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Warwick Institute for Employment Research Working Paper 2017/101

Employment Change in Occupations in Urban India: Implications for Wage Inequality

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January, 2017

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Employment Change in Occupations in Urban India: Implications for Wage Inequality

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Abstract

This article analyses employment and wage change patterns in India for a period spanning almost three decades, 1983 to 2011. Using data from the National Sample Survey Organisation, this study finds evidence of job polarisation (employment growth in low- and high-skill jobs, and reduction in the middle) in urban India during the 1990s and 2000s. However, the 1980s experienced an employment upgrading. The wage change patterns are almost consistent with the employment change patterns. A reduction in employment share in routine task intensive occupations was found which is consistent with the job polarisation literature. It is argued that the reduction in employment share in the middle skill routine occupations is a result of mechanisation and technological upgradation within the Indian industry. On the other hand, increase in employment in both low-skill and high-skill occupations is more of a result of growing self-employment in informal sector in urban India.

Key words: Employment change, polarisation, technological change, wage inequality

JEL classification: E24, J24, J31

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1. INTRODUCTION

Over the last two decades, employment in middle-skilled jobs has been squeezing in many developed countries particularly in the USA and UK (Acemoglu and Autor, 2011; Goos, Manning and Salomons, 2009). For the overall labour force, the employment change from the end of the 1980s to the end of the 2000s is characterised by a U-shape pattern, i.e. employment increases in the high-skill jobs at the top and at the bottom but hardly at all in the middle of the skill distribution. This U-shaped pattern of employment change is termed as 'job polarisation' by labour economists. Job polarisation has often coincided with wage polarisation - a decrease in wages in middle-skill jobs and an increase in wages in low-skill services and high-skill professional and managerial jobs (Acemoglu and Autor, 2011).

The main reason behind job polarisation as discussed in the literature is continual technological progress which favours the high-skill workers in professional, managerial and technical jobs consequently raising their demand as well as their wages, but adversely affects the middle-skill workers in clerical and production jobs. Clerical and production jobs are mostly routine and automated and, thus, easy for technology to emulate, consequently declining the employment share and wages. However, low-skill jobs that are heavily manual and require flexible use of brain, eyes, hands and legs and, therefore, hard to be replaced by technology, increase its employment share and returns over time (Acemoglu and Autor, 2011; Goos and Manning, 2007).[2] Most of the developed countries and some transition countries have been studied for the evidence of job polarisation (Goos and Manning, 2007; Autor, Katz, and Kearney, 2008; Kupets, 2016).[3] However, developing countries still lack this kind of studies which is very interesting from the perspectives of both policymakers and academics.[4]

[2] Some other studies find evidence that trade liberalisation has led to the decline in the middle skilled routine jobs in developed countries by shifting these jobs to China's manufacturing sector (Keller and Utar, 2016). Immigration has also been cited as an important factor behind polarisation in USA as the immigrants supply low-skilled labour and thus are raising the employment share of low-skilled jobs (Wright and Dwyer, 2003; Oesch and Rodriguez-Menes, 2011).

[3] The patterns of employment change, though, varies depending on country and period of study. Some recent papers (Oesch and Rodriguez-Menes, 2011, Fernandez-Macias, 2012) have argued that in Europe polarisation is just one pattern among at least three different types - polarisation (a U-shaped pattern), upgrading (a monotonically upward rising pattern) and mid-upgrading (an inverted U-shaped pattern). But if the patterns are aggregated at the EU level, a pattern of asymmetric polarisation is observed.

[4] Medina and Posso (2010) have analysed the labour markets of Brazil, Colombia and Mexico, and have found evidence of job polarisation in Colombia and Mexico but not in Brazil.

This article contributes to this literature by analysing employment change and concurrent wage change patterns in India, which is the first investigation to focus on this increasingly important research area using Indian data. India is one of the largest emerging economies in the world with almost one-fifth of world's total population. Besides, the country has experienced a series of events starting from the 1950s right after its independence; among them the most important is the economic liberalisation in the 1990s. Trade liberalisation in India culminated in the drastic tariff reductions on imports during the 1990s. According to the prediction of Stolper-Samuelson (SS) theorem, economic liberalisation would raise the demand for and returns to the abundant factor of production—that is, unskilled labour in India like most less developed countries (LDC). On the contrary, Acemoglu (2003) describes how after trade liberalisation in LDCs, increased capital goods imports can lead to a higher demand for skilled workers. In this context, it is worth investigating if employment polarisation has happened in India and how much it has contributed to the growing wage inequality in urban India.

Using detailed data on labour market activities from the household level survey of National Sample Survey Organisation (NSSO) for three subsequent decades starting from 1983-84 to 2011-12, this study tries to answer three research questions:

i. What is the pattern of employment change in the urban labour market of India - polarised, upgrading or downgrading during the periods 1983 to 1993 (1980s), 1993 to 2004 (1990s) and 2004 to 2011 (2000s)?
ii. Does the pattern vary before and after economic liberalisation in India?
iii. What is the implication of this employment change in explaining wage inequality in urban India?

The main findings can be summarised as follows. Evidence of job polarisation was found in urban India during the post-reform period. Between 2004 and 2011 the shares of employment in low- and high-paid jobs increased respectively by 5 and 8 percentage points, and the share of employment in middle-paid jobs decreased by 13 percentage points. Job polarisation occurred primarily in the 1990s and 2000s, whereas in the 1980s changes in the composition of employment were more consistent with general upskilling. An important question which researchers seek to answer is whether technological change has been purely skill-biased, raising demand for skilled versus unskilled workers, or it has been task-biased changing the relative demand for workers according to their skills to perform routine tasks, causing job polarisation.[5]

These findings suggest that while routine occupations are shrinking during this period in urban India, the reduction does not seem to be the consequence of only task-biased technological change or automation. Unlike the developed countries, the decline in routine manual occupations in India seems to be more as a result of mechanisation in manufacturing industry while increase in non-routine occupations is a result of growing informal sector during the 1990s and 2000s. Moreover, this process has led to subsequent reallocation between sectors. A shift-share analysis confirms this pattern by providing evidence of industrial shift as the main driver behind the decline in employment share in routine manual jobs during 1983 to 2011. Second, wage polarisation consistent with employment polarisation was found; being particularly strong in the 1990s. These changes in the employment structure and in average earnings by occupation can explain the increase in earnings inequality that has taken place in urban India.

The rest of the article is organised as follows. The next section provides the background of this study followed by a discussion of earlier research in section 3. Data is presented in section 4 and the methodology used for the analysis is discussed in section 5. Section 6 discusses the results and section 7 concludes.

2. BACKGROUND: URBANISATION IN INDIA

The Indian economy is going through a rapid process of urbanisation. Though the percentage of population living in urban cities is around 30 per cent today, it has increased from less than 20 per cent of its overall population in 1951. The number of people residing in urban areas has also increased from 25.8 million in 1901 to 285.3 million in 2001. There has been continual concentration of population in Class I towns over the years (Datta, 2006).[6] According to the census 2011, urbanisation in India has been faster than it was expected. Urbanisation in India is perceived as a positive factor in the overall development, as 62 per cent of total GDP is attributable to urban sector (Bhagat 2011). Besides the employment in rural area is mostly

[5] For a vivid understanding of skill-biased technological change (SBTC) and task-biased technological change (TBTC) refer to Acemoglu and Autor (2011) and Fernandez-Macias and Hurley (2016).
[6] Class I towns in India are the ones which have a population of 100,000 or more (Census, 2011).

dependent on agriculture (almost three quarters of the rural employment) and the growth in real GDP has been consistently low in agriculture (Table 1 and Table 2).

Table 1: Growth in Real GDP (in %) per Annum

Period	Agriculture	Industry	Services	GDP
1950s	2.7	5.6	3.9	3.6
1960s	2.5	6.3	4.8	4
1970s	1.3	3.6	4.4	2.9
1980s	4.4	5.9	6.5	5.6
1990s	3.2	5.7	7.3	5.8
2000s	2.5	7.7	8.6	7.2
2011-2 to 2015-16 (NS)	1.7	5.5	8.9	6.5

Source: Estimated by Mahendra Dev (2016) for 2011-12 to 2015-16 based on Central Statistical Organization data.

Table 2: Distribution of Workers across Broad Industry Sectors in Rural and Urban India: 1983 to 2011

	1983-1984 (%)		1993-1994 (%)		2004-2005 (%)		2011-2012 (%)	
Industries	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
A Agriculture, hunting, forestry	79.3	11.8	76.3	10.0	70.1	7.1	62.0	5.5
B Fishing	0.4	0.4	0.4	0.4	0.4	0.3	0.4	0.4
C Mining & quarrying	0.6	1.2	0.7	1.2	0.6	0.8	0.5	0.8
D Manufacturing	6.9	26.8	7.7	25.6	8.2	23.8	8.5	23.3
E Electricity, gas and water supply	0.2	1.0	0.2	1.1	0.2	0.7	0.2	0.8
F Construction	2.0	5.0	2.7	6.8	5.5	8.5	11.4	9.7
G Wholesale and retail trade	3.3	15.8	4.1	17.4	5.3	19.8	6.1	19.9
H Hotels and restaurant	0.5	2.5	0.5	2.4	0.7	3.2	0.9	3.8
I Transport, storage	1.3	8.9	1.7	8.5	2.8	9.2	3.3	8.8
J Financial intermediary	0.1	1.6	0.2	2.2	0.3	2.2	0.4	2.6
K Real estate, renting and business activities	0.1	1.3	0.1	1.5	0.3	3.3	0.5	5.2
L Public administration	1.4	9.4	1.4	8.6	1.0	5.6	0.9	4.4
M Education	1.3	4.0	1.3	4.2	1.8	5.1	2.3	5.6
N Health and Social work	0.3	1.9	0.3	1.6	0.4	1.9	0.5	2.3
O Other service sectors	2.4	8.5	2.4	8.6	2.5	8.5	2.1	7.2
Total	100	100	100	100	100	100	100	100

Source: Authors' own calculation using NSS Employment and Unemployment Survey. The sample includes the age group 15 to 65 year who reported as employed in the principal activity status.

Employment in agriculture in India has declined substantially during 1983 to 2004-05 nevertheless a large proportion of the population (70 per cent) remains employed in the agricultural sector in rural India. Between 60 to 80 per cent of rural labour market is concentrated in only two occupations - *Cultivators and Agricultural labourers* (see Table 1). Given the highly concentrated nature of employment in the rural labour market, the analysis in this paper is restricted to the urban labour market.

3. A REVIEW OF EARLIER RESEARCH IN INDIA

Recent research documents that technological change has become a global phenomenon. In that regard, Berman, Somanathan and Tan (2005), and Unni and Rani (2004) investigate if skill-biased technological change (SBTC) was present in Indian labour market during the 1980s and the 1990s. They find that SBTC did in fact arrive in India in the 1990s. Using panel data from the Annual Survey of Industry (ASI), they show that while the 1980s was a period of falling skills demand, the 1990s showed generally rising demand for skills. According to them at least half of this increase in demand can be explained by two related factors - (1) increased output, and (2) SBTC. However, both studies focus on the industries in India and do not answer the question of how the employment in specific jobs or occupations has been affected by SBTC (Berman, Somanathan and Tan, 2005; Unni and Rani, 2004).

In its New Industrial Policy of 1991, the Indian Government had announced establishment of the National Renewal Fund (NRF). The objective of this fund was to provide a safety net to the workers who were likely to be affected by the technological progress and modernisation in Indian industries. This again implies the presence of technological-upgradation in India during the 1990s. However, this policy was later abolished in 2000 due to its inadequate functioning of re-training and rehabilitation of jobless workers. Nagaraj (2004) in his study on organised manufacturing sector shows that 15 per cent of workforce in this sector lost their jobs between the year 1995 and 2000-01. He explains this job-loss as a result of NRF, a lack of labour law enforcement and introduction of information technology. The paper also highlights how the extent of job losses are not reflected at the aggregate level, as additional jobs were simultaneously created, particularly in the informal sector during late 1990s and early 2000s. These jobs, as mentioned in this article, are mostly auxiliary services like transport, security, cleaning, and providing food which are non-routine manual works and require low skill.

In line with this literature, Ramaswamy and Agarwal (2013) and Mehrotra et al. (2014) discuss how non-agricultural industry sectors, especially manufacturing, should expand more to absorb the low skilled young labour force in India in the near future. The World Development

Report 2016 on "Digital Dividends" published by the World Bank analyses employment trends in both developed and developing countries in order to see displacement or automation of jobs by growing technological adoption. According to the report, the average decline in the share of routine employment has been 0.39 percentage points a year or 7.8 percentage points for the period since 1995. But the pace of labour market polarisation is much slower than what is observed in developed countries (World Development Report, 2016). The report also analyses the occupational employment change in India and finds polarising employment trends for the period from 1995 to 2012.

Though very little research has so far focused on employment change and job polarisation, there is a vast literature on economic liberalisation and wage inequality in developing countries particularly in urban India (Azam, 2012; Basu, 2006; Chamarbagwala, 2006; Milner et al. 2005; Kijima, 2004; Banerjee and Piketty, 2005; Bhalotra, 2002). All of these studies have analysed the periods of the 1980s or 1990s focusing on trade liberalisation. Acemoglu (2003) explains how after trade liberalisation in LDCs, increased imports of capital goods can lead to a higher demand for skilled workers as a result of technological progress. This hypothesis is supported by Attanasio, Goldberg and Pavcnik (2004) for Colombia and by Harrison and Hanson (1999) for the case of Mexico. Gorg and Strobl (2002) find an increase in the relative wages of skilled labour in Ghana which according to them is a result of SBTC brought by imports of technology-intensive capital goods. However, Pavcnik (2003) rejects the SBTC hypothesis for Chilean plants.

With a particular focus on globalisation and inequality in India, Basu (2006) in his article has pointed out the negative and positive effects of globalisation. According to his findings while the positive effects are enjoyed by the skilled end of the labour market which has access to technology, the negative effects are borne by the unskilled and illiterate section of the labour market. He argues that as the market opens up suddenly and fully, the prices of goods in poor countries will converge more rapidly toward prices in industrialised countries than the latter converge toward the former since a large share of the world's GDP comes from the industrialised countries (Basu, 2006). While he discusses whether technology favours skilled employment, his article does not really go into the details of employment change in different occupations as a result of technological progress.

Since the start of the economic reform in 1991, there have been serious concerns regarding the increasing income inequality in India. Kijima (2005) studies the reasons behind increasing wage inequality in urban India during the period from 1983 to 1999. This study found that: wage inequality in urban India started increasing before 1991; the increase in wage inequality was mainly attributable to increases in the returns to skills; and the accelerating skill premium was due to increases in the demand for skilled labour. According to this article, the causes of wage inequality in urban India differed between the periods of 1980s and 1990s. He analyses the increasing wage inequality from the perspective of human capital (schooling and working experience), but ignores the occupational change and its impact on wages.

Milner et al. (2005), on the other hand, explore the roles of trade and technological change behind the rising wage inequality observed in Indian manufacturing following the 1991 trade policy reforms. Assuming endogeneity of price and technological change, they find that the rise in inequality post-reform is due only to technological change, and not price changes. Their results confirm the findings of Berman, Somanathan and Tan (2005), who argue that a part of the increase in the relative demand for skilled workers is due to SBTC. This finding is again demonstrated by Chamarbagwala (2006) who finds that increase in relative demand for skilled workers contributed to India's widening skill wage gap and narrowing gender wage differential during the two decades (1980s and 1990s) that coincide with the economic liberalisation in the country (Chamarbagwala, 2006). According to this article, the increase in demand for skilled labour was mostly due to skill upgrading within industries.

In a recent study, Azam (2012) examines changes in the wage structure in urban India during the time periods 1983 to 2004-05 across the entire wage distribution using the Machado and Mata (2005) decomposition approach. He also breaks the two decades in two parts 1983-1994 and 1993-2005 in order to capture any possible changes before and after economic liberalisation. He shows that real wages increased throughout the wage distribution during 1983-1993 and the increase was larger at higher quantiles; however, it increased more in the bottom and top end as compared to the middle of the wage distribution during 1993-2004 for male workers. But his paper does not explain the reason of this U-shaped wage change pattern during the latter period. While all these studies discuss skill-biased technological change and the composition of the workforce, they do not delve into analysing the change in employment across different occupations or jobs and its implications for wage inequality. This study substantially contributes to this debate of trade liberalisation, technological change and increasing wage inequality in urban India by providing a detailed analysis from an occupational perspective.

4. DATA

Data from the employment and unemployment survey conducted by the National Sample Survey Organization (NSSO) Government of India is used in this analysis. There are several rounds of employment and unemployment surveys in recent times conducted in almost every year, though the thick surveys are conducted once in every five years and are called quinquennial rounds. The main objective of this study is to analyse the long run changes in employment (preferably at 10 year intervals). For this reason, the main data used were from four quinquennial rounds from the year 1983-84 (38th round), 1993-94 (50th round), 2004-05 (61st round) and 2011-12 (68th round). In order to identify some trends across the years, data from the intermediate rounds from the year 1987-88 (43rd round), 1999-00 (55th round) and 2007-08 (64th round) were also used.

For simplicity, rounds are referred to by the initial year of the surveys, 1983, 1993, 2004 and 2011. The main sample, thus, consists of four rounds of cross sectional survey data spanning over a period of almost three decades (28 years). This time period enables the capturing of the trend in results before (1983-1993), immediately after (1993-2004) and decade after (2004-2011) the trade liberalisation which was initiated in 1991. The employment and unemployment survey design follows a stratified multi-stage random sampling and all units are assigned with adjusted sampling weights.[7]

The surveys collect socioeconomic and demographic information of households and individual members across all states except some remote and inaccessible pockets. Apart from the demographic characteristics, the surveys collect information on individual occupation, education, industry of employment, status of employment along with last weekly earnings. Moreover, the sample of the survey is representative at national level and therefore, provides a picture of overall labour market in urban India. On an average, there are 125 to 136 thousand individuals in the working age population (15-65 years) in each round with information on demographic characteristics. It is worth mentioning that the sampling strategies and questionnaires are quite similar across rounds and therefore, comparable.

[7] All the results reported in this paper are estimated using proper sampling weights.

5. METHODOLOGY

5.1. Occupational skill level

Defining occupational skill based on the complexity of the jobs or skill requirement to perform the job is one of the most important issues in studying employment change. The literature has grouped low-, middle-, and high-skill occupations in different ways and arrived mostly at the same results. Some studies have ranked them by initial average earnings or average education (e.g. Autor, Katz, and Kearney, 2006; Goos and Manning, 2007). [8] Alternatively, it has grouped managerial, professional, and technical occupations as *high-skill* or *non-routine cognitive*; sales, clerical, production, and operative occupations as *middle-skill* or *routine manual and cognitive*; and service and elementary occupations as *low-skill* or *non-routine manual* occupations (e.g. Acemoglu and Autor, 2010; Cortes, 2012; Jaimovich and Siu, 2012).[9]

However, some studies have used surveys like Dictionary of Occupational Titles (DOT) and its successor Occupational Information Network (O*NET) to measure the tasks and skill content of each occupation or job (Autor, Levy and Murnane, 2003). The occupations are then grouped into *non-routine manual, routine manual, routine cognitive* and *non-routine cognitive* occupations based on their task content.

Both methods are followed to group the occupations. First, the mean earnings of each occupation in 1983 is used to rank them from lowest to highest skilled occupation and also by grouping the broad categories into non-routine manual, routine manual, routine cognitive and non-routine cognitive occupations (the classification is presented in Appendix Table A1). A total of 390 occupations coded following the National Classification of Occupation (NCO) version 1968 in 1983 among which extremely small cells were either dropped or merged with the closest big cell occupations.[10] Broad industry groups were also used to break some

[8] Mean earnings and median earnings have been used to proxy the skill level and rank the jobs in the literature. Our results are consistent using both mean and median earnings to define the skill ranking.

[9] Though these classifications are based on the tasks performed in occupations of USA using International Standard Classification (1988) codes but it has been widely used in other countries including some developing countries like Ukraine (Kupets, 2016) and in Latin America. The actual intensity of different tasks in each detailed occupation may vary if measured, unavailability of this kind of information does not allow us to categorise them based on the actual task intensity. This is a caveat of the analysis based on this categorisation.

[10] There is a total of 450 occupation codes at 3-digit level in NCO 1968 classification. There are 390 occupations in the dataset of 1983. Some occupations are extremely small in terms of number of sample persons. So, the ones with less than 10 observations were dropped, some small cell occupations were merged with the closest possible big cell ones and also desegregate some by broad industry. This exercise leaves us with approximately 280 occupations.

extremely big cell occupations which do not account for industry variation in the classification (like clerk, general; labourers; merchants and shop salesperson). [11] This process leaves us with 287 occupations in urban India with wage data in 1983.[12] The occupations are then ranked based on the mean wage of each occupation. Skill percentiles (quintiles) were then created where each percentile contains approximately 1 per cent (20 per cent) of total employed population in urban India in 1983.

Analysis was performed using NCO 1968 only to the data till 2004 since the occupational classification follows the same version, NCO 1968, until 2004. The surveys afterwards have used the latest version of classification, NCO 2004. A concordance between these two is available at 3 digit NCO 1968 to 4 digit NCO 2004 level. However, the occupations in the survey data are coded at 3-digit level in all the survey rounds. A concordance from around 400 occupations in NCO 1968 to 113 occupations in NCO 2004 can make the results unreliable. So therefore, the old classification (NCO 1968) was used for all the rounds until the year 2004 and convert the latest version of occupational classification (NCO 2004) into old version for the year 2011. The conversion is performed at 3-digit NCO 2004 to 2-digit NCO 1968 following the concordance table. In this way, 113 occupational codes of NCO 2004 were converted into some 93 occupational codes of the old version. These 2-digit occupation codes combined with 1-digit industry codes are ranked based on the mean earnings of the year 2004 to create the skill percentiles and quintiles for the period 2004 to 2011.

5.2. Regression analysis

Once the skill percentiles and occupation groups are created, the changes in employment share and changes in the wages were looked at for three periods: 1983 to 1993 (Period 1), 1993 to 2004 (Period 2) and 2004 to 2011 (Period 3). Such strategy allows us to see the decadal change in employment with the 1991 trade liberalisation in the middle. One of our objectives is to model the relationship between employment change and occupational skill for three subsequent periods. This relationship can be modelled in various ways, there are multiple

[11] NSSO uses National Industry Classification (NIC) codes to classify the industry and National Classification of Occupation (NCO) to classify the occupations of the respondents. Though three different versions of NIC have been used to classify industries in the three periods used in this study, the same version (NCO 1968) has been used to classify the occupations in all the study years (Table 1). So, while it is convenient to rank the occupations using 3 digit NCO 1968 classification alone, combining NCO and NIC at detailed level will make it difficult to use the same ranking across the years.

[12] Wage data are not available for self-employed workers so the skill level of self-employed occupations using the median daily wage of same occupations in casual wage or regular salaried employment was used as a proxy.

econometric techniques that can be applied. Although the simplest method could be estimating a linear regression equation, it does not capture any potential non-linearity in the relationship between the outcome and the explanatory variables. Therefore, use of non-parametric technique is preferred over the traditional parametric models, because it does not require any assumption about the functional form of the expected value of the dependent variable.

Local polynomial smoothing method is one of the better performing methods for non-parametric analysis than other estimators as it has lowest bias and variance. Mean smoothing and locally weighted scatterplot smoothing (LOWESS) are special cases of polynomial smoothing. Most of the studies have used LOWESS to plot the smooth graph of employment change across skill percentile (Acemoglu and Autor, 2011; Autor and Dorn, 2013). For this analysis, the LOWESS smoothing method was followed.[13]

5.3. Shift-share analysis

In order to decompose the change in employment share into between-industry and within-industry components, shift-share analysis was used following Acemoglu and Autor (2011).

$\Delta E_{jt} = \Delta E_t^B + \Delta E_t^W$ ………………….. (1)

Where, ΔE_{jt} is the total change in employment share in job *j* in time interval *t* and

$$\Delta E_t^B = \sum_k \Delta E_{kt}\, \gamma_{jk} = between\ industry\ change.$$

$$\Delta E_t^W = \sum_k \Delta\, \gamma_{jkt} E_k = within\ industry\ change$$

This analysis will enable us to understand to what extent the changes in employment share in broad occupations and four task-based occupation categories are attributable to changes in industry shift (ΔE_t^B) and to changes in the occupational shift with industry (ΔE_t^W). This decomposition exercise is implemented using ten broad occupational categories based on NCO 68 and 10 broad industry categories based on NIC 98. The results discussed in the next section are presented in Table 3.

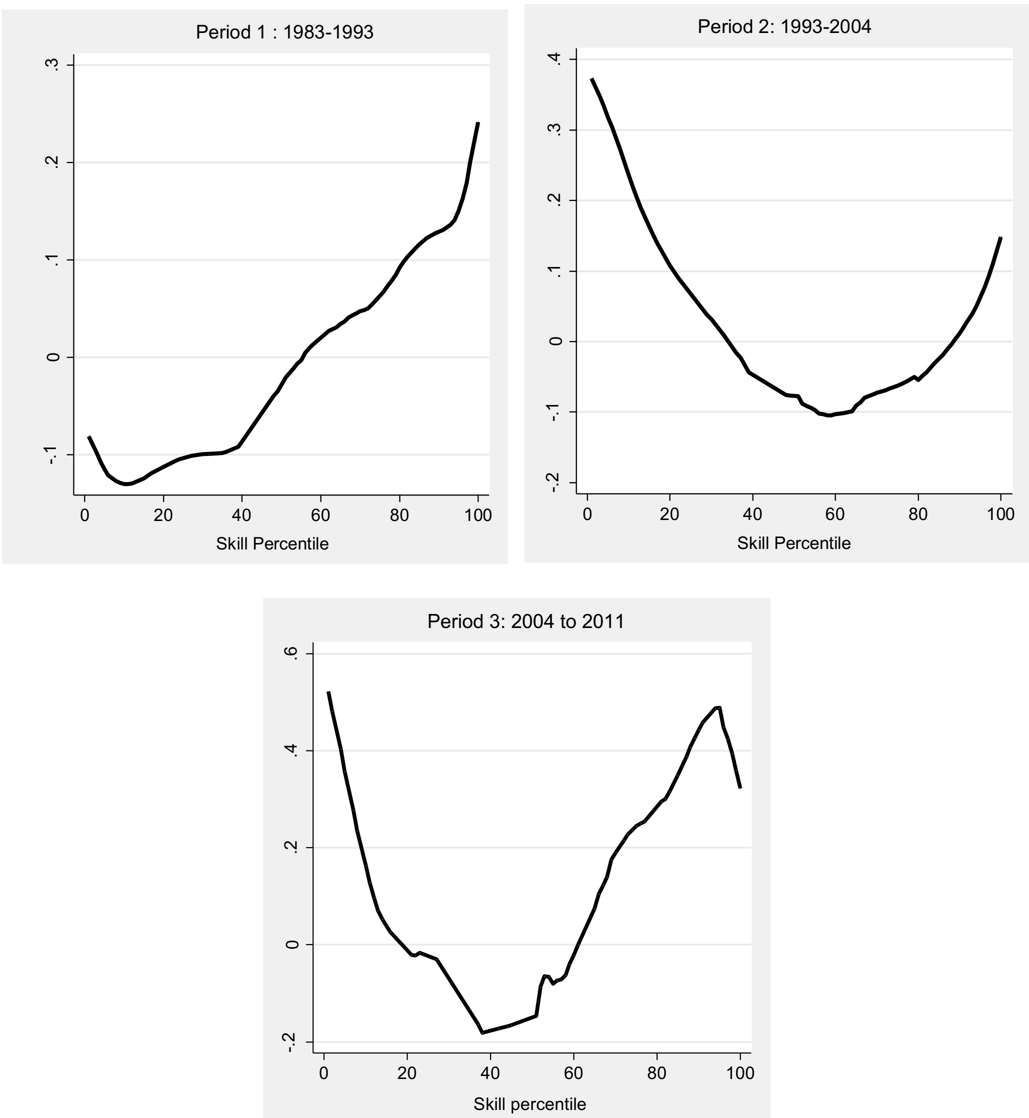
[13] For a detailed discussion on local polynomial smoothing, please refer to the Fan and Gijbels (1996).

6. EMPERICAL RESULTS

6.1. Employment change

Evidence of employment polarisation was found in urban India post-liberalisation. Figure 1 and Figure 2 plot the percentage change in employment share during the three periods by occupational skill percentile and quintiles. As mentioned earlier occupational skill is measured using mean wage of the year 1983 (using 3-digit occupation) and mean wage of the year 2004 (using combination of 2-digit occupation and 1 digit industry). The figures show different pattern in three decades.

Figure 1: Smoothed Changes in Employment Share by Occupational Skill Percentile

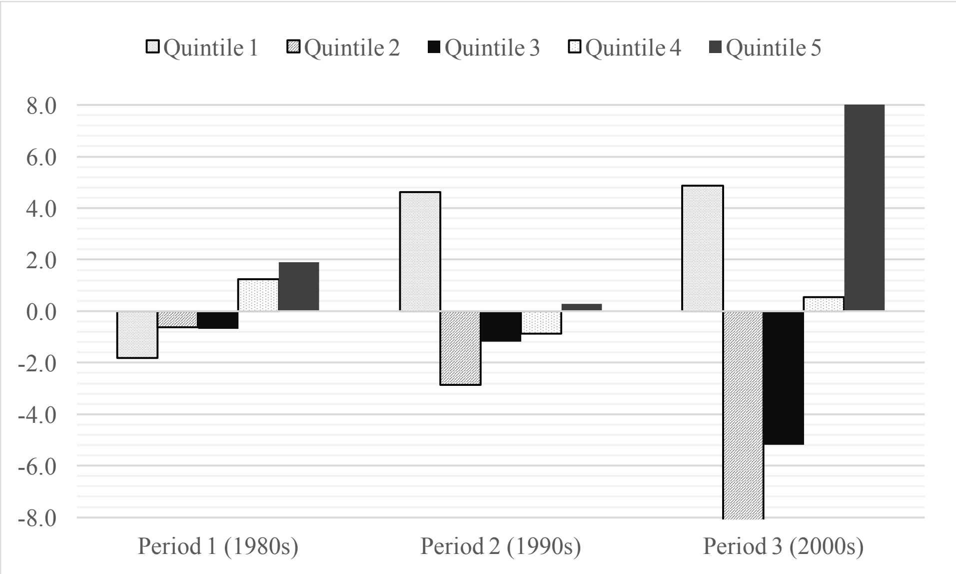


Source: Authors' own calculation using NSS Employment and Unemployment Survey. The sample includes the age group 15 to 65 year who reported as employed in the principal activity status excluding agricultural sector.[14]

[14] Note: Occupational skill percentile is created by dividing 281 occupations into approximately 100 equally weighted groups in 1983 based on the mean earnings of the same year for the period 1983 to 2004. For period 3 (2004 to

Both the figures show an upgrading employment change in the 1980s and a polarised U-shaped employment growth during the 1990s and 2000s. Strong growth is observed in the share of employment in the top quintile in each of the past three decades. Employment shares of the second lowest and middle quintiles decreased in all the three decades. For occupations in the lowest quintile the employment share fell in the 1980s, and rose considerably in the 1990s and 2000s.

Figure 2: Changes in Employment Share (in %) across Occupational Skill Quintiles



Source: Authors' own calculation using NSS Employment and Unemployment Survey. The sample includes the age group 15 to 65 year who reported as employed in the principal activity status excluding agricultural sector.[15]

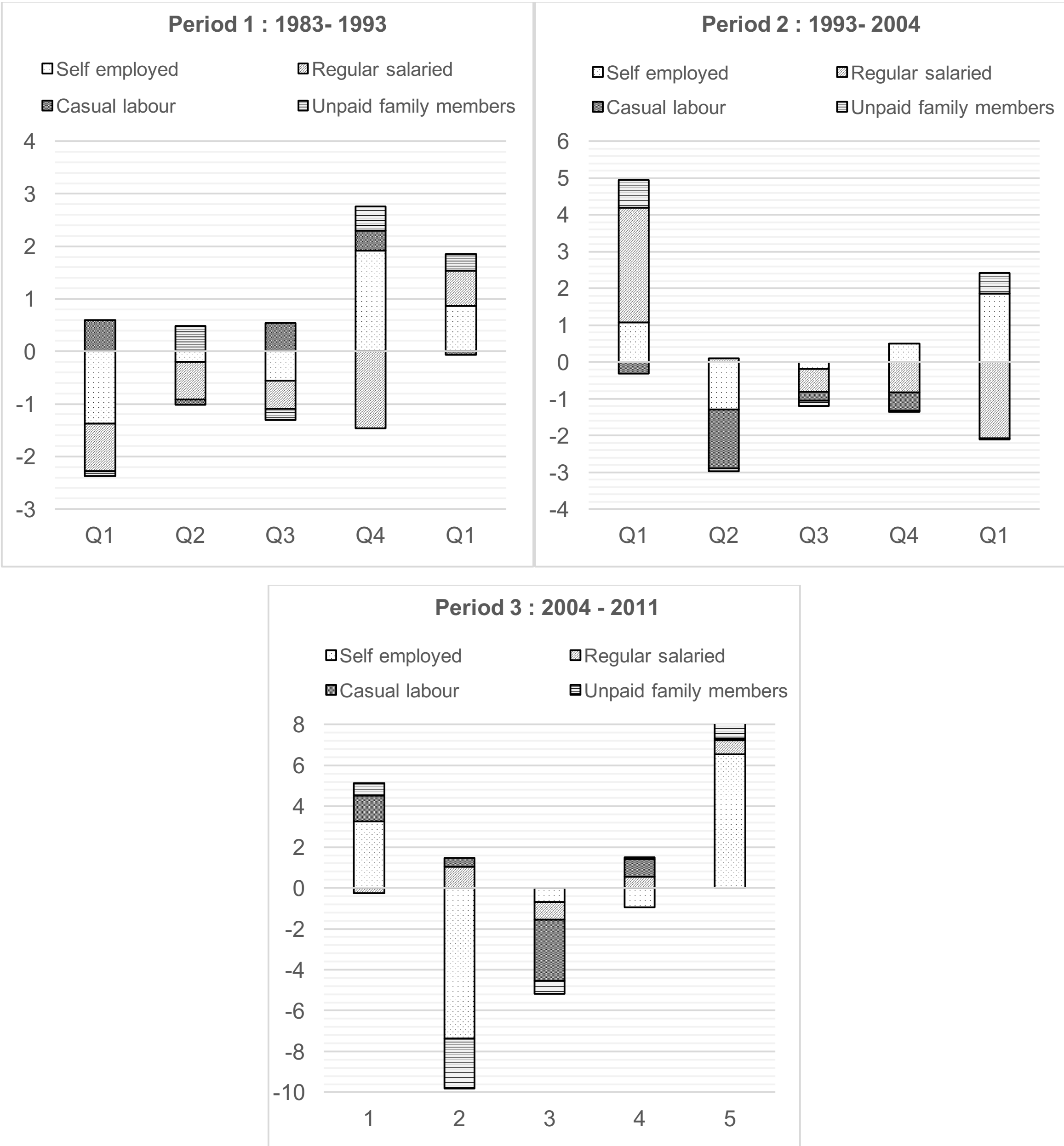
However, a decomposition into self-employed, regular salaried and casual wage earners (Figure 3) reveal that most of the growth in the lowest and the highest quintiles during the 1990s and 2000s is due to the increase in self-employed in both the quintiles in the two extreme poles of the skill distribution. These are the occupations of tailors, dress makers, low skilled sales and shop assistants in the bottom quintiles, and working proprietors and managers in the top quintiles (Table A2). There is evidence in the literature which suggests that micro and small enterprises (MSE) have increased in 2011-12 which might have created managers in the top quintile (Mehrotra et al., 2014). A further decomposition of the changes in employment across the skill quintiles reveal that the sharp increase in employment share in the bottom and

2011), NCO 2004 3 digit occupational codes are matched to NCO 1968 codes at to 2-digit level and then the combination of occupation and broad industry has been grouped into percentile using mean wage of the year 2004.

[15] *Note:* Occupational skill quintile is created by dividing 281 occupations into approximately 20 equally weighted groups in 1983 based on the mean earnings of the same year for the period 1983 to 2004. For period 3 (2004 to 2011), NCO 2004 3 digit occupational codes are matched to NCO 1968 codes at to 2-digit level, and then the combination of occupation and broad industry has been grouped into quintiles using mean wage of the year 2004.

top most quintiles is due to the high growth in employment share in the informal sector (Figure 4).[16]

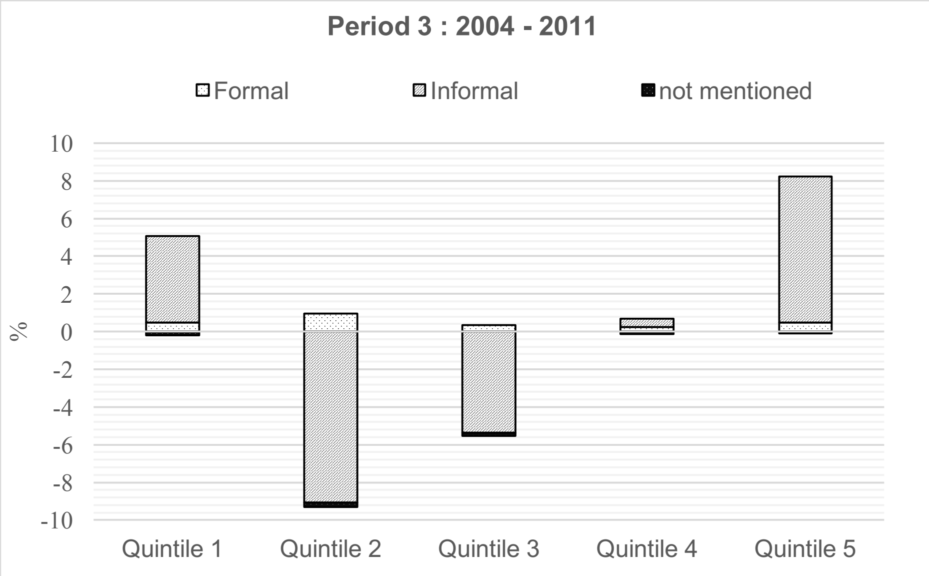
Figure 3: Decomposition of the Changes in Employment Share by Employment Type (in %)



Source: Authors' own calculation using NSS Employment and Unemployment Survey. The sample includes the age group 15 to 65 year who reported as employed in the principal activity status excluding agricultural sector.

[16] NSS has information on formal and informal sector in the rounds surveyed in 1999 and onwards. So the decomposition analysis was only provided for the recent decade, 2004 to 2011.

Figure 4: Decomposition of the Changes in Employment Share by Formal and Informal Sector (in %)



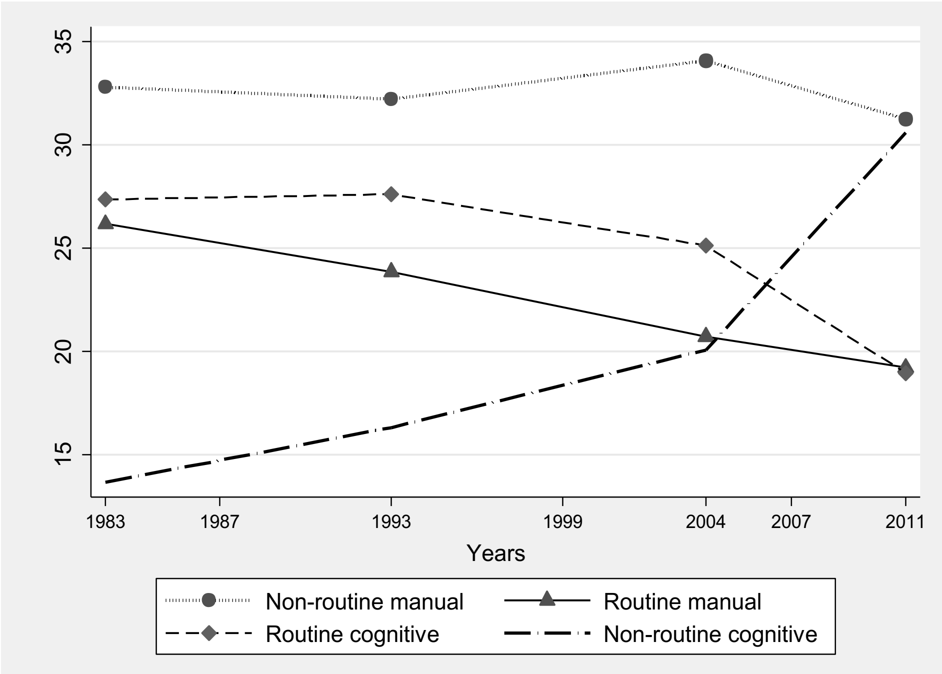
Source: Authors' own calculation using NSSO 61st and 68th round of Employment and Unemployment Survey. The sample includes the age group 15 to 65 year who reported as employed in the principal activity status excluding agricultural sector.[17]

6.2. Employment change by task-based occupations

The earlier section provides evidence of employment upgrading in period 1 and employment polarisation in period 2. In this section, the changes in employment share in urban India were analysed across four task-based occupation categories. The classification of NCO 1-digit occupations into four non-routine and routine task-based categories is presented in the appendix (Table A1). Figure 5 provides the employment share in each of the four categories across the years, 1983 to 2011. Clearly, both the routine categories have experienced decline in their employment share during this period - the employment share in routine manual and routine cognitive occupations has gone down from above 25 per cent in 1983 to below 20 per cent in 2011. On the other hand, the shares of non-routine occupations have shown continuous increasing trend during this period which is particularly strong for non-routine cognitive occupations.

[17] *Note:* NSSO has information on formal and informal sector in rounds 1999 onwards. So it was not possible to present the results for period 1 and period 2.

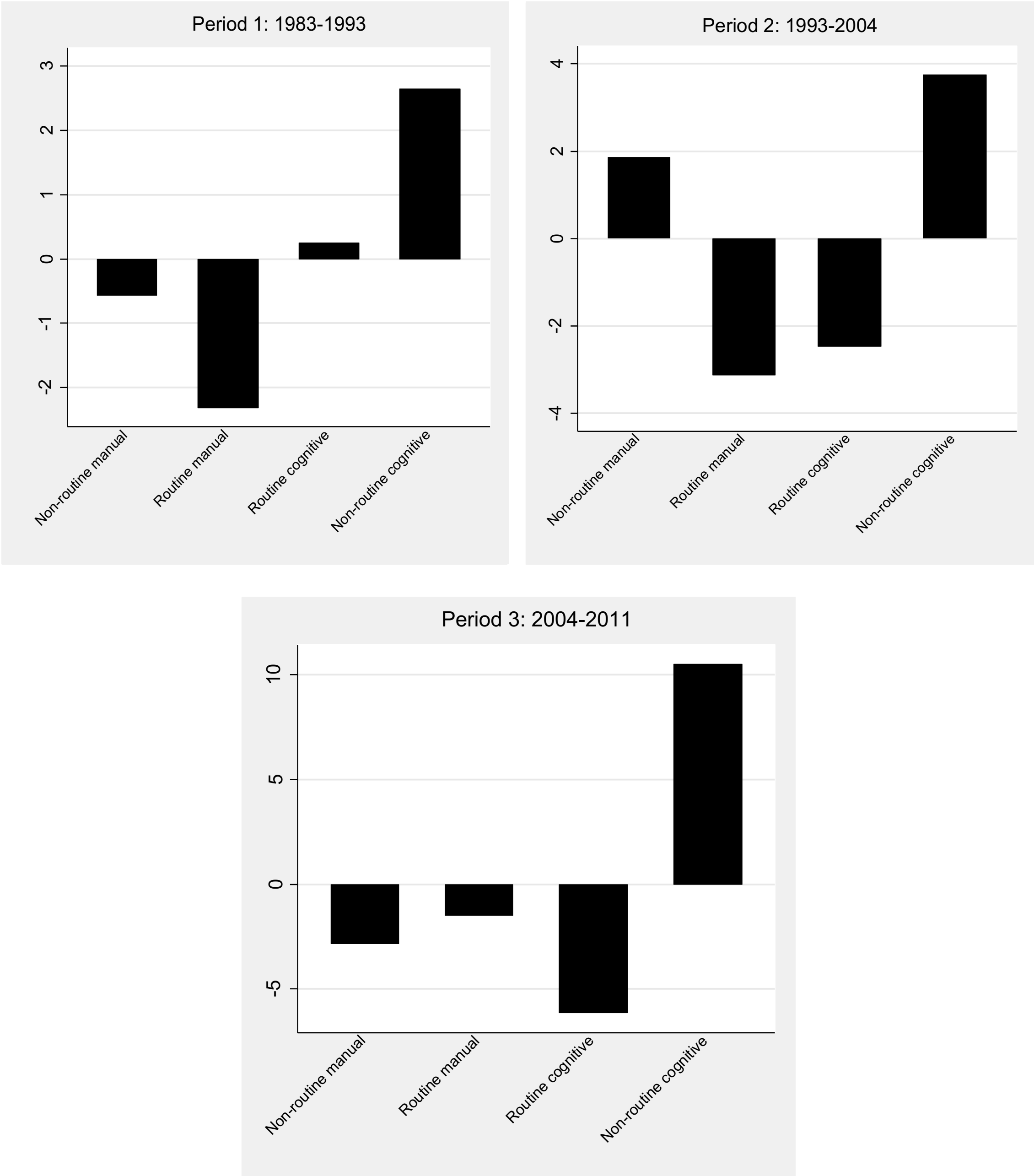
Figure 5: Employment Share in Task-based Occupation Categories across Years (in %)



Source: Authors' own calculation using NSSO 61st and 68th round of Employment and Unemployment Survey. The sample includes the age group 15 to 65 year who reported as employed in the principal activity status excluding agricultural sector.

The changes can be easily seen in the next figure (Figure 6) where the estimated percentage change in employment share for three periods is presented. It gives similar trends of somewhat employment upgrading and strong polarisation for the period 1 and period 2 respectively. The recent period, on the other hand, have experienced reduction in employment share in non-routine manual occupations along with routine occupations. One possible reason why no further increase in non-routine manual occupations was found is because the employment share in non-routine manual occupations has already been quite high at 33 per cent in 2004. It started increasing in 1990s, in the period immediately after trade liberalisation. This can be a result of both economic liberalisation giving a push to demand for low-skilled labour as well as a rural-to-urban migration during this period.

Figure 6: Change by Task-based Occupation Categories



Source: Authors' own calculation using NSSO 61st and 68th round of Employment and Unemployment Survey. The sample includes the age group 15 to 65 year who reported as employed in the principal activity status excluding agricultural sector.

The similarities in observed employment change among the three periods are decreasing share of routine manual jobs and increasing share of non-routine cognitive jobs. Routine manual jobs are mostly concentrated in manufacturing sector (Appendix Table A4). Most of the industries in manufacturing sector have undergone mechanisation in India in the recent past. Mechanisation in manufacturing started in the early 1970s particularly in textile manufacturing. The evidence in the existing literature suggests that there has been employment destruction in manufacturing sector during the 1980s and the 1990s (Jain, 1983; Nagaraj, 2004). While the employment loss in 1980s can be attributable partly to mechanisation (adaptation of power loom etc.), the 1990s employment loss is explained as a result of technological-upgradation and modernisation of industries. Whether the increase and decrease in employment are results of industrial shift or occupational shift is revealed in the next section.

6.3. Sources of employment change – within-industry or between-industry change?

The results of shift-share analysis presented in Table 3 suggest that all the increase and decrease in these four task-based occupation categories are the results of occupational shift within-industry employment change in all the periods; the only exception is the decrease in routine manual occupation share in the first period which is largely attributed to the industrial change.

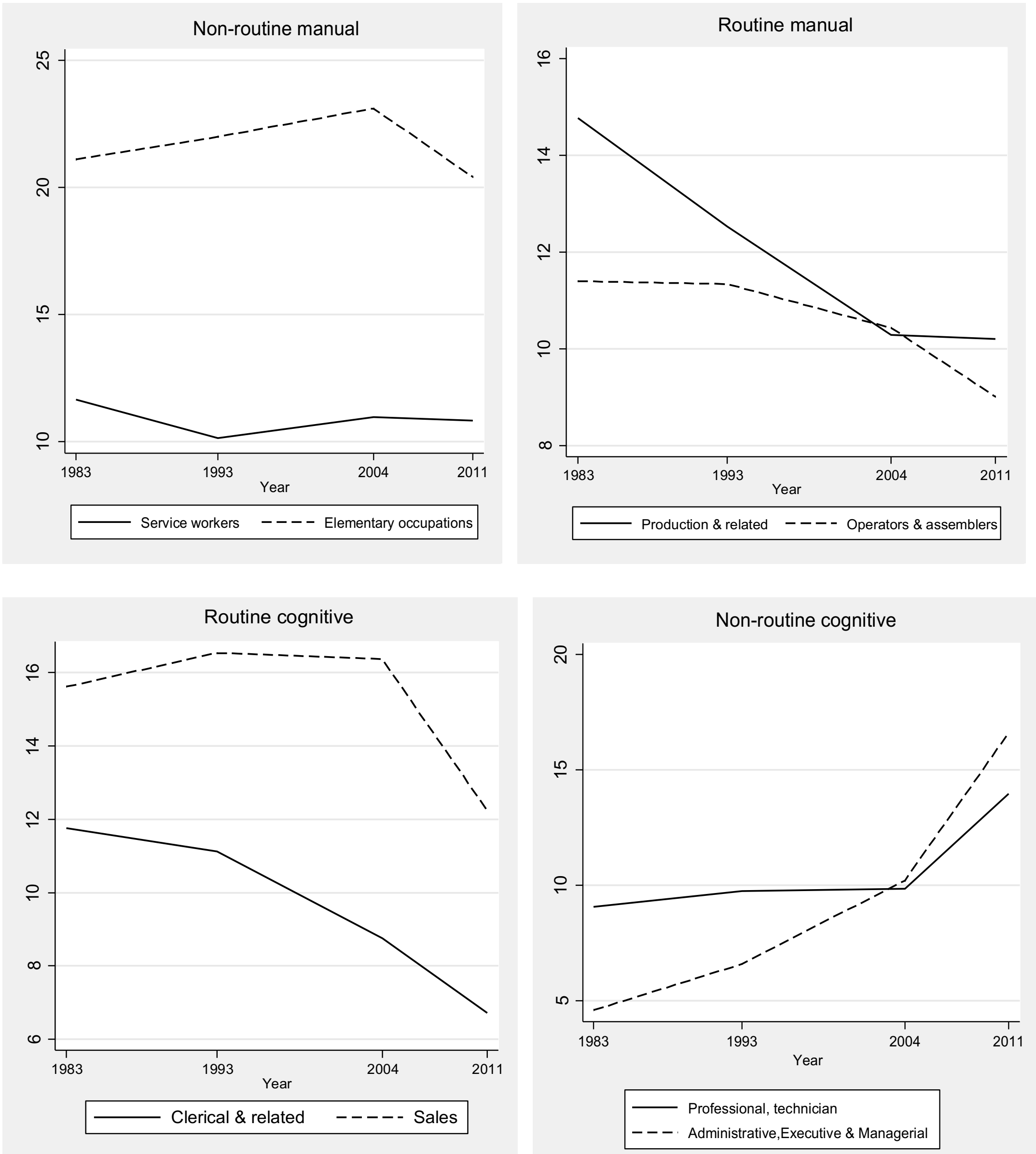
Table 3: Shift-share Analysis

Categories	Period 1 (1983-1993)	Period 2 (1993-2004)	Period 3 (2004-2011)
Non-routine manual			
Total change	-0.63	1.94	-2.82
Industry change	2.30	0.05	2.62
Occupational change	-2.93	1.89	-5.44
Routine manual			
Total change	-2.31	-3.14	-1.51
Industry change	-2.19	-0.75	-0.52
Occupational change	-0.12	-2.40	-0.99
Routine cognitive			
Total change	0.28	-2.53	-6.17
Industry change	0.29	2.24	-1.94
Occupational change	-0.01	-4.77	-4.22
Non-routine cognitive			
Total change	2.66	3.74	10.50
Industry change	-0.40	-1.54	-0.15
Occupational change	3.06	5.27	10.65

Source: Authors' own calculation using NSS Employment and Unemployment Survey. The sample includes the age group 15 to 65 year who reported as employed in the principal activity status excluding agricultural sector.

As discussed in earlier section, routine manual occupations are mainly concentrated in the manufacturing industry. Production and related workers in manufacturing sector has experienced a sharp decrease in employment share until 2004 while employment in operative occupation has remained almost stable over the years (Figure 7). This finding is consistent with the literature which suggests that there was huge employment destruction in manufacturing because of mechanisation particularly in textile and clothing in India during 1980s (Jain, 1983).[18] Workers in weaving and knitting jobs lost their employment once the power loom took over in 1974. It is also worth noting that the reduction in routine cognitive category is mainly due to the reduction in clerical occupation which has experienced a sharp decline after 1993 and has reduced from around 11 per cent to 7 per cent in 2011.

Figure 7: Employment Share in 1 digit Occupations under Each Task-based Categories (in %)



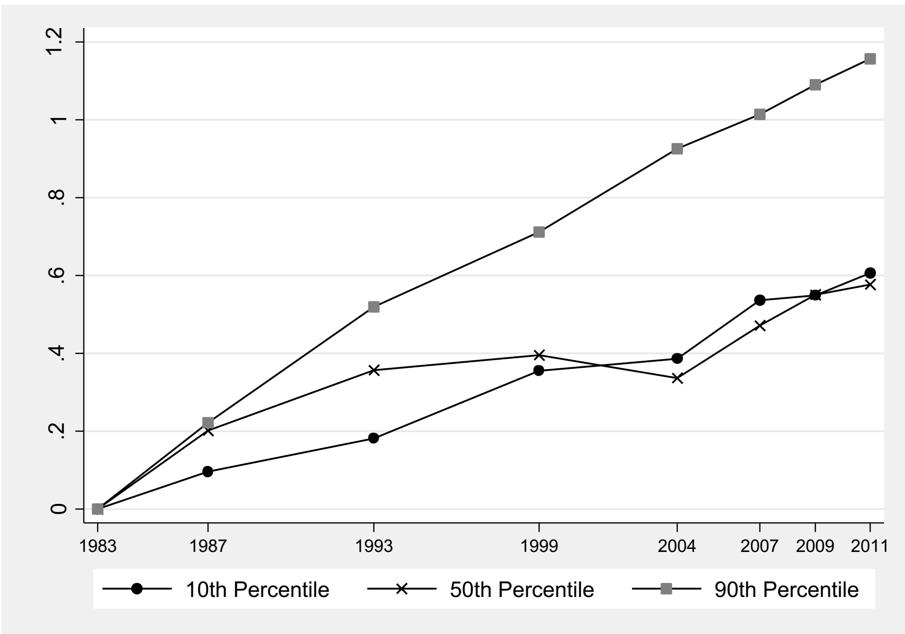
Source: Authors' own calculation using NSS Employment and Unemployment Survey. The sample includes the age group 15 to 65 year who reported as employed in the principal activity status excluding agricultural sector.

[18] A power loom is a mechanised loom powered by a line shaft, and was first introduced in the industrialisation of weaving during the early 1970s. As written by Jain (1983), "the resultant loss of employment in weavers' household is unimaginable" and the real number of affected persons as estimated by him is 5.5 million men and women in 1980s.

6.4. Wage change

Employment and wage changes are the observable effects of labour market polarisation. To understand overall wage inequality trends analysis began by looking at the changes in daily wage of urban salaried and casual wage earners at 10th, 50th and 90th percentile. Figure 8 plots the log real daily wages of both male and female working for at least 5 days a week at these three percentiles of wage distribution during 1983 to 2011. The wages for these three groups are all normalised to 0 in 1983; it therefore gives the change in real daily wage in the respective percentile from the year 1983. The figure shows that the real daily wages for the highest (90th) and the lowest (10th) groups show sharp and monotonic rise during this period while the median (50th) wage group shows a decline in real daily wage after 1999. Moreover, the increase in median wage was lower than the 10th percentile in 2004 and it continues to be so until 2011. So, the increase in the inequality between 1983 and 2004 has been mainly due to the increasing divergence between the wealthy and the middle class as shown in the figure. The findings are consistent with that of Azam (2012), Kijima (2005) and also consistent with the SS theorem, which predicts increasing return to unskilled labour which is measured by the wage of 10th percentile in this figure.

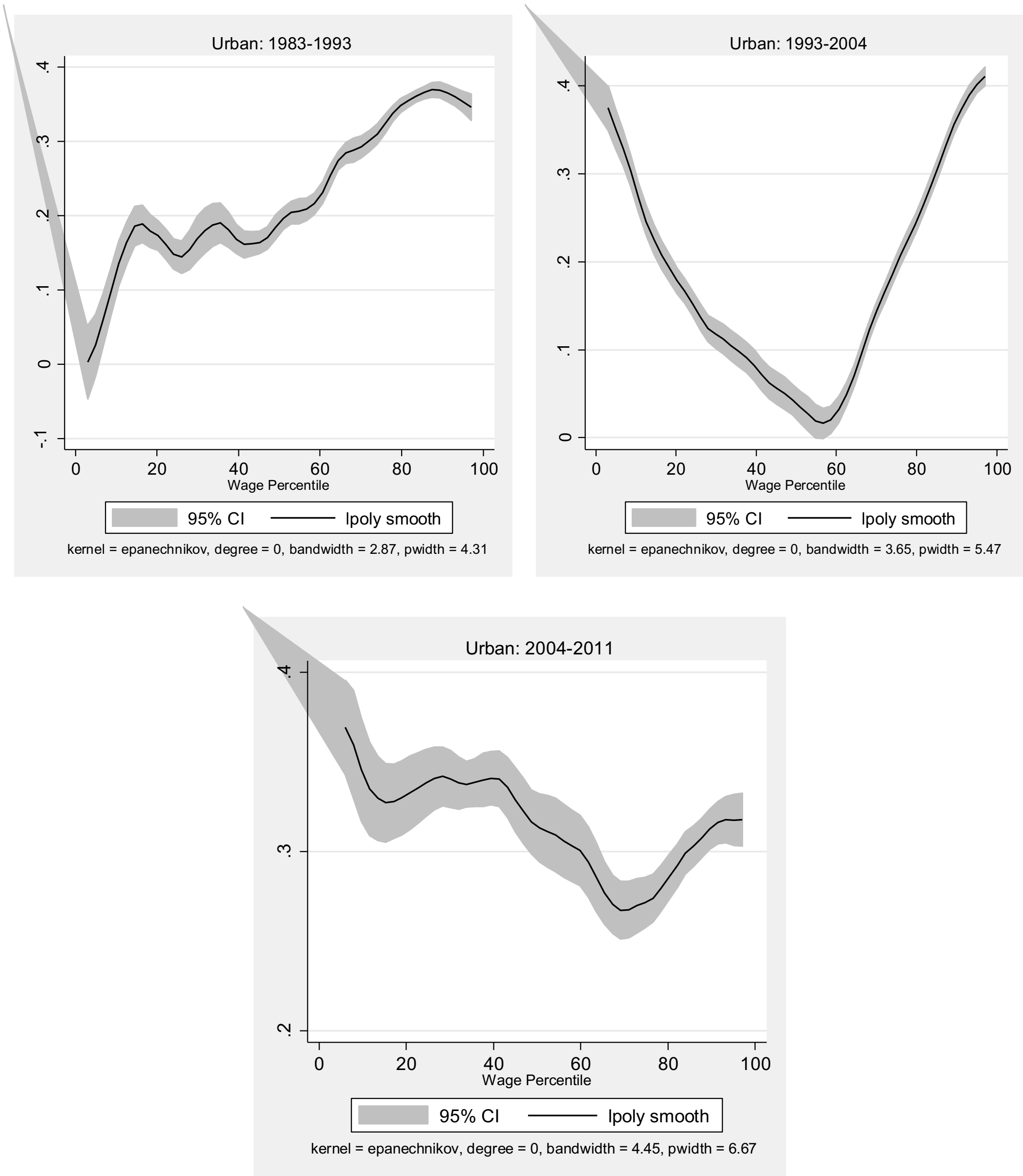
Figure 8: Normalised Real Daily Wage for Urban Male and Female- 1983 to 2011 (in Rs.)



Source: Authors' own calculation using NSS Employment and Unemployment Survey. [19]

[19] *Note:* This figure is obtained by computing the real daily wage for each year at the 10th, median and 90th percentiles of the wage distribution. The sample includes male and female working for at least 5 days a week. The real daily wages are computed using CPI for industrial workers at base year 1982.

Figure 9: Changes in Log Real Daily Wages by Wage Percentile for Urban Workers - 1983 to 2011



Source: Authors' own calculation using NSS Employment and Unemployment Survey.

In order to know if the wage gap is limited only to comparisons of the highest, medium and least skilled workers, Figure 9 also plots the log real wage changes between the three periods (1983-93, 1993-2004 and 2004-11) across the wage percentile. The figure shows that real daily wage increased monotonically from lowest to highest percentile of wage during the first decade. As noted in earlier figure, the monotonic growth in real daily wage in the 1980s is notably non-monotonic during the subsequent two decades. Consistent with the employment change, the real daily wage increased more in the bottom and top compared to the middle of the wage distribution creating a perfect U-shaped polarised growth in the second decade. The recent period, in contrast, has experienced an asymmetric polarised wage growth - highest growth in the bottom tail, somewhat less growth in the top tail and lowest growth in the middle of the wage distribution.

If the wage change is induced by changes in the demand for workers by occupation, there may be a positive co-variation. For instance, it might be the case that increased demand for high skill workers may raise wages in high skill occupations. This is explored in Table 4 by providing the changes in average earnings across the task-based occupational groups as well as the skill quintiles. The figures in both the upper and lower panels reveal that earnings growth has been highest in the high-skill and non-routine cognitive occupations over the three periods. This should lead to overall earnings inequality. The increase in average earnings in the top quintile as well as in the non-routine cognitive occupations has been doubled in period 2 (the 1990s) while comparing with the earlier decade. However, earnings growth is quite similar (lower) in the top quintile (non-routine cognitive jobs) during the 2000s and in the 1990s. Not only that, the lowest quintile has also experienced relatively higher earnings growth compared to the middle quintiles during the 1990s and the 2000s.

Table 4: Changes in Real Daily Wages across Occupational Categories

Categories	Change in mean real daily wage		
	Period 1	Period 2	Period 3
By task-based occupational groups			
Non-routine manual	3.1	2.9	8.6
Routine manual	4.7	2.2	6.2
Routine cognitive	8.3	7.7	8.8
Non-routine cognitive	13.4	25.5	17.1
By occupational quintiles			
Quintile 1	2.3	3.6	6.5
Quintile 2	2.6	1.8	7.1
Quintile 3	4.1	1.9	6.3
Quintile 4	5.7	7.2	13.4
Quintile 5	12.5	23.5	29.0

Source: Authors' own calculation using NSS Employment and Unemployment Survey.

7. CONCLUSION

There has been considerable interest globally in how technological change has affected employment in different occupations. This article analyses employment change and wage change trends in urban India for the last three decades covering 1983 to 2011-12. This period also allows us to see the changes for the decade before and after economic liberalisation in India. Many industrialised countries have exhibited employment change pattern consistent with job polarisation (the UK, USA, Australia and some European countries). The focus now has shifted to the developing countries. Recent research on some developing and transition countries has provided evidence of job polarising pattern in countries such as Colombia, Mexico, and Ukraine (Medina and Posso, 2010; Kupets, 2016). This manuscript adds to this evidence to show that urban India has also experienced job polarisation.

During the 1990s and the 2000s employment as well as wage has increased more in the lower and upper tails compared to the middle of the skill and wage distribution. Both routine manual and routine cognitive jobs have reduced their employment share which seems to be consistent with the task biased technological change hypothesis. However, our results suggest that routine manual jobs started shrinking its employment share during the 1980s. This might be the consequence of mechanisation in the manufacturing industry which replaced huge amount of manual labour during this period as evident in the literature. However, the large decline in employment shares in both clerical and sales occupations may be an indication that computerisation has started replacing some routine tasks in urban India, particularly in last few years.

Finally, high-paid occupations corresponding to the abstract reasoning, creative, and problem-solving tasks performed by professionals, managers, administrative officers and some technical occupations have been expanding during all the three periods; the increase is much higher during the 2000s. However, this does not necessarily imply an increase in quality employment in India during this period. Our analysis reveals that the high increase in low- and high-skill jobs has mainly been in the informal sector and very little growth has occurred in the formal sector. Self-employment in wholesale and retail trade industry has increased employment in low-skill sales jobs and high-skill managerial jobs in micro and small enterprises.

It was further found that earnings change during this period is consistent with the employment change pattern. Employment expansion in both low-skill and high-skill jobs appears to be one of the contributing factors in increasing earnings inequality in urban India. Therefore, the structural employment change across occupational skill distribution remains an important factor for understanding earnings inequality in India.

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APPENDIX

Table A1: Classification of Task-based Occupation Categories

Task-based categories	Broad NCO 1968	Specific tasks
Non-routine manual		
	5-Service Workers 9-Elementary Occupations	Non-methodical, flexible use of brain, eyes, hands and legs
Routine manual		
	7-Production and related workers, transport workers 8-Plant and Machine Operators and Assemblers	Repetitive works which involve systematic physical movement, use of fingers and hands
Routine cognitive		
	3- Clerical and related 4-Sales workers	Calculating, bookkeeping, correcting texts/data, and measuring following a well-defined method
Non-routine cognitive		
	0-1- Professional, technical and related 2-Administrative, executive and managerial	Analysing, interpreting, thinking creatively, guiding, directing, establishing relationship

Note: For a more detailed understanding of job-tasks refer to Acemoglu and Autor (2011) and Fernandez-Macias and Hurley (2016)

Table A2: Largest Decrease and Increase in Employment Share in Jobs (in %)

Industry	Occupation	Quintile	Change in % share
Loss in employment share			
Period 1 (1983- 1993)			
Textile manufacturing	Tailors and dress makers	1	-1.7
Other service	Sweepers, cleaners and related workers	2	-0.5
Manufacture of tobacco product	Bidi makers	1	-0.4
Period 2 (1993-2004)			
Manufacturing	Labourers	2	-1.1
Wholesale & Retail Trade	Merchants and shop keepers	2	-1.0
Other service	Labourers	2	-1.0
Period 3 (2004-2011)			
Transport	Transport Equipment Operators	4	-2.2
Manufacturing	Production and Related Workers	3	-1.3
Manufacturing	Spinners, Weavers, Knitting, and Related Workers	2	-1.3
Increase in employment share			
Period 1 (1983- 1993)			
Construction	Labourers	1	1.4
Manufacturing	Working Proprietors, Directors and Managers	5	0.5
Service	Working Proprietors, Directors and Managers	5	0.4
Period 2 (1993-2004)			
Textile manufacturing	Tailors and dress makers	1	1.8
Wholesale & Retail Trade	Salesmen, Shop Assistants and Demonstrators	2	1.1
Service	Working Proprietors, Directors and Managers	5	1.0
Period 3 (2004-2011)			
Wholesale & Retail Trade	Working Proprietors, Director & managers	5	5.1
Wholesale & Retail Trade	Salesmen, Shop assistants, & Related Workers	1	4.1
Manufacturing	Material Handling & Related Equipment Operators	2	2.9

Source: Authors' own calculation using NSS Employment and Unemployment Survey. The sample includes the age group 15 to 65 year who reported as employed in the principal activity status excluding agricultural sector.

Table A3: Employment share in each of the skill quintiles by gender, caste, employment type, industry sector and level of education

Components	Quintile 1		Quintile 2		Quintile 3		Quintile 4		Quintile 5	
	1983	2011	1983	2011	1983	2011	1983	2011	1983	2011
Gender										
Male	72.3	77.6	85.8	76.5	93.8	92.2	95.3	79.8	85.0	87.3
Female	27.7	22.4	14.2	23.5	6.3	7.8	4.7	20.2	15.1	12.7
Average age (in year)	33.3	36.4	33.9	34.8	33.9	36.5	34.8	37.7	36.7	40.0
Caste										
Sc/St	17.2	21.7	20.8	16.3	18.2	22.3	13.5	20.3	7.9	11.4
Others	82.8	78.3	79.2	83.8	81.8	77.7	86.5	79.7	92.1	88.6
Employment type										
Self-employed	41.6	34.2	41.6	22.0	27.2	29.6	17.5	21.0	14.9	47.1
Regular salaried	25.4	32.6	32.0	51.4	45.8	37.8	71.9	67.7	81.3	43.1
Casual labour	22.7	23.1	15.9	17.6	19.9	27.7	8.0	8.5	0.9	0.7
Unpaid family worker	10.3	10.2	10.5	9.0	7.1	4.9	2.7	2.9	3.0	9.0
Industry sector										
Manufacturing and Mining Quarrying	33.3	7.1	30.7	85.5	44.6	35.6	34.7	15.1	18.4	21.9
Construction	10.2	22.1	0.3	0.0	12.9	23.1	2.0	8.3	2.8	0.9
Service	56.5	70.8	69.0	14.5	42.5	41.3	63.3	76.6	78.8	77.2
Level of education										
Below primary	54.5	31.5	48.6	29.3	44.3	29.2	24.4	13.1	5.1	8.4
Primary completed	34.4	34.7	35.4	42.5	39.8	34.6	40.5	24.2	14.9	16.8
Secondary completed	9.7	15.9	12.4	16.9	13.4	20.3	28.2	20.4	41.2	18.3
Tertiary or above completed	1.5	17.9	3.7	11.2	2.4	15.8	6.9	42.3	38.9	56.6
Number of jobs.	**11,105**	**12,386**	**13,276**	**12,102**	**6,386**	**10,480**	**10,354**	**11,673**	**11,263**	**11,249**

Source: Authors' own calculation using NSS Employment and Unemployment Survey. The sample includes the age group 15 to 65 year who reported as employed in the principal activity status excluding agricultural sector.

Table A4: Employment share in each of the task-based occupation categories by gender, caste, employment type, industry sector & level of education

Components	Non-routine manual		Routine manual		Routine cognitive		Non-routine cognitive	
	1983	2011	1983	2011	1983	2011	1983	2011
Gender								
Male	82.2	82.9	85.1	82.5	91.3	87.6	80.2	79.8
Female	17.9	17.1	14.9	17.5	8.7	12.4	19.8	20.2
Average age (in year)	34.0	37.4	34.4	38.2	34.6	38.3	35.7	38.4
Caste								
Sc/St	26.2	27.5	15.1	16.3	8.2	13.9	8.0	10.8
Others	73.8	72.5	84.9	83.7	91.8	86.1	92.0	89.3
Employment type								
Self-employed	25.0	18.7	27.4	28.7	37.3	32.1	30.9	48.1
Regular salaried	43.6	51.2	44.4	43.6	50.6	55.2	62.3	42.5
Casual labour	26.7	27.7	20.2	18.2	2.7	2.8	1.0	0.4
Unpaid family worker	4.8	2.5	8.1	9.6	9.4	9.9	5.8	8.9
Industry sector								
Manufacturing and Mining Quarrying	18.0	17.9	80.8	68.6	8.1	6.9	19.0	18.2
Construction	14.1	20.5	1.3	12.9	0.5	0.8	4.0	3.8
Service	67.5	61.3	17.8	18.4	91.0	92.2	76.7	77.5
Level of education								
Below primary	55.9	33.4	44.2	27.8	20.0	9.7	9.3	7.5
Primary completed	33.4	37.6	39.2	39.4	32.6	20.0	17.0	15.2
Secondary completed	9.4	23.6	15.1	19.9	31.0	37.4	35.7	29.4
Tertiary or above completed	1.4	5.4	1.6	12.9	16.5	32.9	38.1	47.9
Number of jobs	16,716	16,130	13,283	8,739	15,956	10,839	7,847	16,394

Source: Authors' own calculation using NSS Employment and Unemployment Survey. The sample includes the age group 15 to 65 year who reported as employed in the principal activity status excluding agricultural sector.