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Structural changes in the employment structure of India in 2012-2020: job upgrading or polarization?

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Structural Changes in the Employment Structure of India in 2012-2020: Job upgrading or polarisation?

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Abstract

This paper analyses employment growth across occupations and sectors in India for the period that goes from 2011-12 to 2019-20. Using data from the National Sample Survey Organisation and the Periodic Labour Force Survey, this study finds evidence of mid-upgrading (relatively higher employment growth in low-mid paid and high-paid jobs) in India during the study period, where jobs are ranked using median daily wages in 2011-12. A decomposition analysis reveals that this pattern is due to the employment growth in jobs in construction, wholesale & retail trade, and transport, storage and communication industries in India. The study also finds a reduction in the employment share of routine task intensive occupations along with a growth in employment in non-routine task intensive occupations (both manual and cognitive) in both rural and urban India.

Keywords: employment change; job polarization; technological change; India

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Related publications and reports:

Torrejón Pérez, S., Hurley, J., Fernández-Macías, E., Staffa E., Employment shifts in Europe from 1997 to 2021: from job upgrading to polarisation, JRC Working Papers on Labour, Education and Technology, European Commission, Seville, 2023, JRC132678.

Rodrigues-Silveira, R, Structural Changes in Brazilian Employment (2002-2021), JRC Working Papers on Labour, Education and Technology 2023/01, European Commission, Seville, 2023, JRC132269.

Gimpelson, V. and Kapeliushnikov, R. (2023), Shifts in the Composition of Jobs: The Case of Russia (2000-2019), JRC Working Papers on Labour, Education and Technology 2023/03, European Commission, Seville, 2023, JRC132708.

Hong, M, Structural Changes in South Korea Employment (2000–2021), JRC Working Papers on Labour, Education and Technology 2023/02, European Commission, Seville, 2023, JRC132566.

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Contents

Executive summary

- From 2012 to 2020, employment growth in India exhibited a pattern closer to mid-upgrading (i.e., employment growth biased towards low-mid and high paid jobs) when jobs are ranked and arranged based on their median daily wages. The higher the wages, the higher employment growth, with a notable exception that breaks that potential monotonic relationship: employment growth in quintile 2 was the fastest during the period analysed.

- Patterns of employment change are also analysed separately for rural and urban India. While in rural India the pattern is similar to the one experienced in India as a whole (*mid-upgrading*), in urban India there has been middling, as opposed to job polarisation (an inverted 'U' shape). This implies that there were net employment gains in intermediate quintiles (quintile 2, 3 and 4), while employment in low and high-paid jobs decreased.

- The patterns described above result from the decline in agricultural subsistence jobs, that are mostly routine manual in nature, and from the expansion of jobs in construction and in services such as wholesale and retail trade and transport, storage and communications. Moreover, the increase in employment share towards the high-paid jobs can also be partly attributed to an increased supply of educated workers in India and an increase in managerial jobs. However, these jobs may not be automatically termed as good jobs with decent quality as some of them might be in the informal sector. We have not explored the informality aspects of the jobs in this article.

- Males in India have experienced net employment losses, that are highly concentrated in quintile 1. In the meantime, women have experienced net employment gains, with fastest female employment growth in quintiles 2 and 5.

- Results on employment trends by job-wage quintile are complemented with a task-based analysis, consisting on characterising different groups of jobs by the type of activities that are required to be performed in those positions. Both routine manual and routine cognitive jobs have reduced their employment share, which seems to be consistent with the Routine-Biased Technological Change (RBTC) hypothesis. On the other hand, non-routine task intensive jobs (both manual and cognitive) have been growing in the recent years. These trends are visible in both rural and urban India.

- Despite differences regarding economic specialisation and the degree of development, institutional settings and many other factors, employment change patterns in India are somehow aligned with those identified in many other developing and developed countries, with job upgrading patterns prevailing over the latest decades also in many European countries (Torrejón et al. 2023; Oesch and Piccito, 2019), Russia (Gimpelson and Kapeliushnikov, 2023), Brazil (Rodrigues-Silveira, 2023), Canada (Willcox and Feor, forthcoming), and Argentina, Chile and Mexico (Maurizio et al., forthcoming), among others.

1 Introduction

The rapid structural change in the occupation and industry sector has been a central focus of labour market research in many developed countries. A significant body of research talks about the expansion and contraction of employment by industry and occupations particularly in the 1980s and 1990s in the USA and Europe (Wright and Dwyer, 2003; Goos and Manning, 2007; Autor, 2010; Acemoglu and Autor, 2011; Oesch and Rodriguez-Menes, 2011; Fernandez-Macias, 2012). Several studies document the pattern of employment growth for different occupations defined by their job quality, where quality is defined by the average or median wage of the occupation or the actual skill level (Wright and Dwyer, 2003; Goos, Manning and Salomons, 2009; Fernandez-Macias, 2012).

These patterns vary across countries depending on the differences in institutions, demographic characteristics and the time period of the study. Though the nuances vary across countries and time periods, in the United States and Europe a pattern of asymmetric polarization received special attention for a long time. This has been marked by a strong employment growth in high-skilled/high-paid jobs/occupations alongside moderate growth at the bottom-level jobs and weak growth in the middle-level jobs. This U-shaped pattern of employment change is termed as ‘job polarization’ by labour economists and other social scientists. In other European countries, researchers have argued that polarization is just one pattern among at least three different types – polarization (a U-shaped pattern), upgrading (a monotonically upward rising pattern) and mid-upgrading (an inverted U-shaped pattern) (Oesch and Rodriguez-Menes 2011, Fernandez-Macias 2012; Torrejón et al. 2023).

Such a structural change can partially be attributed to Skill-Biased Technological Change (SBTC) and Routine-Biased Technical Change (RBTC), globalisation and increasing supply of educated workers coupled with rising immigration to the developed world (Fernandez-Macias and Hurley, 2017; Goos, Manning and Salomons, 2009). According to the theory of SBTC, technology complements high skilled jobs (managers, professionals and technicians) consequently raising the demand for high-skilled workers. On the other hand, RBTC explains that technology has more to do with job tasks and less with the skills of the workers: it complements non-routine cognitive jobs (performed by high-skilled workers) while emulating the more routine, codifiable jobs (clerks, office assistants, book keepers etc.). Technology cannot replace some lowest-paying jobs (hairdressers, restaurant services and sales jobs) which are non-routine in nature and require flexible use of brain, eyes, hands and legs and therefore hard to be emulated (Acemoglu and Autor, 2011 Goos and Manning, 2007). According to RBTC hypothesis, these jobs should grow in terms of their labour share.

Keller and Utar (2015) find evidence that trade liberalization leading to import competition has led to the decline in the middle-skilled routine jobs in Denmark by shifting these to China’s manufacturing sector. This is partly because jobs that can be broken down into simple, routine tasks (that are often located in the middle of the wage structure) are easier to offshore (Blinder, 2009; Blinder et al. 2013). Immigration has also been cited at least in the case of Europe and the US as an important factor behind polarization, as the immigrants largely supply low-skilled labour, thus raising the employment share of low-skilled, low-paid jobs (Wright and Dwyer, 2003; Oesch and Rodriguez-Menes, 2011).

However, similar research studying the labour markets of developing countries has been modest. The SBTC and RBTC have been perceived largely as a phenomenon of middle income and OECD countries. The slim literature on developing countries suggests the presence of SBTC in the Indian economy (more precisely, in the manufacturing sector) during the 1990s (Berman, Somanathan and Tan, 2003; World Bank, 2016) and in other developing countries post the opening up of world economy. The 2016 World Development Report “Digital Dividends” shows that the labour market is hollowing out in the middle of the wage distribution in developing countries such as India, due to technological changes (World Bank, 2016). This literature, however, falls short in providing a detailed analysis of Indian labour market as it focuses on more than 30 developing countries across the world.

In this context, the key contribution of this study is to provide evidence to the slim literature on changes in the employment structure in the case of India, using recent labour force survey data from the year 2011-12 to 2019-20. Using detailed data on labour market activities from the Employment-Unemployment Survey and Periodic Labour Force Survey (PLFS) for the years 2011-12 and 2019-20, this study tries to investigate the patterns of employment change for both, India as a whole, and separately for rural and urban India.

We follow two methods to group jobs. The first method requires to define the jobs as combinations of occupations and sectors, and once this is done to rank them using the median daily wages of the job in the year 2012. In total, there are 226 jobs that we rank using the median daily wages in the initial year and then group them into 5 equally weighted quintiles[1]. The second method is a task-based grouping of occupations into four groups: non-routine manual, routine manual, routine cognitive, and non-routine cognitive.

Our main findings suggest that employment growth in India exhibits a pattern closer to mid-upgrading (i.e., employment growth biased towards mid-low and high-paid jobs) when jobs are ranked and arranged based on their median earnings. While investigating the patterns separately for rural and urban India, then we identify mid-upgrading in rural India, and middling (as opposed to job polarization, that is, an 'U' inverted shape) in urban India.

In addition, as revealed by the task-based analysis, in both rural and urban India routine manual and routine cognitive jobs have reduced their employment share, which seems to be consistent with the RBTC hypothesis. In the meantime, non-routine task intensive jobs (both manual and cognitive) have been growing in the recent years in both rural and urban India.

The rest of the paper is organised as follows. Next section presents a review of relevant literature on the topic focused on the case of India. In section 3 we present the data and section 4 discusses the methodology used for the analysis. We describe our results in Section 5 and conclude in section 6.

2 Literature on occupational change in India

In recent times, few studies have analysed the structural change in employment in the Indian labour market and have investigated its role in explaining earnings inequality in India. The first paper that has analysed job polarization in India is Sarkar (2019). The study has analysed nationally representative data from the year 1983 to 2011-12 and found evidences of job upgrading in the 1980s, and evidences of job polarization in urban India during the 1990s and 2000s.

By combining O-Net data with NSS EUS data, Vashisht and Dubey (2018) find that, similar to the global patterns, the non-routine cognitive (both analytical and interactive) task intensity of jobs has increased in India, while manual task intensity has declined, what is consistent with job polarization.

These studies also raise some questions about the origin and nature of polarisation observed in India (Sarkar, 2019; Vashisht and Dubey, 2018). They argue that, unlike in the US and Europe, the nature and origin of the change in employment patterns cannot be entirely attributed to automation in India. Both studies observe that the routine cognitive task content has not declined much in India in the last few decades, as expected by the RBTC. In addition, the decline in routine manual occupations has been partly driven by mechanisation. All this suggest that India is still less technologically developed, and that more advanced digital technologies (such as industrial robots, or ICT technologies) have a lower penetration in India. Sarkar (2019) also indicates that the increased relative demand for high and low-skill jobs registered during the 1990s and the 2000s was also due to

[1] Quintiles are supposed to have a similar size, with each of them containing about 20% of total employment. However, given that there are some jobs that after being ranked are located close to the boundaries between quintiles and are huge in terms of employment (in India, this happens with agricultural jobs), this can make from the size of the quintiles to differ.

growing self-employment in the informal sector (in Manufacturing, and Wholesale and retail trade), rather than entirely driven by routine-biased technological change. In this sense, although job polarization has been also observed in India at least in the 1990s and 2000s, it seems that the drivers explaining this pattern (mechanization, informality) might not be the same than those explaining job polarization in developed countries (automation, but also the institutional settings and labour regulation, etc).

Khurana and Mahajan (2020) analyse changes in earnings inequality and in task contents of jobs in the non-agricultural sector in urban India across three decades, 1983–2017. Using same data source as the previous two studies and adding the latest data from Periodic Labour Force Survey of India, they find that earnings inequality increased during 1983–2004, was largely stable during 2004–11, and decreased during 2011–17. They explore whether decline in routine jobs and change in demand for skills has shaped evolution of earnings inequality in India. Their analysis also shows changes in routine task intensity in occupations in India during the study period. However, this paper focuses more on earnings inequality and less on the topic of our interest: employment change across jobs and occupations in India.

This study extends the analysis undertaken by Sarkar (2019) for the year 1983 to 2011-12 to the most recent year available, 2019-20. Using the same analytical approach, we analyse the most recent data from the Periodic Labour Force Survey of India from the year 2019-20 and look at the employment change pattern between the years 2011-12 and 2019-20.

3 Data

The data used in this study comes from the recent Periodic Labour Force Survey (of the year 2019-20) and from the Employment and Unemployment survey conducted by the National Sample Survey Organization (NSSO) for the year 2011-12. The surveys conducted by NSSO and PLFS are both annual data covering a period of 12 months (starting in year 2011 and 2019 and ending in year 2012 and 2020 respectively).

Our main objective is to investigate changes in employment patterns across occupations and jobs in India during the last decade, adding new findings to the already existing evidences. This period has an added benefit from the analytical perspective as both surveys use the same National Classification of Occupation (NCO) codes, NCO 2004, and National Industry Classification (NIC) code, NIC 2008. This allows us to use exactly the same occupation-industry cells/ combinations for the whole period under analysis. Since this study mainly focuses on employment change across occupations and industry combinations, using similar NCO and NIC codes is important to ensure consistency for the analysis. Therefore, our sample consists of two rounds of cross-sectional survey data spanning a period of 8 years. Both surveys collect socioeconomic and demographic information of households and individual members across all states except some remote and inaccessible pockets. NSSO collects information on individuals' education, training, personal background as well as occupation and industry along with last weekly earnings and number of days work in the week. Moreover, the sample of the survey is representative at national level and therefore, is able to provide a picture of overall Indian labour market. Our final analytical sample is the employed population, including both wage/regular salaried employees and the self-employed.[2]

[2] NSSO informs about weekly earnings of wage-employees, but not about those of the self-employed. In order to also count on the latter group in our analytical sample, in a way that we can have a more reliable approximation of how all employment is evolving, we apply the following procedure: we extrapolate earnings from wage employees working in a given job to the self-employed working in the same job. That is, we assume that wages for wage employees and the self-employed working as *teaching professionals in the human health sector* or in any other job are the same, and rank and allocate them into quintiles accordingly. Although one can expect there can be some differences between the earnings of

This is a stratified multi-stage sample and, therefore, all units are assigned with adjusted sampling weights. In our analysis, all results are reported using sample weights. It should be noted that sampling strategy and questionnaire are similar across rounds. Therefore, complications regarding comparability issues do not arise. More precisely, the surveys collect information on individual occupation, education (disaggregated categories), industry of employment, age, sex, marital status, status of employment, and on other variables. It also collects household level characteristics like monthly consumption spending, social group, religion, household size, etc. On an average, there are 200,000 individuals in working age population (15-65) in each round whose information on occupation, industry and individual characteristics is available.

4 Methodology

The paper follows the 'jobs approach' as developed by Eurofound (Hurley and Fernandez-Macias, 2008) to analyse the employment change patterns in India. This method was first developed by Joseph Stiglitz (CEA, 1996) and later modified by Wright and Dwyer (2003) to study occupational changes in the USA. Stiglitz constructed an occupation-by-sector matrix using the Current Population Survey data of 1994-96 to see the evolution of each cell. A similar approach has later been adopted by many researchers while analysing employment change dynamics (Hurley and Fernandez-Macias, 2008; Goos, Manning and Salomons, 2009). The basic idea behind using combinations of occupations and sectors as the unit of analysis is that same occupation title may have different tasks to perform depending on the industry where this occupation is located, but also different wages and employment conditions. In other words, jobs as combinations of occupations by sectors better account for the heterogeneity that exist within broader categories (occupations or sectors).

Depending on tasks, the educational and skill requirements of the jobs are different in different industries which consequently impact the earnings. Sector characteristics, and not only occupations, are able to explain inequality and employment trends. Thus, it is also useful to capture this information dimension. In addition, jobs defined as combinations of occupations and sectors provide more detailed and intuitive categories, that help to better understand employment dynamics and economic restructuring: jobs inform about both, the type of tasks, role and position the worker plays within an organisation (the occupation, that make reference to the vertical division of labour) and the market segment where he/ she works (the sector, or the horizontal division of labour). Examples of jobs are (observe that in all the cases the occupation is followed by the sector): managers of small enterprises in the manufacture of beverages; managers of small enterprises in the manufacture of textiles; teaching professionals in education or teaching professionals in human health activities.

Finally, there are also pragmatic reasons promoting the use of jobs as the unit of analysis, given that there are international classifications in many countries and surveys that allow for its application and for international and over time comparability.

In this study jobs are created as the combination of 2-digit National Classification of Occupations (NCO 2004) and 2-digit National Industry Classification (NIC 2008). After removing small jobs (those that only exist theoretically as potential combinations of occupational and sectoral titles, but that do not employ many people in the precise moment used to define all jobs), we are left with 226 jobs in India for the analysis.

both groups, these are not expected to be as high as to allocate the jobs in different quintiles, and thus this is not expected to bias the results.

Once all jobs are defined, they are ranked based on their median daily wages in the initial year (2012). Next, we create employment quintiles where each quintile contains approximately 20 percentage of total employed population in India in 2012. This exercise is done at the aggregate level, but also separately for rural and urban India. The reason for analysing rural and urban labour market separately is that they are very different in nature. As presented in Appendix Table 3, rural India has 60% of its employment concentrated in agriculture, while this percentage is only around 5% in urban India in 2019-20. On the other hand, urban employment is concentrated in manufacturing (around 50% of employment) and wholesale and retail trade sector. Therefore, occupational and sectorial composition, as well as the nature of jobs and earnings across jobs ranges from rural to urban India, which makes it necessary to do a location wise analysis.

Once jobs are defined, ranked and allocated into quintiles, the only remaining task is to observe net employment change in all quintiles. These trends are represented in figures, in which the bars representing low-paid jobs are located in the left side of the panel, and the bars representing high-paid jobs are located in the right side of the panel, with the rest of the quintiles being located also ordinally. Four significant patterns of labour market transformation can be identified in a very visual way in these figures: *job polarization* appears when employment growth is faster in low and high-paid jobs relative to mid-paid jobs, drawing a 'U' shape pattern. *Job upgrading*, on the other hand, means that the higher the wages, the higher the employment growth. This manifests a general movement towards higher-quality jobs; *middling* can be conceived as the opposite of job polarization, that is, an inverted 'U' shape that implies a reduction or slower growth of the jobs located in the poles of the wage distribution. Finally, *downgrading* implies that employment growth is fastest in low-paid jobs relative to the higher paid jobs.

An alternative method used in the literature to group the occupations in order to observe patterns of employment change is by categorizing the occupations/jobs based on their task contents itself (Acemoglu and Autor, 2011; Cortes, 2012; Jaimovich and Siu, 2020). This way jobs or occupations can be classified by their routine character, because they entail a high level of intellectual or cognitive tasks, because they require a high degree of social interaction, and by other type of activities or work methods. However, such data is not available for every country. Some studies have used surveys like the Dictionary of Occupational Titles (DOT) and its successor, the Occupational Information Network (O*NET), to measure the tasks and skill content of each occupation or job (Autor, Levy and Murnane, 2003). However, this data is collected in the US, and thus it has a limited application outside the frontiers of that country. There are other sources providing data on tasks and work activities, but these have been again developed mainly in Europe and the US -for a comprehensive review of available sources and tools, see section 2 in Bisello et al. (2021) and Fana et al. (forthcoming)-. Apart from those, a new taxonomy and database that uses European data and allow to shed light on the task content of jobs and occupations has also been developed more recently (Bisello et al. 2021; Fana et al. forthcoming). Following this second method from the literature, we group the 2-digit NCO 2004 occupations into four task-based categories created by using the Routine Task Intensity Index calculated using the O*NET database (Autor and Dorn, 2013; Goos et al. 2014): non-routine manual, routine manual, routine cognitive and non-routine cognitive occupations (the classification is presented in Appendix Table 2). Then we analyze how these categories have evolved over time during the same period (2012-2020). This is presented as a complementary analysis, that serves well to qualify previous results, and to know more on the nature and characteristics of the jobs that are growing and decreasing in India. It is important to note that, by contrast with employment quintiles, these four groups of jobs are nominal and defined by their task content, but not by their earnings.

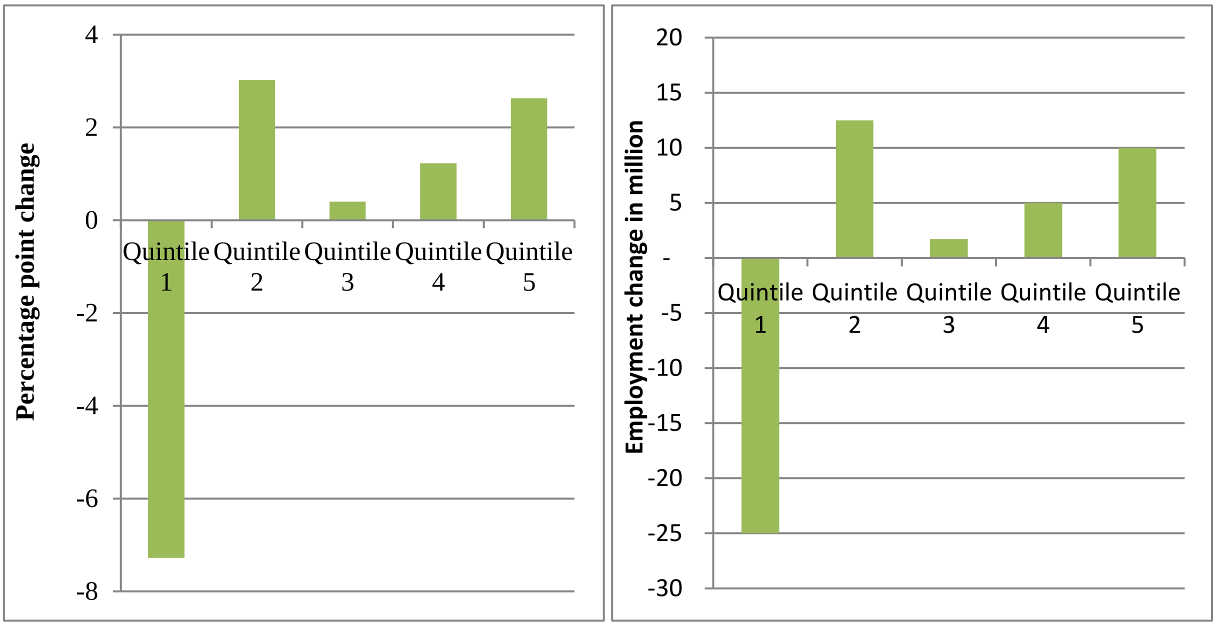
5 Analyses and findings

This is the main analytical section, where main patterns of employment change in India from 2012 to 2020 are described. In section 5.1 we present patterns of change by job-wage quintile, as well as some decompositions, using as breakdowns the sex, the broad sector and a variable differentiating between rural and urban employment. This second exercise serves to identify where employment growth has been concentrated in the period under analysis, what can tell us something on the drivers explaining those changes. In section 5.2 we present the results of the task-based analysis. Section 5.3 is an informative note on the differences between the wage-quintile method and the task-based approach.

5.1 Employment change patterns by wage quintiles: job upgrading or polarization?

Figure 1 presents the changes in employment share across the wage quintiles for the period 2012-2020. We first present the changes in employment share across wage quintiles for overall India and then also separately for rural and urban India in Figure 4. The first figure shows a *mid-upgrading* pattern in the Indian labour market. The higher the wages, the more intense tend to be employment growth. But there is one exception that makes from India not to be a perfect upgrading case: this is quintile 2 (mid-low paid jobs) experiencing the fastest employment growth. As consequence, employment growth from 2012 to 2020 was more intense in mid-low (quintile 2) and high-paid jobs (quintile 5 and 4). The employment share has increased the most in the jobs in wage quintile 2 and wage quintile 5 followed by wage quintile 4 and 3. On the contrary, there has been a sharp decrease in the employment share of wage quintile 1 (low-paid jobs).

Figure 1. Changes in employment share (left panel) and in absolute number (right panel) in India by job wage quintile: 2012- 2020



***Note**: Occupational wage quintiles are created by dividing 226 jobs (combination of 2-digit NCO and 2-digit NIC) into approximately five equally weighted groups in 2011-12 and 2019-20 based on the median earnings of the base year, 2011-12 for all India. The sample in the figure includes the age group 15–65 years who reported as employed in the principal activity status. **Source**: author's calculation using unit level data from National Sample Survey, Employment and Unemployment round, 2011-12 and Periodic Labour Force Survey, 2019-20.*

As we decompose patterns of employment change by sex, we see that the decrease in the lowest wage quintile is driven by the strong decrease in male employment share and by a moderate decrease in women employment share (Figure 2). As consequence of this, and since male employment gains in other quintiles do not offset the pronounced hollowing out of quintile 1, men have experienced net employment losses in the period under analysis. Although the pattern for men is one of job upgrading (employment decreased in the bottom of the wage structure, and increased in the top), over the period there has been a reduction in the total number of male employees. The situation is very different for women: they have benefited from net employment gains, with employment creation being more salient in quintile 5 and especially 2. The sharp increase in employment share in wage quintile 2 result from the increase in women employment share in these jobs. Whereas, the increase in employment share in the top wage quintile is driven by both male and female employment.

These numbers suggest at least two things:

- That male workers have contributed more than female workers to promote job upgrading in India, although this pattern has a high associated cost in the form of net employment losses.
- That there has been a process of feminization of employment in India in the latest years, contrary to what happened in a previous period (Klasen and Pieters, 2015).

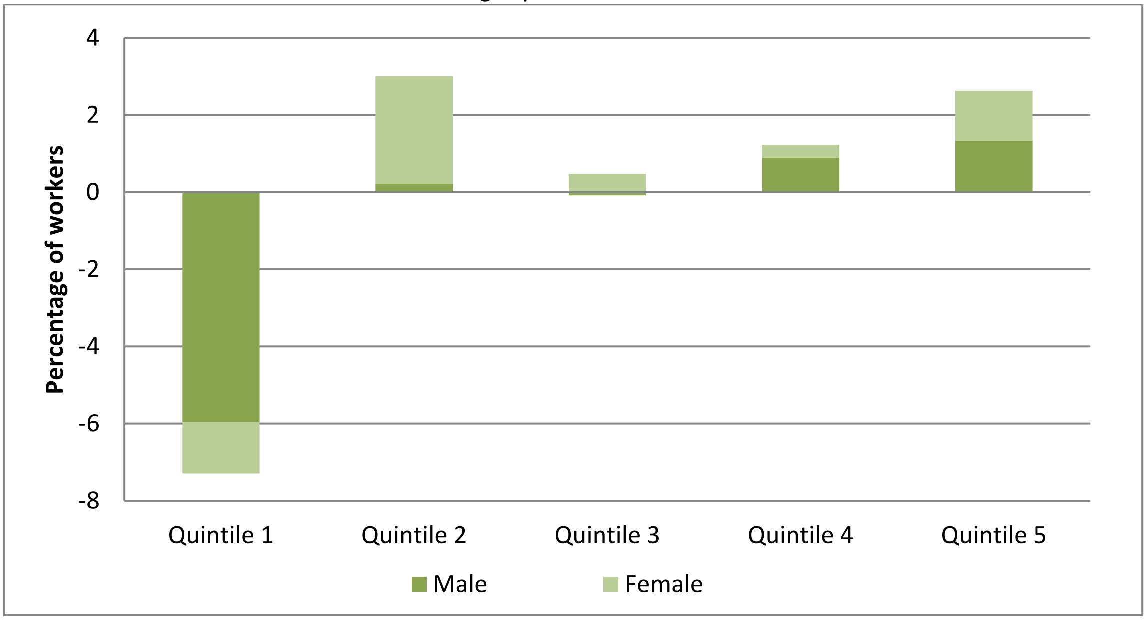
We also decompose patterns of employment change by six broad industry sectors. As can be seen in Figure 3, the decrease in employment in low-paid jobs is driven by the agricultural jobs, while job gains in quintile 2 are also driven by the same broad sector. These jobs in lowest quintile are elementary and subsistence agricultural jobs, while the jobs in quintile 2 are skilled agricultural jobs. This implies a restructuring of the agricultural sector over the latest years in India, with jobs within this sector benefiting from a clear upgrade in terms of earnings (and probably also in terms of their working conditions). Given that changes in quintile 1 and 2 are those that have been more salient in India, we can state that the agricultural sector play a key role at the time of explaining employment dynamics and transformations in India over the latest years. In any case, job losses in quintile 1 in agriculture were more intense than job gains in quintile 2 in the same sector, what implies that the agriculture sector in India has the potential to offer better jobs than in the past, but less jobs than in the past, given that it has reduced its size from 2012 to 2020.

On the other hand, employment growth in the top of the wage structure (quintiles 4 and 5) is mainly driven by the increase in employment in the construction sector (in quintile 4), but also in service jobs such as wholesale and retail, transport, storage and communication and other services (quintile 5).

In summary, job upgrading in India is explained by both, employment losses in the agricultural sector in the bottom of the wage structure, and employment gains in the service sector and the construction sector in the top of the wage structure. While agricultural jobs explain the upgrade there has been in the bottom of the wage structure and the hollowing out of low-paid jobs, service jobs and the construction sector are responsible of making from top-wage jobs to increase in India.

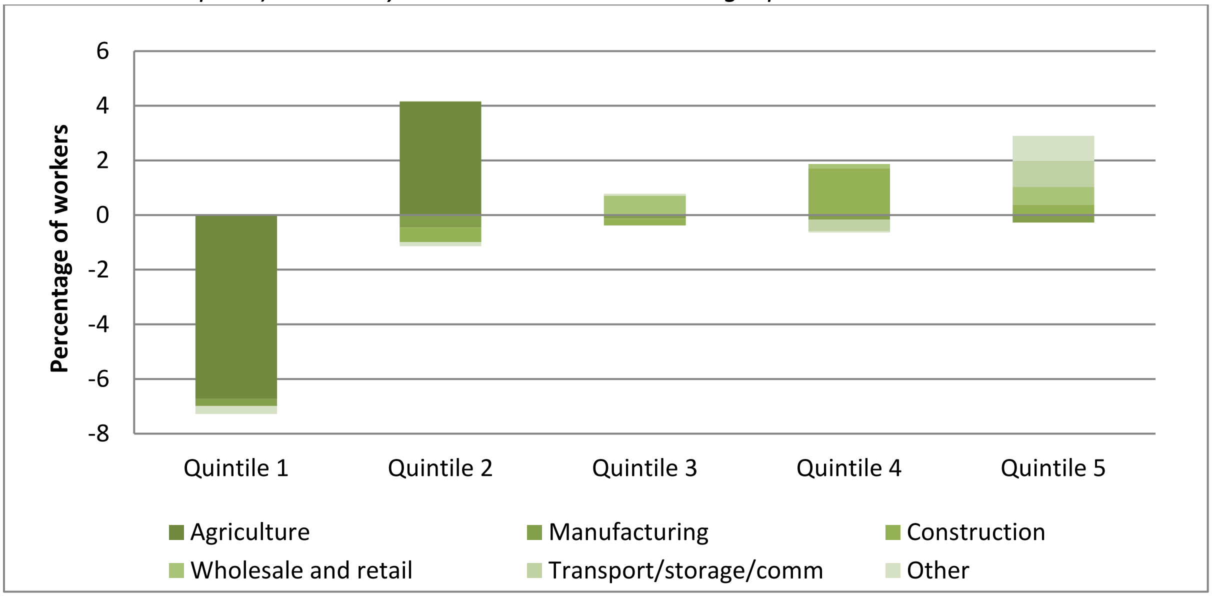
This expansion in non-agricultural industries in the top of the wage structure has been accompanied by the rise in general education levels of the workforce, as presented in Figure 9 in appendix. There has been an increase in workers with education levels middle/secondary, higher secondary and diploma, and graduate and above. Workers with below primary and primary education have declined by 9 percentage points between the years 2012 and 2020. The increasing levels of education also contribute from the supply side to fill the increasing higher demand for mid-high and high-paid jobs in services and the construction.

Figure 2. Decomposing the changes in employment share (in percentage point) in India by sex across wage quintiles: 2012- 2020



Note: *Occupational wage quintiles are created by dividing 226 jobs (combination of 2-digit NCO and 2-digit NIC) into approximately five equally weighted groups in 2011-12 and 2019-20 based on the median earnings of the base year, 2011-12 for all India. The sample in the figure includes the age group 15–65 years who reported as employed in the principal activity status.* ***Source***: *Author's calculation using unit level data from National Sample Survey, Employment and Unemployment round, 2011-12 and Periodic Labour Force Survey, 2019-20.*

Figure 3. Decomposition by industry Decomposing the changes in employment share (in percentage point) in India by broad industries across wage quintiles: 2012- 2020



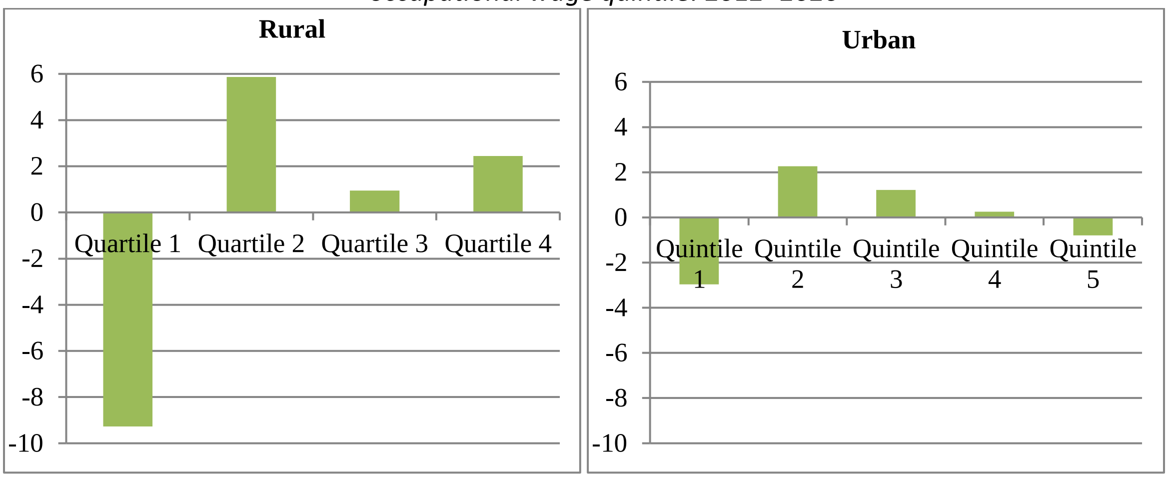
Note: *Occupational wage quintiles are created by dividing 226 jobs (combination of 2-digit NCO and 2-digit NIC) into approximately five equally weighted groups in 2011-12 and 2019-20 based on the median earnings of the base year, 2011-12 for all India. The sample in the figure includes the age group 15–65 years who reported as employed in the principal activity status.* ***Source***: *Author's calculation using unit level data from National Sample Survey, Employment and Unemployment round, 2011-12 and Periodic Labour Force Survey, 2019-20.*

Figure 4 presents the changes in employment share across wage quintiles separately for rural and urban India. Rural India also exhibits a pattern of mid-upgrading (as in the case of India as a whole), with employment growth being more pronounced in quartile 2 and 4. On the other hand, the pattern in urban India is closer to one of *middling*, as opposed to job polarization: employment growth has been more prominent in quintiles 2 and 3, while the jobs in both extremes of the employment distribution (quintile 1 and 5) have reduced their share.

This suggest that the upgrading pattern experienced in India as a whole in the period under analysis (see figure 1) is largely explained and driven by employment dynamics in rural India due to a larger share (around 70%) of Indian population living in rural India. Employment in rural India plays a key role at the time of explaining recent employment developments in this country. This do not come as a surprise, since we can expect job upgrading to be more likely to happen in rural India. This is because the share of agricultural jobs was higher and the share the service sector lower at the beginning of the period in rural vis-à-vis urban India (see figure 5). In this sense, the process of tertiarisation, that is often associated to job upgrading patterns (because it implies that low-paid agricultural jobs are replaced by better-paid service jobs, as figure 3 indicates), is still ongoing and being consolidated in rural India, while in urban areas is already consolidated.

Finally, figure 4 also shows that employment transformations and re-structuring in rural India have been faster and more pronounced than in urban India in the latest years. Structural change in employment in India has been more intense in rural areas.

Figure 4. Changes in employment share (in percentage points) in rural and urban India by occupational wage quintile: 2012- 2020



Note*: Occupational wage quartiles/quintiles are created by dividing 226 jobs (combination of 2-digit NCO and 2-digit NIC) into approximately four/five equally weighted groups in 2011-12 and 2019-20 based on the median earnings of the base year, 2011-12, separately for rural and urban India. The sample includes the age group 15–65 years who reported as employed in the principal activity status.* ***Source****: Author's calculation using unit level data from National Sample Survey, Employment and Unemployment round, 2011-12 and Periodic Labour Force Survey, 2019-20.*

In Appendix Figure 8 we also present the changes in the employment share across wage quintiles for urban non-agricultural sectors from 1983 to 2012, taking evidence from Sarkar (2019). This way we can complement the original results presented here, and have a better idea of changes in the long run. As mentioned earlier, job-quality in this other case is measured by using average wages of occupations in the base year of any particular period/ decade, and wage quintiles are created by dividing all jobs into approximately 5 equally weighted groups in the base year (for instance, for the period 1983-1994 the base year is 1983). The figure shows different patterns in three previous sub-periods: job upgrading in the 80s and job polarization during the 90s and the 2000s (although job polarisation was asymmetric from 1994 to 2005, with employment growth being more biased towards low-paid jobs). These polarising trends experienced from the nineties until 2012 contrast with the mid-upgrading pattern experienced in the latest years, as indicated in figure 1.

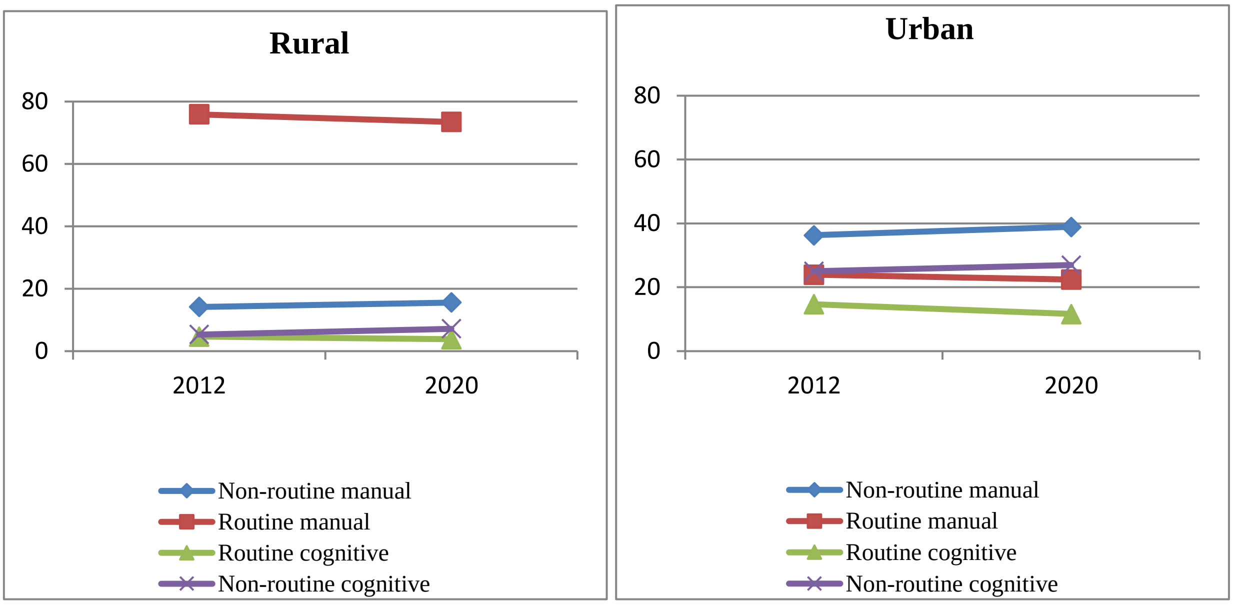
One consistent finding is that there has been positive growth in the employment share of top two quintiles in each of the past four decades. For occupations in the lowest quintile the employment share fell in the 1980s, rose considerably in the 1990s and the early 2000s (when there was job polarisation), and fell again from 2012 onwards. This increase in the bottom wage quintile, as argued in the literature, was led by low-paid salaried and casual wage earners in the 1990s, and mostly by low-earning self-employed in the early 2000s. It is likely that, after trade liberalization in 1991, demand for unskilled labour increased in India, as predicted by the Stolper–Samuelson theorem. These occupations are mainly tailors and dressmakers in textile manufacturing industry, and salesman, shop assistants and related workers in wholesale and retail trade industry in urban India (Sarkar, 2019).

5.2 Employment change patterns by task-based categories

In this section, we analyse the changes in the employment share in rural and urban India across four task-based occupation categories for the same period. The classification of occupations into four non-routine and routine task-based categories using NCO 2- digit codes is presented in the appendix (Table 2). According to this classification, non-routine manual occupations comprise personal and protective service workers, models, sales and demonstrators, drivers, and similar occupations. These are occupations that require manual dexterity but do not use a standardized procedure. This group accounted for 19.53% of total employment in 2012. On the other hand, routine manual occupation category consists of occupations such as machine operators and assemblers, labourers in construction or agricultural workers. These jobs also need manual dexterity but involve repetitive works using a standardized procedure. This group accounted for 63.29% of total employment in 2012. The next category, routine cognitive, includes occupations such as office clerks, customer service workers and precision workers. These jobs need cognitive skills like calculating, bookkeeping, correcting texts/data, etc., but following a well-defined method. This group accounted for 7.1% of total employment in 2012. The fourth category, non-routine cognitive, includes high skilled occupations such as legislators and senior officials, managers, teaching professionals, etc. Jobs in this category require analysing, interpreting, creative thinking, guiding, directing, and establishing relationships. Therefore, tasks in these occupations need cognitive and analytical skills, and do not usually follow any repetitive method. This group accounted for 10.1% of total employment in 2012.

Figure 5 provides the employment share in each of these four categories in 2012 and 2020 by type of location. There is a difference in the employment shares across these task categories between rural and urban India: both non-routine cognitive and non-routine manual occupations in urban India have highest shares of employment, while in rural India it is the routine manual group (that includes agriculture) the one accounting for the highest employment share.

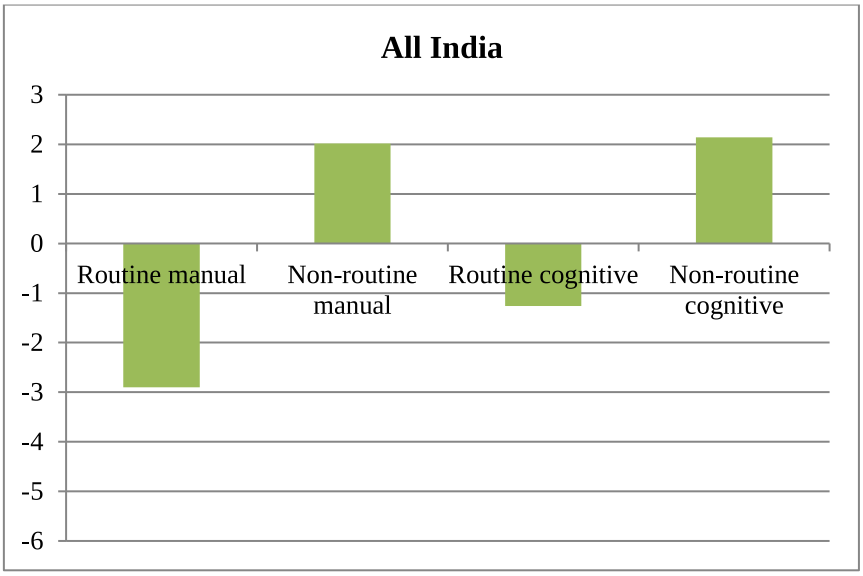
Figure 5. Employment share (in %) in task-based occupations in 2012 and 2020



***Note**: Figures present percentages of workers in each of the task-based occupational categories in 2012 and 2022 in rural (left panel) and urban (right panel) India. The task-based occupational categories are created by grouping 2-digit NCO 2004 occupations into categories (including agriculture) using the Routine Task Intensity index used in the literature (e.g., Autor and Dorn, 2013 and Goos, Manning and Salomons, 2014). **Source:** Author's calculation using unit level data from National Sample Survey, Employment and Unemployment round, 2011-12 and Periodic Labour Force Survey, 2019-20.*

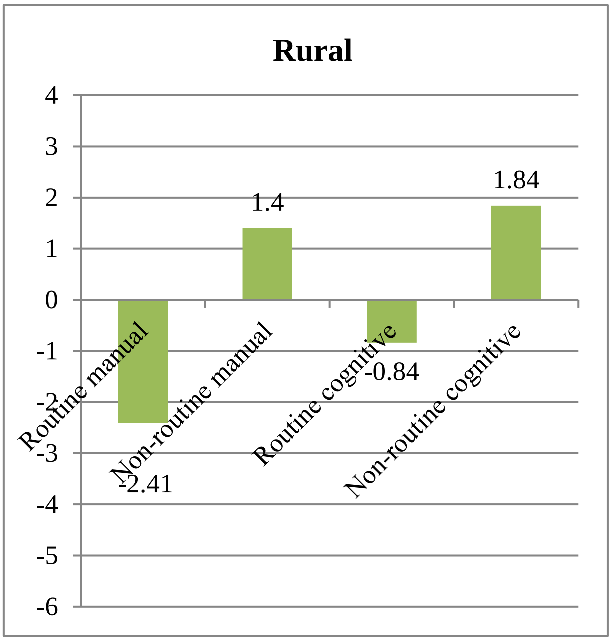
In Figure 6 and 7, we look at the changes in employment shares in these task-based categories in all India and separately in rural and urban India. Patterns of employment change are very similar in all India and separately for rural and urban India, with an increase in both non-routine manual and non-routine cognitive employment shares, and a decline in the share routine jobs represent. Main difference between rural and urban India is that while in the former employment creation has been more pronounced and biased towards non-routine cognitive occupations, in the latter employment creation has been more biased towards non-routine manual occupations. This is normal considering that the size of non-routine manual jobs in rural India was much higher than in urban India at the beginning of the period, but also that the share of non-routine cognitive occupations was much higher in urban India at the beginning of the period. Accordingly, changes (1.4 and 1.9 percentage points respectively) are smaller for these categories in each case. But, on the other hand, this indicates there has been some convergence in terms of the type of work workers have to perform in rural and urban India.

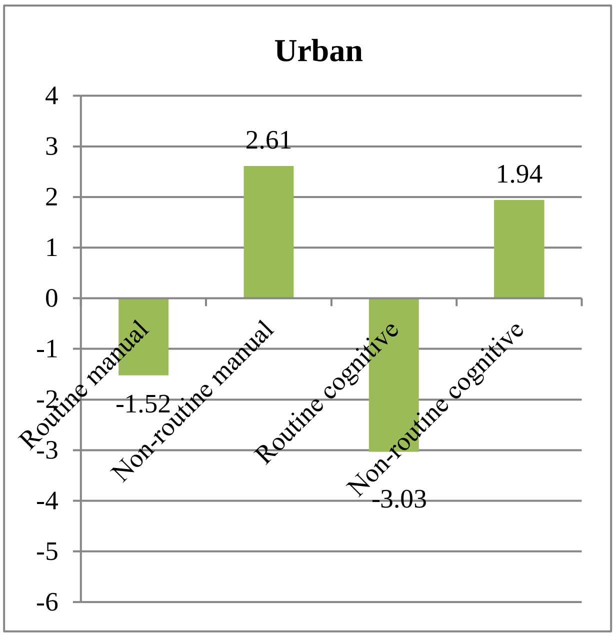
Figure 6. Changes in employment share (in pp) across task-based occupation categories in India between 2012 and 2020



Note*: Figures present percentage point (pp) change in employment share in each of the task-based occupational categories between the years 2012 and 2020 in all India. The task-based occupational categories are created by grouping 2-digit NCO 2004 occupations into categories using the Routine Task Intensity index used in the literature (e.g., Autor and Dorn, 2013 and Goos, Manning and Salomons, 2014). Agricultural occupations are included into routine manual category.* ***Source****: Author's calculation using unit level data from National Sample Survey, Employment and Unemployment round, 2011-12 and Periodic Labour Force Survey, 2019-20.*

Figure 7. Changes in employment share (in pp) across task-based occupation categories in rural and urban India between 2012 and 2020





Note*: Figures present percentage point (pp) change in employment share in each of the task-based occupational categories between the years 2012 and 2020 in rural (left panel) and urban (right panel) India. The task-based occupational categories are created by grouping 2-digit NCO 2004 occupations into categories using the Routine Task Intensity index used in the literature (e.g., Autor and Dorn, 2013 and Goos, Manning and Salomons, 2014). Agricultural occupations are included into routine manual category.* ***Source****: Author's calculation using unit level data from National Sample Survey, Employment and Unemployment round, 2011-12 and Periodic Labour Force Survey, 2019-20.*

5.3 Differences in patterns in earnings-based and task-based categories

Patterns of employment change vary depending on how jobs are classified. First, this is because the number of resultant categories (and bars) is not the same. Second, because the size of the categories in terms of employment is different: while each quintile should represent approximately 20% of all employment, the four task-based categories have very different employment weights, as seen in figure 5. Third, and more importantly, because with the wage quintile method the five resultant groups of jobs are ordered from lowest wages to highest wages, while the task-based categories are nominal. However, to offset this limitation and for the sake of clarity we represent the task-based categories of jobs of figure 6 and 7 in a way that the jobs with lower wages are in the left-side part of the panel and jobs with higher wages are int he right-side of the panel.

All these differences result in a potential misalignment of jobs and occupations in these groups. The occupations that are classified under the non-routine manual group, for instance, are not necessarily the same occupations falling in the lowest wage quintile, even though they are mostly low-skill and low-paid jobs. This is the case in India. In particular, agricultural labourers are classified in the routine manual category, while in India they are in the lowest wage quintile in the jobs-based approach. Agricultural jobs have been declining in India over the last few decades. The decline in employment share in the lowest wage quintile is thus driven by the decline in agricultural jobs which is captured in the routine manual group in the task-based analysis.

In order to make this puzzle clear, we include in Table 1 average daily earnings for the four task-based categories. Routine manual jobs have the lowest earnings, followed by non-routine manual and routine cognitive jobs. Non-routine cognitive jobs have the highest earnings. Following this information, columns in figure 6 and 7 are displayed this way, with lower paid jobs being located in the left-side of the panel and higher paid jobs in the right side of the panel. Since this partially follows the quintile method logic, this way we ensure that the comparison of results is more straightforward, but also that this second method serves as a kind of sensitivity check. In this sense, the evidence provided with the task-based method (figure 6 and 7) is consistent with the idea of India experiencing job upgrading or 'mid-upgrading' from 2012 to 2020[3], a process that has been driven by the increase of employment in non-routine jobs and a decrease of employment in routine jobs.

Table 1. Average daily earnings of task-based occupational categories

Task categories	Average daily earnings/wage	
	Mean	**Median**
Non-routine manual	214.82	160.00
Routine manual	148.18	120.00
Routine cognitive	306.83	200.00
Non-routine cognitive	624.67	533.29

***Note**: The tables present weighted percentage of workers in each of the broad industry categories from 1983-84 to 2019-20 separately for rural and urban India. Broad industry categories are created by following National Industrial Classification (NIC) 2008 of India to classify economic activities. **Source**: Author's calculation using unit level data from National Sample Survey, Employment and Unemployment round, 2011-12 and Periodic Labour Force Survey, 2019-20.*

[3] In any case, and for the all reasons mentioned in the first paragraph of this sub-section, we think that the quintile method prevails over the task-based approach at the time of identifying patterns of employment change. Still, the task-based method is useful to qualify employment trends.

6 Conclusions

This study analyses employment change patterns in rural and urban India for a recent period using data from 2012 and 2020. We know that many developed countries have exhibited employment change patterns that range from job polarization to job upgrading (the UK, USA, Australia and some European countries). On the other hand, recent research on some developing and transition countries has provided evidence of job polarizing pattern in countries such as Colombia, Mexico, Ukraine and urban India (Medina and Posso, 2010; Kupets, 2016; Sarkar, 2019). However, literature on structural change in employment in developing countries is scarcer. In this context, this paper adds to this body of research to show the employment change patterns across jobs using most recent data in India. It analyses employment trends at the aggregate level and separately for rural and urban India.

The findings suggest that employment growth in India exhibit a pattern closer to mid-upgrading (i.e., employment growth biased towards the middle and the top of the employment distribution) when jobs are ranked and arranged based on their median earnings. A decomposition analysis reveals that this pattern is due to the decline in agricultural subsistence jobs and to employment growth in jobs in Construction, Wholesale & retail trade, and Transport, storage and communication industries in India. We have also seen that there are differences between employment dynamics in rural India (where there has been mid-upgrading) and urban India (where there has been a middling pattern). Employment dynamics of rural India, that is the area that employ more people in this country, are driving aggregate patterns of structural change in India.

Patterns of employment change by sex reveal that men have experienced net employment losses in recent years, with these losses being concentrated in low-paid agricultural jobs. On the other hand, women have benefited from net employment creation, especially in quintile 2 and 5. Due to this, there has been a process of feminization in employment in India in recent years.

Finally, the task-based analysis indicates that in India both routine manual jobs (that include agricultural occupations) and routine cognitive jobs (clerks, etc) have reduced their employment share, while non-routine jobs (both cognitive and manual) have been growing in the recent years in both rural and urban India.

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Appendix

Table 1. Three largest (in terms of share of employment) jobs under each of the wage-based quantiles

Rural India		
Quintile 1		
9201	92 Agricultural, Fishery and Related Labourers	01 Agriculture, Hunting, Forestry
6201	62 Subsistence Agricultural and Fishery workers	01 Agriculture, Hunting, Forestry
7412	74 Other Craft and Related Trades Workers	12 Manufacture of tobacco products
Quintile 2		
6101	61 Market Oriented Skilled Agricultural Work	01 Agriculture, Hunting, Forestry
5247	52 Models, Sales Persons and Demonstrators	47 Wholesale and retail trade ; repair of motor vehicles, motorcycles and personal and household goods
7414	74 Other Craft and Related Trades Workers	14 Manufacture of Textiles
Quintile 3		
7141	Extraction and Building Trades Work	41 Construction
9341	93 Labourers in Mining, Construction, Manufacturing and Transport	41 Construction
9349	93 Labourers in Mining, Construction, Manufacturing and Transport	49 Land transport and transport via pipelines
Quintile 4		
1247	12 Corporate Managers	47 Wholesale and retail trade ; repair of motor vehicles, motorcycles and personal and household goods
8349	83 Drivers and Mobile-Plant Operators	49 Transport, storage and communications
3385	33 Teaching Associate Professionals	85 Education
Urban India		
Quintile1		
9201	92 Agricultural, Fishery and Related Labourers	01 Agriculture, Hunting, Forestry
6201	62 Subsistence Agricultural and Fishery workers	01 Agriculture, Hunting, Forestry
7414	74 Other Craft and Related Trades Workers	14 Manufacture of Textiles
Quintile 2		
5247	52 Models, Sales Persons and Demonstrators	47 Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods
9341	93 Labourers in Mining, Construction, Manufacturing and Transport	41 Construction
9349	93 Labourers in Mining, Construction, Manufacturing and Transport	49 Transport, storage and communications
Quintile 3		
8349	83 Drivers and Mobile-Plant Operators	49 Transport, storage and communications
7141	71 Extraction and Building Trades Work	41 Construction
5156	51 Personal and protective services workers	56 Food and beverage service activities
Quintile 4		
1247	12 Corporate Managers	47 Wholesale and retail trade ; repair of motor vehicles, motorcycles and personal and household goods
3385	33 Teaching Associate Professionals	85 Education
2469	24 Other Professionals	69 Legal and accounting activities
Quintile 5		
2385	23 Teaching Professionals	85 Education
1256	12 Corporate Managers	56 Food and beverage service activities
4184	41 Office clerks	84 Public administration and defence; compulsory social security

Table 2. Task-based categorisation

Non-routine manual (19.5 % of total employment in 2019-20)	
51	Personal and Protective Service Work
52	Models, Sales Persons and Demonstrators
71	Extraction and Building Trades Work
83	Drivers and Mobile-Plant Operators
91	Sales and Services Elementary Occupations
Routine manual (63.29% of total employment in 2019-20)	
61	Market Oriented Skilled Agricultural Workers
62	Subsistence Agricultural and Fishery Workers
72	Metal, Machinery and Related Trades
81	Stationary Plant and Related Operators
82	Machine Operators and Assemblers
92	Agricultural, Fishery and Related Labourers
93	Labourers in Mining, Construction, Manufacturing and Transport
Routine cognitive (7 % of total employment in 2019-20)	
74	Other Craft and Related Trades Work
42	Customer Services Clerks
73	Precision, Handicraft, Printing and
41	Office Clerks
Non-routine cognitive (10% of total employment in 2019-20)	
11	Legislators and Senior Officials
12	Corporate Managers
13	General Managers
21	Physical, Mathematical and Engineering Professionals
22	Life Science and Health Professionals
23	Teaching Professionals
24	Other Professionals
31	Physical and Engineering Science Associate Professionals
32	Life Science and Health Associate Professionals
33	Teaching Associate Professionals
34	Other Associate Professionals

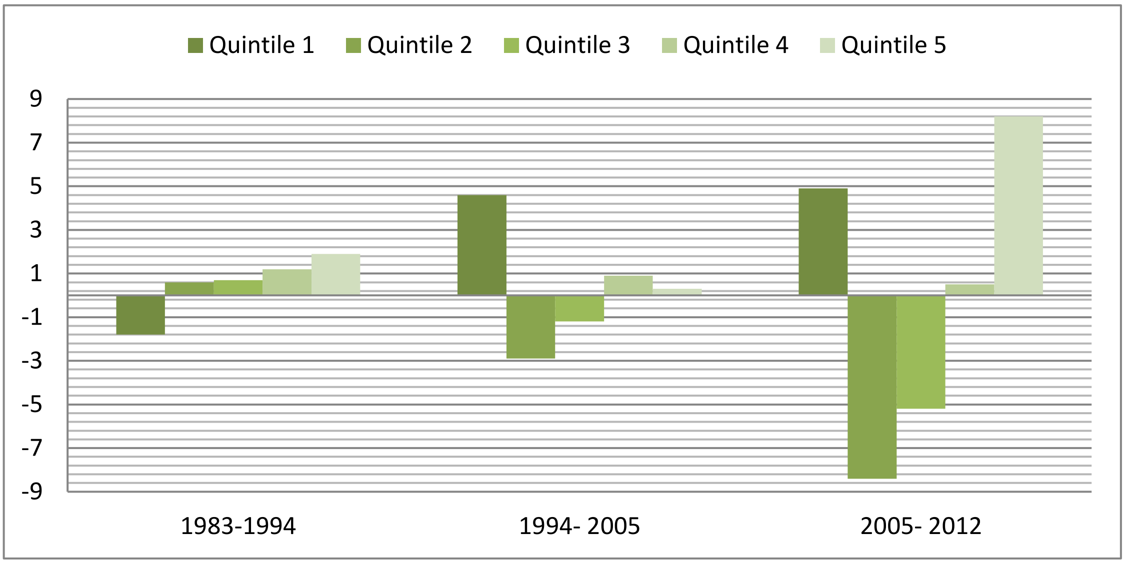
***Note**: Occupations are from National Classification of Occupation 2004 (NCO 2004) used in India to classify occupations. The occupations in agriculture are included in routine manual category following the literature. **Source**: following Autor and Dorn (2013) and Goos, Manning and Salomons (2016).*

Table 3. Distribution of workers across broad industry sectors in rural and urban India: 1983-2019/20

	1983-'84 (%)		1993-'94(%)		2004-'05(%)		2011-'12(%)		2019-'20(%)	
Industries	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
A-Agriculture, hunting, forestry	79.3	11.8	76.3	10	70.1	7.1	62.07	5.51	60.49	4.98
B-Fishing	0.4	0.4	0.4	0.4	0.4	0.3	0.34	0.33	0.31	0.2
C-Mining & quarrying	0.6	1.2	0.7	1.2	0.6	0.8	0.5	0.75	0.19	0.45
D-Manufacturing	6.9	26.8	7.7	25.6	8.2	23.8	8.71	23.49	7.5	21.07
E-Electricity, gas and water supply	0.2	1	0.2	1.1	0.2	0.7	0.21	0.76	0.3	0.88
F-Construction	2	5	2.7	6.8	5.5	8.5	10.92	9.28	11.14	9.26
G-Wholesale and retail trade	3.3	15.8	4.1	17.4	5.3	19.8	6.24	20.13	7.17	24.52
H-Hotels and restaurant	0.5	2.5	0.5	2.4	0.7	3.2	0.96	3.8	1.06	3.47
I-Transport, storage and communication	1.3	8.9	1.7	8.5	2.8	9.2	3.32	8.71	3.96	8.15
J-Financial intermediary	0.1	1.6	0.2	2.2	0.3	2.2	0.37	2.59	0.51	2.65
K-Real estate, renting and business activities	0.1	1.3	0.1	1.5	0.3	3.3	0.51	5.22	0.95	6.7
L- Public administration	1.4	9.4	1.4	8.6	1	5.6	0.91	4.32	1.06	3.2
M-Education	1.3	4	1.3	4.2	1.8	5.1	2.3	5.55	2.78	6.2
N-Health and Social work	0.3	1.9	0.3	1.6	0.4	1.9	0.53	2.29	0.73	2.42
O-Other service sectors	2.4	8.5	2.4	8.6	2.5	8.5	2.11	7.27	1.84	5.85
Total	100	100	100	100	100	100	100	100	100	100

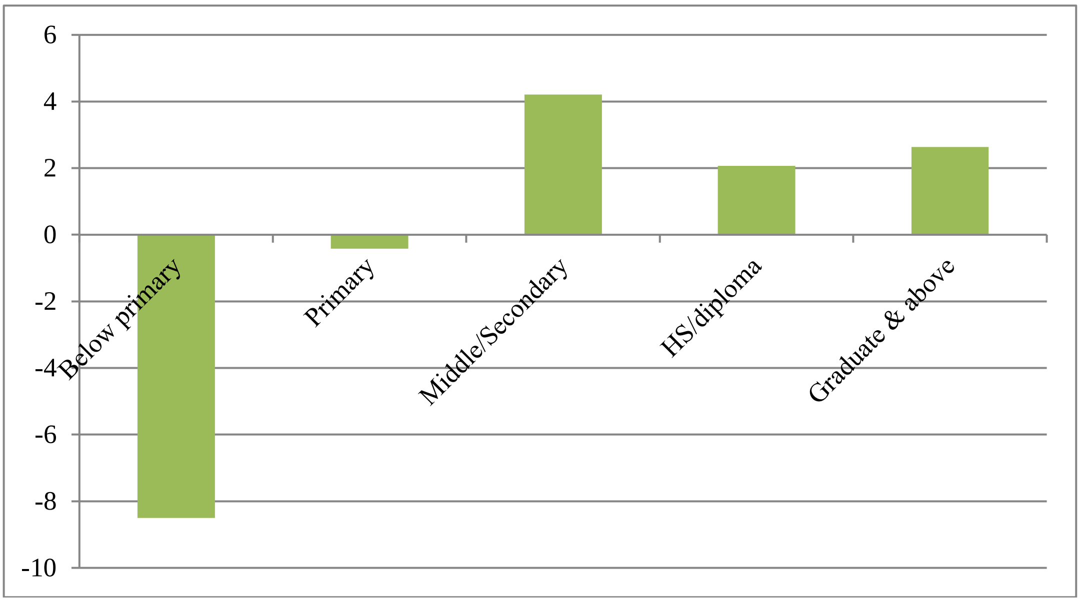
***Note**: The tables present weighted percentage of workers in each of the broad industry categories from 1983-84 to 2019-20 separately for rural and urban India. Broad industry categories are created by following National Industrial Classification (NIC) 2008 of India to classify economic activities. **Source**: Author's calculation using unit level data from National Sample Survey, Employment and Unemployment round, 2011-12 and Periodic Labour Force Survey, 2019-20.*

Figure 8. Changes in employment share (in pp) across wage quintiles in urban India: 1983 to 2012



Note: *Occupational wage quintile is created by dividing the 3-digit occupations into approximately 5 equally weighted groups in 1983 (for Period 1), 1994 (for Period 2), and 2005 (for Period 3). The sample includes the age group 15–65 years who reported as employed in the principal activity status excluding the agricultural activity.*
Source: *Sarkar (2019).*

Figure 9. Changes in educational distribution (in pp) in India: 2012- 2020



Source: *Author's calculation using unit level data from National Sample Survey, Employment and Unemployment round, 2011-12 and Periodic Labour Force Survey, 2019-20.*

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