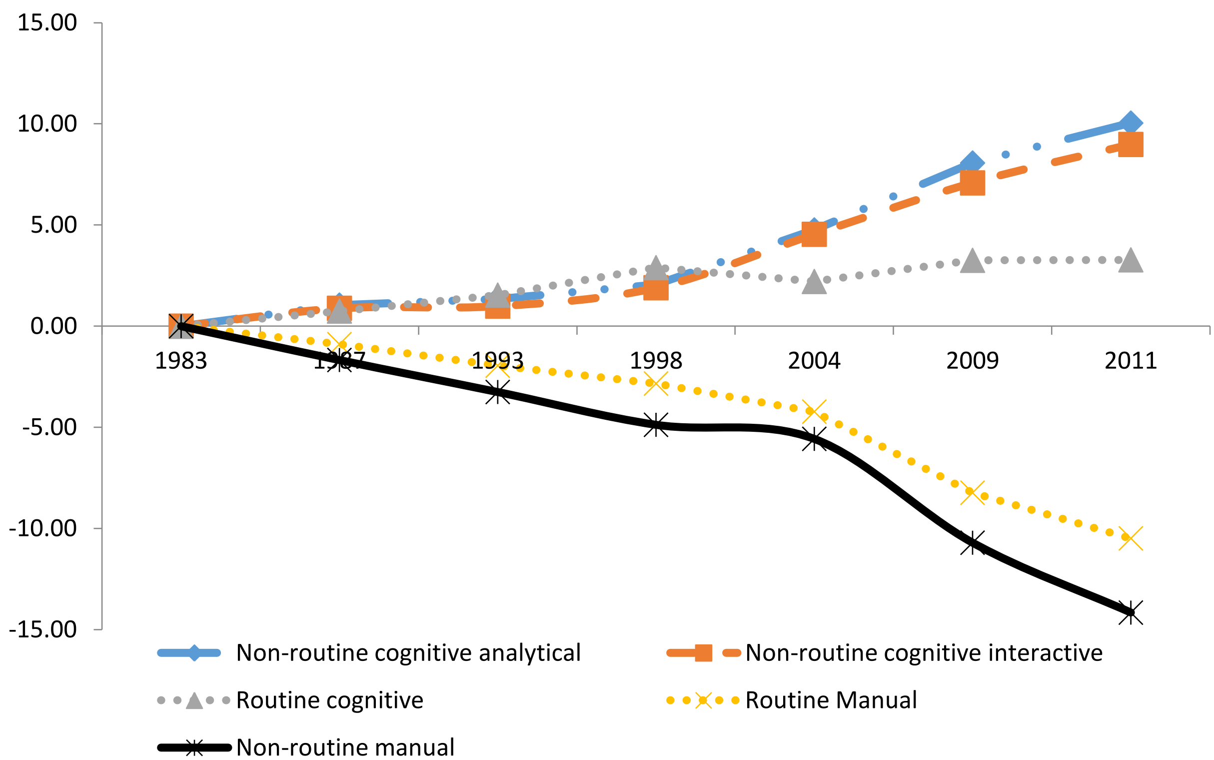
4. Task Content of Jobs in India

4.1 Overall Trend

The five task intensities, calculated using the methodology explained above, are shown in Figure 2. Our results show that the task content of jobs in India has changed significantly over the last three decades. In line with the global trend, non-routine cognitive task intensities of jobs in India have increased. Between 1983-84 and 2011-12, the non-routine congestive analytical and non-routine cognitive personal task content of jobs in India increased by 10 and 9 percentage points respectively. Notably, the most significant increase in non-routine cognitive task intensities has been observed after 1998. The non-routine cognitive analytical task intensity grew on an average, by 0.14 percentage points between 1983-84 and 1998-99. However, the average rate of growth increased to 0.57 percentage points after 1998-99. Similarly, the average rate of increase in non-routine cognitive interactive task intensity has been four time higher in the post 1998-99 period as compared to pre 1998-99 period.

Manual task contents, both routine and non-routine, declined during 1983-84 to 2011-12. The decline in non-routine manual task intensity has been significantly higher than routine manual task intensity. Our results further show that routine cognitive task intensity of Indian jobs has not declined. In fact, the routine cognitive task intensity of Indian jobs has increased by 3.2 percentage points between 1983-84 and 2011-12. However, most of the observed increase in routine cognitive task intensity took place before 1998-99. Since 1998-99, the routine cognitive task intensity has been rather constant. A sectoral analysis suggests that routine cognitive task has been constant because of the services and agriculture sectors. Both these sectors have witness increase in routine cognitive task intensity. In contrast, there has been a complete de-routinisation of jobs in the manufacturing sector after 1998 (Annexure 1). It perhaps shows that the Indian manufacturing sector has gone for rapid automation since 1998 when 100 percent foreign direct investment was allowed in most manufacturing industries.

Figure 2: Evolution of Task Content of Jobs in India



4.2 Intergenerational Dimensions of Task Content

The overall change in task content can be driven by the cohort effect, the unobserved heterogeneity. Since the younger generation has access to better and more relevant educational opportunity, it is possible that young entry cohorts can have a higher level of analytical activities. In fact, in the case of Poland, Hardy et al (2016) have shown that task content of jobs in Poland has been strongly driven by the cohort effect. To evaluate this possibility, we estimated the task intensity for different birth cohorts. The results are shown in Table 4. The first birth cohort consists of individual born before 1947, the second cohort consists of individual born between 1948 and 1957 and third cohort consists of individuals born between 1958 and 1967 and so on. A birth cohort can be followed by moving horizontally along the same row, while the same age group can be tracked by moving diagonally downward. Within cohorts, the change in particular task content can be attributed to age and time effects. The age effect depicts how the task content of a given cohort changes as the cohort ages while the time effect explains how the task content of a cohort changes due to macro economic shocks. In contrast, the change within an age group could be attributed to cohort or time effects. The cohort effect describes the difference between cohorts that may be because of differences in educational opportunities (Spitz-Oener 2006).

Our results in Table 4 show two interesting results. First, it is shows that older cohorts have experienced the same trend as younger cohorts. Notably, in line with Hardy et al (2016), we found that the relative change in the task intensities of the younger cohorts has been higher than the older cohorts. For example, the non-routine cognitive analytical task intensity of cohort born between before 1947 increased by 7.55 percentage points while for all age cohorts born after 1958, the increase in non-routine cognitive analytical task intensity during the studies period was higher than 13 percentage points. Similarly, the changes in manual task intensities have also been higher for younger cohorts. However, the difference is not as stark as report by Hardy et al (2016) for Poland. Second, it is evident from the table that change in task intensities in India has occurred both within age group as well as within birth cohorts. Notably, for all task intensities except the Non-routine manual task intensity, the changes in within cohorts has been more pronounced than the changes among age groups. For example, the non-routine cognitive analytical task intensity within a cohort increased by 0.51 percentage points annually while the average annual increase in among age groups was only 0.35 percentage points. These results suggest that the time effect rather than age and cohort effect has been the prime driver of change in task intensities observed during 1983-84 to 2011-12.

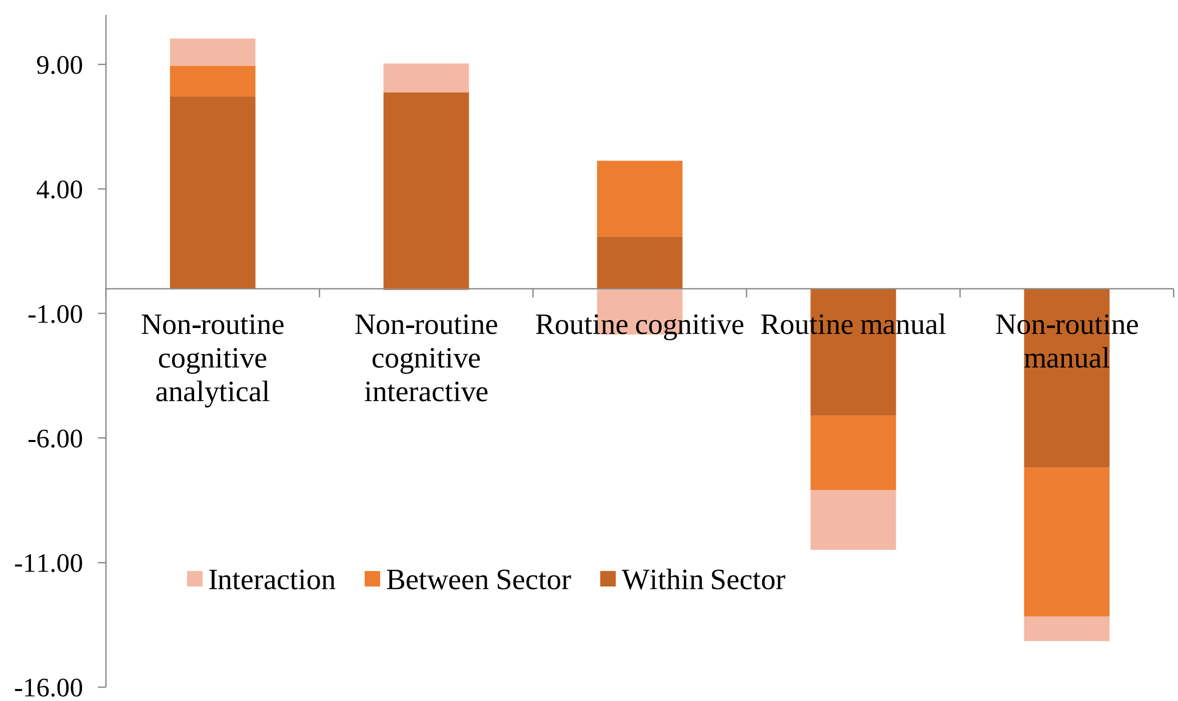
Table 4: Trend in Task Intensities by Birth Cohort

	1983-84	1988-89	1993-94	1998-99	2004-05	2009-10	2011-12
Non-routine Cognitive Analytical							
Before 1947	0.62	2.12	2.86	3.78	6.20	7.76	8.07
1948 - 1957	-0.74	0.93	2.47	4.31	7.14	9.52	10.48
1958 - 1967	-2.95	-1.44	0.50	1.92	5.35	9.80	12.02
1968 - 1977	-2.61	-2.89	-1.83	0.38	4.13	8.15	10.68
1978 - 1987			-3.87	-3.54	1.47	6.93	9.63
Average Annualised Change 1983-84 to 2011-12							
Within Cohort	0.51						
Within Age Group	0.35						
Non-routine Cognitive Interactive							
Before 1947	0.13	1.63	2.38	3.54	6.29	8.94	10.02
1948 - 1957	-1.92	-0.48	0.87	3.03	6.13	8.65	10.50
1958 - 1967	-3.21	-2.23	-1.00	0.87	4.33	7.95	10.17
1968 - 1977	-2.47	-2.84	-2.49	-0.62	3.04	6.22	8.68
1978 - 1987			-3.65	-3.67	0.42	4.46	7.13
Average Annualised Change 1983-84 to 2011-12							
Within Cohort	0.45						
Within Age Group	0.22						
Routine Cognitive							
Before 1947	-0.59	-0.34	-0.10	1.27	-0.52	1.14	0.32
1948 - 1957	1.23	2.26	3.08	4.77	2.83	3.47	2.90
1958 - 1967	-2.07	-0.12	2.48	3.70	2.72	4.62	4.42
1968 - 1977	-4.43	-3.90	-1.04	1.91	2.36	2.95	3.21
1978 - 1987			-4.45	-2.48	0.05	2.16	2.46
Average Annualised Change 1983-84 to 2011-12							
Within Cohort	0.21						
Within Age Group	0.16						
Routine Manual							
Before 1947	-0.93	-1.74	-2.99	-4.03	-4.17	-5.31	-4.74
1948 - 1957	-0.17	-2.03	-4.28	-5.90	-7.28	-9.07	-9.40
1958 - 1967	3.38	1.26	-2.34	-3.82	-5.90	-10.75	-13.47
1968 - 1977	3.38	4.67	1.93	-1.44	-4.43	-9.58	-12.52
1978 - 1987			4.74	4.00	-0.17	-7.19	-10.80
Average Annualised Change 1983-84 to 2011-12							
Within Cohort	-0.52						
Within Age Group	-0.49						
Non-routine Manual							
Before 1947	-1.56	-2.77	-4.09	-5.74	-3.66	-6.81	-6.54
1948 - 1957	-1.66	-4.35	-7.36	-9.65	-9.35	-12.03	-13.34
1958 - 1967	3.30	0.10	-4.72	-6.97	-8.06	-14.44	-18.41
1968 - 1977	5.54	5.70	1.26	-3.70	-6.69	-12.76	-16.96
1978 - 1987			5.67	3.88	-1.48	-9.81	-14.70
Average Annualised Change 1983-84 to 2011-12							
Within Cohort	-0.70						
Within Age Group	-0.77						

4.3 Structural Change and Task Content

Given the fact that the task intensity of jobs varies from sector to sector, a shift in employment from one sector to another can potentially change the overall task composition of jobs in a country. In fact, Barany and Siegel (2015) have argued that job polarisation in the US has been closely linked to the shift in employment from manufacturing to services. India has also witnessed a significant change in the structure of employment over the last three decades. In order to quantify the role of structural change in shaping task intensities, we use shift share decomposition[iv]. We decompose the observed change in five task intensities into three components; (i) within sector change, i.e., contribution of change in task intensity within a particular sector over time, (ii) between sector change, i.e., contribution of change in the structure of employment and (iii) contribution of the interaction between these two. The results of our shift share analysis are shown in Figure 3.

Figure 3: Decomposition of change in task intensities in India during 1983-84 to 2011-12



It is evident from Figure 3 that the change in non-routine cognitive analytical task intensity is strongly driven by within sector change. Our analysis suggests that more than 77 per cent of the change in non-routine cognitive analytical task intensity can be attributed to within sector change, while another 11 per cent can be attributed to the interaction between within and between sector effects. Only 12 per cent of the change in non-routine cognitive analytical task intensity can be attributed to a change in the employment structure. The within sector effect has been even stronger in the case of non-routine cognitive interactive task intensity as it accounts for more than 88 per cent of the observed increase in non-routine cognitive interactive task intensity. Notably, the contribution of a change in employment structure to a change in non-routine cognitive interactive task intensity has been 0. In contrast, structural shift in employment has played a significant role in shaping the remaining three task intensities. Almost 50 per cent of the observed change in routine and manual task intensities has been driven by a shift in employment from high routine and manual task intensive sectors to less routine and manual task intensive sectors.

4.4 Task, Technology and Education

It is evident from the section above that the change in task intensities in India is not purely driven by structural change in the economy. In fact, the two non-routine cognitive task intensities have been solely driven by the within sector effect. The within sector effect can be explained either by change in the supply of labour (supply side) or change in technology (demand side). Some studies have argued that the change in task content has been purely driven by technology, while other studies have attributed the change in task content change to the educational attainment of labour. In this section, we analyse the relative role of demand and supply side factors in shaping the task content of jobs in India during the period 1983-84 to 2011-12. For this, following Autor et al (2004), we regress the task content intensities on demand and supply side factors in a panel data framework. We have estimated the following regression equation to quantify the impact of technology and education on task intensities.

$$Y_{it} = \alpha + \beta_1 H_{it} + \beta_2 M_{it} + \beta_3 T_{it} + \tau_i + \epsilon_{it} \qquad 4$$

where

Y is the task intensity, H is the share workers with tertiary education, M is the share of workers with secondary education, T is a technology proxy, τ is the sector specific fixed effect and ϵ is random disturbance term, i stands for the i^{th} sector and t stands for time.

Following standard literature, we estimate separate regression equations for each of the five task content intensities. Literature has used R&D or use of ICT capital as a proxy for technological change. Unfortunately, detailed sector wise data on R&D or ICT capital is not yet available for India. Therefore, we have used total factor productivity (TFP) as a proxy for technological change. The data for sector wise TFP has been taken from KLEMS India data base. The sector wise share of workers with high and medium education has been compiled from NSSO data. The results of our fixed effect regression analysis are given in Table 5. We started our regression analysis by simply regressing the non-routine cognitive analytical task intensity on the share of workers with high and medium education and the results are reported in column 1. Our results show that educational upskilling is positively associated with non-routine cognitive analytical task intensity. In particular, the coefficient of the share of workers with tertiary education is positive and significant at one per cent. In column 2, we control for technology. The inclusion of TFP in the equation has two significant effects. First, it increases the overall explanatory power of the equation as the value of r square goes up substantially. Second and more importantly, the inclusion of TFP in the equation reduces the magnitude of the coefficient of tertiary education and renders it insignificant. The coefficient of TFP turned out to be positive and significant. These results suggest that the increase in non-routine cognitive analytical task intensity is driven by technological change rather than upskilling.

In column 3 and 4, we repeat our specifications for non-routine cognitive interactive task intensity. The results are similar to that for non-routine cognitive analytical task intensity; the non-routine cognitive interactive task intensity in India is also driven by technology. We do find a positive association between the share of workers with tertiary education and non-routine cognitive interactive task intensity. However, the association turned insignificant when we included TFP in regression equation. In column 5 and 6 of table 5, we repeat the same specifications for routine cognitive task intensity. Our results suggest that an increase in the relative supply of workers with medium education is positively associated with routine cognitive task intensity. However, a simple back of the envelope calculation suggests that an increase in the supply of workers with medium education explains only 14 per cent of the observed increase in routine cognitive task intensity. Moreover, a very low value for R square suggests that the model has a very low explanatory power. Given the fact that routine cognitive task intensity is mainly driven by structural change, these results are not very surprising.

Our results suggest that upskilling has been the main driver of change in routine and non-routine manual task intensities. The results in column 7 and 8 of Table 5 show that an increase in the relative supply of workers with tertiary as well as secondary education is negatively associated with routine manual task intensity. The supply of workers with tertiary education during 1983-84 to 2011-12 has increased by 14.4 percentage points. A simple decomposition of change in routine manual tasks, using the coefficient reported in column 8 of Table 5, shows the hat around 57 per cent of the change in routine task intensity can be attributed to the increase in the supply of workers with tertiary education alone, while another 20 per cent can be attributed to the increase in supply of workers with secondary education.

Similar results can be seen for non-routine manual physical task intensity in columns 9 and 10 of Table 5. The results show that the coefficient of TFP is not significantly different from 0, while supply of workers with tertiary and secondary education is negatively associated with non-routine manual physical task intensity. Our decomposition exercise suggests that the increase in the supply of workers with tertiary and secondary education accounts for around 55 and 20 per cent respectively of the observed change in non-routine manual physical task intensity. To sum up, our regression analysis suggests that technology is driving the change in two non-routine cognitive task intensities, while upskilling has shaped manual task intensities.

Table 5: Fixed Effect Regression: Change in Task content, Technological change and Education

	Non-routine Cognitive Analytical		Non-routine Cognitive Interactive		Routine Cognitive		Routine Manual		Non-routine Manual Physical	
	1	2	3	4	5	6	7	8	9	10
High Education Share	0.029* (.003)	0.004 (.005)	0.029* (.004)	0.005 (.006)	0.002 (.003)	0.001 (.004)	-.042* (.004)	-.041* (.006)	-.049* (.005)	-.053* (.006)
Medium Education Share	-0.007 (.011)	0.004 (.003)	-0.007 (.012)	0.003 (.002)	.009*** (.004)	.009** (.002)	-.037* (.005)	-.038* (.004)	-.053* (.002)	-.052* (.003)
Total Factor Productivity		.013* (.002)		.012* (.003)		.000 (.00)		-.001 (.002)		-0.001 (.003)
No. of Observations	42	42	42	42	42	42	42	42	42	42
Within R Square	0.35	0.62	0.30	0.55	0.02	0.02	.56	.57	0.57	0.58

Note: *Estimation using Driscoll Kraay standard error.* The *standard error is given in parenthesis*.
** Significant at 1 per cent level*
** Significant at 5 per cent level*
**** Significant at 10 per cent level*

4.5 Social Dimension of Task

With the changing nature of jobs, the quality of education is going to be the key for job seekers in the Indian labour market. Unfortunately, India has a very complicated and inefficient education system. It has some very good private schools where the quality of education is comparable to global standards. However, access to these schools is primarily restricted to the economically well off section of the society. In contrast, a large section of Indian society still relies on government schools for the education of their children. It is widely documented that government run schools are in disarray and fail miserably to impart basic reading and computational skills to their students. A recent survey shows that 74 per cent of students in Delhi government run schools fail to read a paragraph in Hindi, the native language, while 64 per cent student fail to do simple 3 digits by one digit division. Given this stark difference in the quality of education between government and private schools, the changing nature of jobs can further exacerbate the existing economic inequality. Our data does not allow us to examine the task content of jobs according to the economic status of an individual. However, it does allow us to examine the task content of jobs as per the social status of an individual. Since the incidence of poverty is higher among the socially weaker sections, *i. e.* Scheduled Castes and Scheduled Tribes, we estimate the task content of jobs performed by different social groups in Indian society to gauge the implications of the changing task consent of jobs for social and economic inequality. Our analysis suggests that cognitive task intensities of jobs performed by socially forward castes, denoted as others, is very high. It implies that the employment of socially forward sections of society is concentrated in occupations which require cognitive skills (Table 6). In contrast, the employment of socially backward castes, specifically the Scheduled Castes, is more concentrated in occupations which require manual skills and therefore, the manual task content of their jobs is relatively high. Since the overall demand for manual tasks is declining, these results suggest that the changing task content of jobs in India may pose a big challenge for socially backward communities.

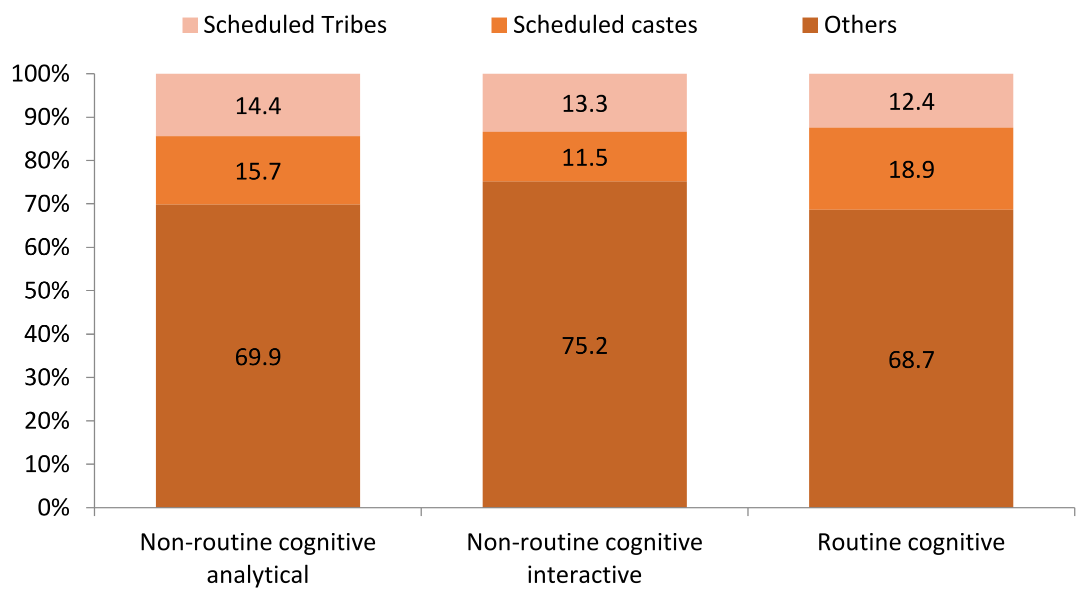
Figure 6: Average Task Content of Jobs by Social Groups

	Others	Scheduled Castes	Scheduled Tribes
Non-routine cognitive analytical	5.55	-5.13	1.25
Non-routine cognitive interpersonal	3.71	-4.44	2.04
Routine cognitive	3.01	-2.64	-3.34
Routine Manual	-6.16	3.57	0.56
Non-routine manual physical	-9.63	4.93	2.61

However, a mere decline in manual jobs may not hurt socially backward sections if their participation in cognitive jobs goes up. A temporal analysis of task content by social groups suggests that the trend in task intensities has been similar for all social groups. It implies that the change in task intensities has not been driven by any single social group. However, as expected, the contribution of different social groups to the observed change in different task intensities varies significantly. We estimated the contribution of different social groups in the change of three task contents that have increased over the period and results are shown in

Figure 4. Contrary to expectations, our analysis suggests that the contribution of two socially backward communities to the change in non-routine cognitive analytical (NRCA) task content has not been lower than their share in total population. In fact, the contribution of schedule tribes to the change in NRCA task content has been significantly higher than their share in total population[v] while in the case of schedule castes, it has been marginally lower than their share in the total population. Our results further suggest that the combined contribution of the two socially backward communities to the observed change in non routine cognitive interactive task intensity has also been more or less in line with their share in total population. However, if we look at the contribution of these two groups separately, we do find that the contribution of scheduled castes to the change in non-routine cognitive interactive task content has been significantly lower than their share in total population, while the contribution of scheduled tribes has been much higher than their share in total population. Therefore, these results suggest that socially weaker sections have not been lagging behind as far as their participation in non-routine cognitive task intensive occupations is concerned and this may be due to the government's affirmative action in the form of reservation in education and jobs for these groups.

Figure 4: Contribution to Change in Non-routine Cognitive Task Contents



5. Conclusion

The ongoing digital revolution has brought enormous benefits. It has increased productivity and made life much easier. However, it has also created significant challenges, especially in labour markets. Studies have shown that the rapid improvement in digital technology and the consequent decline in the cost of automation have changed the task content of jobs in many countries. In this paper, we analyse the task content of jobs in India between 1983 and 2011. Combining the O-Net data with NSS EUS data, we find that, in line with global trends, the non-routine cognitive analytical as well as the non-routine cognitive interactive task intensity of jobs has increased in India, while manual task intensity has declined. However, unlike in the US and Europe, the routine cognitive task content has not declined in India. Moreover, we find that the change in task intensities has not been driven by cohort effect as all birth cohorts have witnessed a similar trend in their task intensities. Our analyses further shows that the change in the two non-routine cognitive task contents has been strongly related to the change in total factor productivity. Therefore, technology seems to be a major factor behind the evolution of non-routine cognitive tasks in India. However, this needs further investigation as change in TFP is not a direct measure of technology. Our results show that manual task intestines have been shaped by structural change and change in the supply of labour.

The changing task content of jobs in India has significant implications for education and skill formation. With the rapidly declining manual task intensities of jobs, the role of education and skill has increased substantially in the Indian labour market. The latest Talent Shortage Survey corroborates this and shows that 48 per cent of employers in India face difficulties in filling job vacancies due skill and talent shortage (Manpower Group 2016). If not addressed urgently, skill shortage can be fatal for growth and job creation in India. Fortunately, the Government of India has realised the growing role of skills and has started an ambitious skilling programme under the Pradhan Mantri Kaushal Vikas Yojana (PMKVY). With this scheme the government aims to provide soft and other industry relevant skills to 10 million youths. Apart from this, the government has also notified National Apprenticeship Promotion Scheme to provide apprenticeship training to 5 million youth by 2019-20. Although, these are steps in the right direction, they are not directed towards cognitive skill formation and therefore, cannot be a substitute for the quality of formal education given at various levels. Government has to introduce the short term skilling programmes because the formal education system in India has failed miserably at all levels. From time to time, research has highlighted the failure of schools in India to impart basic reading and computational skills to their students. A recent survey by the Delhi government’s Directorate of Education shows that 74 per cent of students in Delhi government run schools failed to read a paragraph in Hindi, the native language, while 64 per cent student failed to do simple 3 digits by one digit division. With this kind of basic schooling, it is no wonder that the quality of vocational and higher education in India has remained substandard. Employers in India frequently argue that youth even with graduate degrees are not employable. Since the demand for cognitive skills is expected to increase further in the years to come, the government should focus more on the quality of education at all levels to address the issue of growing skill shortage.

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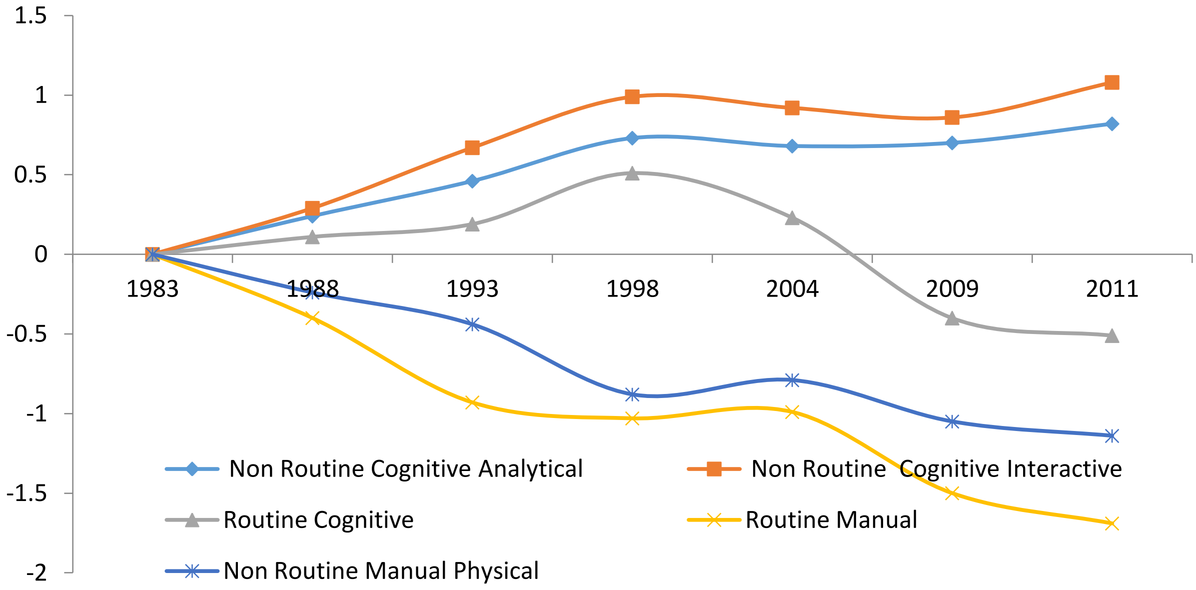
Annexure 1: Changing task Content of Manufacturing Sector Jobs



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[i] Various task intensities in O-Net data have been measured at a scale of 1 to 5. For a detailed overview of O-Net data please see Hardy et al (2015)

[ii] The crosswalk tables are available on demand.

[iii] EUS is a quinquennial survey conducted by National Sample Survey Office, MOSPI - GOI is the official source of information on employment and labour conditions in India.

[iv] Mathematically, the shift share decomposition can be depicted as $\Delta T_{jt} = \sum_s(\Delta E_{st}\, \gamma^*{}_{st}) + \sum_s(\Delta\gamma_{st} E^*{}_s) + \sum_s(\Delta E_{st}\Delta\gamma_{st})$ where E is share of sector in total employment, γ is task intensity, s stands for sector, t stands for time, overhead * denotes the initial value. The first term in the equation captures the between sector effect, second terms captures the within sector effect and third terms captures the interaction between within and between effect.

[v] According to the 2011 Census, schedule tribes and schedule castes account for 8.6 and 16.8 per cent respectively of the Indian population.