Skills, Productivity and Employment: An Empirical Analysis of Selected Countries

Suresh Chand Aggarwal

1 Introduction

Skills development is central to economic performance of the countries in the current milieu when 'disruptive' technology is evolving at a fast pace. Many of the new technology—Internet Of Things (IOT), Artificial Intelligence (AI), achine learning, 3D Printing, etc. is changing the face of how we work, and the skills we need to succeed in our jobs. The new technology may push some workers either temporarily out of employment or into low wage jobs, as the new jobs require higher level of skills (World Development Report 2019). While opening many new windows for investment and increase in productivity and employment, the new technology is simultaneously disturbing the existing technological complementarities and exerting a lot of pressure on the supply of the matching skills. Many jobs which exist today would disappear tomorrow and many new jobs which do not exist today will get created tomorrow. So there is a simultaneous creation and destruction of jobs. The net impact of this process thus depends upon their respective pace. The shortages of 'new' skills put several constraints on growth and development by curtailing the prospects for increases in job creation and income. The mismatch between supply and demand of skills constrains productivity improvements and adds to production costs within firms, which makes it difficult for the domestic firms to compete internationally. As a result, the growth prospects of these firms get adversely affected.

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S. C. Aggarwal (✉)
Retired Professor, Department of Business Economics, University of Delhi South Campus, Delhi, India
e-mail: sureshchag@yahoo.com

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Internationally the skill mismatches are even more pronounced. In some developing countries, particularly in Africa and South Asia, while tens of millions of young people join the labour market looking for jobs and face uncertain demand due to lack of matching skills; these countries also face the problem of the unavailability of the required skills for the new jobs. Even in advanced economies (OECD 2015) the skill mismatches and shortages are common. According to OECD (2015) "In all, more than 40% of European workers feel their skill levels do not correspond to those required to do their job, with similar findings for Mexico, Japan and Korea. Australia, Finland, Italy and New Zealand experience lower rates of mismatch, but even in these countries more than 30% of workers report mismatch. In parallel, many employers report that they face recruitment problems due to skill shortages." The skill mismatches thus could also lead to underutilization of labour. It does not, however, mean that skill supply is stagnant and is not responding to changing skill needs. It has evolved over the period through better quality of education, expansion of education, increased intensity (hours) of work, etc.

Skill mismatches and skill shake-ups have increased the need for regular skilling, and up-skilling throughout a person's career, because people with low skills are generally the first to lose jobs. But the speed at which jobs are transforming and the workers' capacity to adapt to such changes are not uniform across industries and countries and is also influenced by access to education, availability and cost of Information and Communication Technology (ICT) and the opportunities for lifelong learning[1] inside and outside the workplace. Lifelong learning is needed to resolve both the immediate challenge and to add value through skills in the future. Policy interventions can help in addressing some of the skill mismatches and shortages.[2]

Some of the concerns of the pessimists towards slow or zero employment growth due to new technology have however been dispelled recently by World Development Report (2019) which did not find much empirical support for the same and finds that the share of manufacturing sector jobs has been relatively stable in most developing countries in which the impact of technology on jobs was expected to be more widespread. However, in US and some European countries, the report finds some evidence of shorter job tenures, rise of temporary contracts and increase in part-time employment but the trend need not necessarily be due to only technological change but possibly also due to demographic changes, free trade, and rise in flexible jobs (and time). Greatz and Michaels (2017) also do not find any jobless recovery in developed countries outside US. They explain the jobless recovery in US, based partially on the nature of technology adoption, extension of unemployment benefit extensions and weakening of trade unions. However, the survey by The Economist Intelligence Unit (2018) finds that countries are not yet prepared for the challenges and opportunities of intelligent automation. Only a few countries—Korea, Singapore and Germany

[1]World Development Report (2019, page 47) has suggested "three ways to improve adult learning—more systematic diagnoses of the specific constraints that adults are facing, pedagogies that are customized to the adult brain, and flexible delivery models that fit well with adult lifestyles.".

[2]OECD (2015) identifies mismatch by field of study as the most common form of mismatch, followed by qualification mismatch.

have taken some individual initiatives in this context. The report mentions that the middle income countries may find it even more difficult to adapt to the new skill requirements because of huge policy initiatives required for it.

But to meet the growing challenge of 'new' skills requirement, we have to recognize existing skills, understand skill demands, create right mix of expertise—especially on the job training and learning, and reach out to those firms and people who need it most—the small and medium enterprises (SME), the low skilled workers, and older workers. Since better skills are likely to lead to quick employment and higher income, for them acquiring and updating skills would be the best insurance against job losses. More investment in human capital is thus required at all levels by individuals, firms and government, and public investment alone is not sufficient. Firms have to invest in their employees. Workers, in turn, need to invest in their continuous education. It is all the more necessary as return to different skills[3] is changing fast. While the returns to general cognitive and social-emotional skills are rising, the returns to job-specific skills are uncertain—have increased in some jobs and declined in others.

However, higher economic growth and income also in turn, help a country with the resources to improve the opportunities for acquiring and developing skill base through the expansion of education and training, leading to a virtuous chain of growth in income, skills, productivity and employment. The World Economic Forum Report (WEF 2016a) on The Human Capital Report also finds a clear correlation between the economy's income level and the human capital score (which is a composite score of different parameters and includes enrollment and quality of education; and skills distribution among others (WEF 2016a)), but with overlaps between countries wherein some low income countries have surpassed others on the score and vice versa. There are still quite a few countries, including India which even though have achieved high economic growth, but struggle with low human capital scores; indicating their neglect in expanding education and imparting necessary skills.

The link between skills, productivity and employment has not only been discussed but has also been empirically tested. Fields (1980) had concluding way back in 1980 that education (skills) have a positive impact on the level of income by paving new opportunities for many who acquire the skills. Skills thus help in employment and income. However, a wide gap between skills of the workers may lead to wide disparities in income when workers are paid wages as per their productivity. The survey of adult skills by OECD (2013) also found a positive association between the mean skill level (measured by numeracy score) and the economic performance across countries (measured by PCI (per capita income) in PPP). The significance of skills (talent) in an economy to reap the benefits of the tech revolution and achieve higher productivity and employment has also been pointed out by the WEF (2016b) in its Global Competitiveness Report: 2016–17.

The paper in part I explores this crucial linkage between skills distribution, (labour) productivity and growth in employment both at the national level as well

[3] World Development Report (2019) has identified and defined three types of skills—cognitive skills, job-specific skills, and socio-emotional skills.

as at disaggregate industry level for few selected economies like *BRIC economies, Indonesia, Mexico, South Korea*, *Taiwan, and Turkey* all of which have faced the similar challenges. The exercise is also carried out separately in part II for formal (organized) and informal (unorganized) sectors of the Indian economy, as it is expected that formal sector firms, which are also generally relatively large in size are likely to hire more skilled labour and spend more not only in R&D but also on the job training, resulting in better skills proficiency. So the formal sector firms are expected to experience higher productivity and growth in employment.

The rest of the paper is organized as follows. The next section describes the data used and the research methodology. The discussion about the link between skill, productivity and employment in selected emerging economies is included in part I, in which the pattern in the distribution of employment by skill is discussed in Sect. 3. Section 4 is devoted to the analysis of the structure of the economy with focus on the contribution of high capital intensive industries. Estimates of an econometric model are presented in Sect. 5. In part II on the link for India's organized and unorganized sectors, Sect. 6 describes the distribution of employment by skill in the organized and unorganized sectors in India. Section 7 includes the analyses of skill and employment in the high capital intensive industries in India. Finally, Sect. 8 sums up the main findings and concludes the study.

2 Data and Methodology

As the first part of the study is related to analysis of skill and productivity at the aggregate and disaggregate level of industry for the selected countries, the only data source currently available for skill distribution by industry for international comparison is WIOD database, version 2013 updated in July 2014, which classifies the industries according to ISIC revision 3 and adheres to 1993 version of the SNA. WIOD has revised and published in Feb 2018 the data release of November 2016 where it has classified the industries by ISIC revision 4 and adhered to SNA 2008; but has not updated the data on distribution of employment by skill (education). The 2014 version has data on few variables, e.g. Value added and employment from 1995 to 2011, but the data on distribution of employment (hours worked) by skill is from 1995 to 2009 only. The period for the current study is therefore restricted to only 1995–2009; a period of 15 years.[4] WIOD (2012)[5] has grouped skill into three levels and has defined low skill as education up to primary education, medium-skill as primary to higher secondary education and high skill as higher secondary and above education level. The same grouping has been used in both the sections of the current study. In the first section, the analysis and the data are restricted to a small set of countries which include the BRIC countries along with few other emerging

[4]The short time period is a serious limitation of the study and may not fully capture the impact of recent technological changes. However, the study may show the preliminary results.

[5]WIOD (2012). Socio-Economic Accounts (SEA): Sources and Methods.

economies from different regions—Indonesia, Korea, Mexico, Taiwan and Turkey all of which have faced similar challenges in skilling (up-skilling and re-skilling) their labour force.

The second section of the study relates to the organized and unorganized sectors of the Indian economy and the period of the analysis is 1999–00 to 2011–12. The main data sources for India are National Accounts Statistics for Value added, Wholesale Price Index for price deflators, Employment and Unemployment Survey (EUS) for employment and skill data. The time period of this section is dictated by the fact that data on organized and unorganized employment and on skill are both possible from EUS only since 1999–00 and the latest year for which it is available is only 2011–12.[6] So mainly three rounds of the EUS 1999–00 (55th), 2004–05 (61st) and 2011–12 (68th) are used.

The methodology used in both the sections of the study to map the non-agriculture industries is based on capital intensity of the industry, which is defined as real gross fixed capital formation per person engaged (K/L). It is expected that the industries with high capital labour ratio would generally be the ones using better (may be latest) technology and more skilled labour. One-third of the industries with highest K/L are grouped as high capital intensive industries; the middle one-third are grouped as medium capital intensive industries; and the bottom one-third of the industries are classified as low capital intensive industries.[7] The importance of high capital intensive industries is discussed based on their relative share in the economy's total real value added and total employment. For analyzing the relationship between skill and labour productivity, labour productivity is calculated in section one as real value added per hour worked (OECD 2018) and in section two as double deflated[8] real value added per person employed.

Part I: Skill, productivity and employment in Selected Emerging Economies

3 Pattern in the Distribution of Employment by Skill

Over the years, the labour force in a country becomes more educated as more and more capital investment is made in its population. Investment in human capital has been widely recognized to be the key to increase in labour productivity and to growth of national income (WEF 2016a). The role of education in human capital is but too obvious. The challenges of new technology have made it more imperative to invest

[6]See Appendix for details of methodology to estimate organized and unorganized employment.

[7]Agriculture has been excluded from this exercise.

[8]Double deflated RVA means both output and inputs are deflated by their separate price deflators.

in human capital and develop the 'right' skills.[9] Now there is awareness among countries to invest in education of its population and its labour force for both increases in national income as well as to get ready to embrace the ever-changing technology. However, we observe a wide variation in the skill composition of the labour force of the countries around the world. WEF (2016a) has come out with The Human Capital Report 2016 highlighting differences in the score on the selected human capital indicators. The difference in skill composition in the selected countries is part of the discussion in the next section.

3.1 Distribution and Growth in Employment (Hours Worked) by Skill

The average distribution of total hours worked in the non-agriculture sectors of the economies by skill of the persons engaged during 1995–2009 is shown in Fig. 1. It is seen from it that there are large variations in the average share of hours worked by high-skill persons engaged among the selected nine countries. While the share is around 13–15% in Brazil, India, Mexico, Russia, and Turkey; the share is just 8–9% in China and Indonesia and is moderately high in Taiwan at 27% and significantly high in Korea at 42%. It seems this high-skill advantage to Taiwan and Korea and relative disadvantage to other countries is partially reflected in their production pattern and

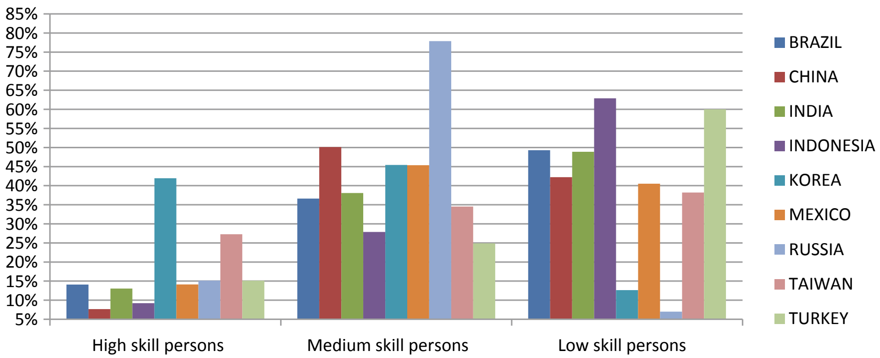

Fig. 1 Average percentage distribution of hours worked by skill of the persons engaged in selected nine countries (1995–2009). *Source* Author's calculations based on data from WIOD database (2014)

[9]However, the development of skills is required not only for better productivity but also for better well being. Education by providing access to more opportunities also facilitates upward income mobility.

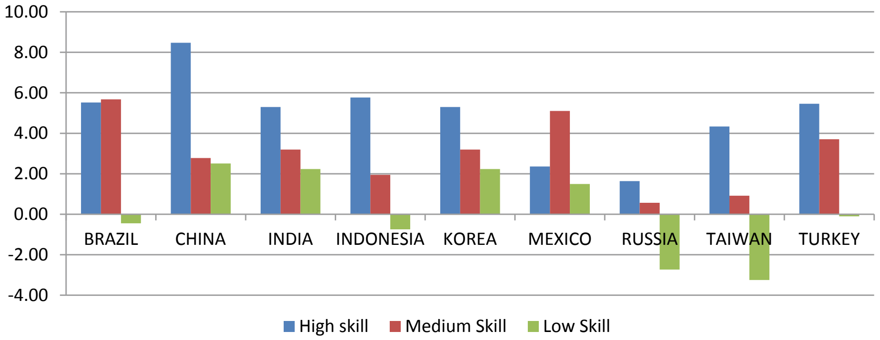

Fig. 2 Average annual growth rate of hours worked by skill of the persons engaged in non-agriculture economy of selected countries (1995–2009). *Source* Author's calculations based on data from WIOD data base (2014)

international trade.[10] The figure also shows that the distribution of hours worked by medium-skill persons also varies among the selected countries. While the share is just 25–28% in Indonesia and Turkey, it ranges between 35 and 40% for Brazil, India and Taiwan; and between 45 and 50% for China, Korea and Mexico. Russia is the only country which has a very high share of hours worked by medium-skill persons engaged (78%) and a very low share of hours worked by low-skill persons engaged (just 7%). The share of hours worked by low-skill persons engaged is around 40–50% for majority of the selected countries—Brazil, China, India, Mexico and Taiwan; a high of 63% in Indonesia and significantly low in Korea (13%) and Russia (7%).

To add more clarity to the pattern of employment by skill, an analysis of growth of employment by skill is undertaken. In Fig. 2, the average annual growth rate of hours worked during 1995–2009 by skill level of the persons engaged for non-agriculture sectors[11] of the economy is shown for all the selected countries. It shows that though the share of high-skill persons engaged as depicted in Fig. 1 is low in majority of the countries, but the growth rate of high-skill persons engaged is higher (or almost same for Brazil) than the growth rate of medium and low-skill persons in all the countries except Mexico. On the contrary, the growth rate of employment of low-skill persons is quite low and is even negative in few of the selected countries, which could be possibly due to the changes in the nature of work where the technology-induced new jobs require significantly higher level of human capital (World Development Report 2019).

[10]While Korea was exporting 47% of its GDP in 2009, the ratio was just 11% for Brazil; around 21–24% for China, India, Indonesia, and Turkey; and 28% for Mexico, Russia and South Africa (World Bank 2018).

[11]Agriculture has been dropped as, in most of the countries it is low-skill intensive with hardly any change in skill composition.

The distribution and growth of skills of persons engaged reflect that while there is a lot of potential for many of these countries to catch up with other countries both within the group as well as with other countries outside the group, the catching up process is on with fast growth in hours worked by high-skill persons engaged. The research question which then arises is how change in skill composition affects labour productivity and growth in employment. The answer to it is being attempted in the next Sect. 3.2.

3.2 Skill Composition, Labour Productivity and Growth in Employment

The relationship between skill composition and labour productivity can be viewed in two perspectives—either at the level of labour productivity or at the growth rate of labour productivity. The paper discusses the relationship at both the ‘level’ as well as at ‘growth’. In Fig. 3, the change in the average annual share of hours worked by high-skilled person engaged in total hours worked; the percentage change in the average level of labour productivity; and the percentage change in the average level of total employment for the two periods of 1996–2002 and 2003–2009 are depicted for the selected countries.

It is clear from the figure that in all the countries, with an increase in the average share of high-skill persons in total hours worked, the average labour productivity has increased (in Mexico, both have reduced) between the two sub-periods. There is thus a positive association between change in the average share of high-skill persons in total hours worked and change in average labour productivity. It is noticed that the average level of employment has also increased in the second sub-period as compared to the first sub-period in all the countries, except Turkey. The empirical evidence thus

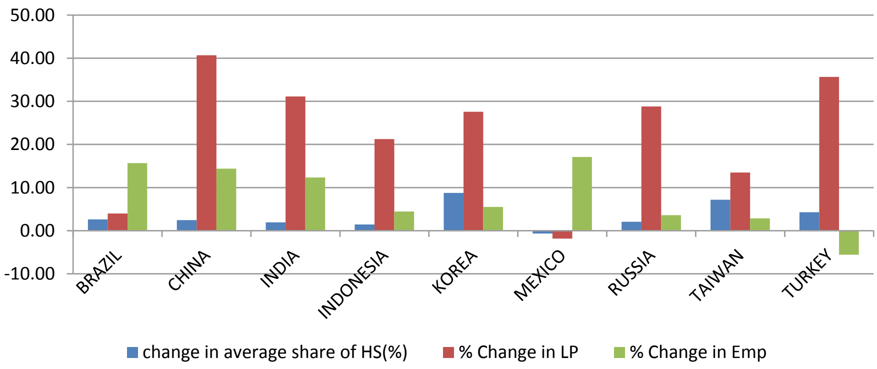

Fig. 3 Change in average share of hours worked by high-skill persons engaged, percentage change in average labour productivity and percentage change in average total employment between 1996–2002 and 2003–2009. *Source* Author’s calculations based on data from WIOD data base (2014)

corroborates the argument that increase in skill level may increase labour productivity and employment. However, one may argue that increase in labour productivity (and employment) may be induced by other factors like capital intensity[12] and not necessarily by change in the skill level. An econometric analysis using the panel data has been performed in Sect. 5 to validate the postulated relationship.

The relationship between the change in the share of hours worked by high-skill persons and change in the average growth rates of labour productivity and of employment is presented in Fig. 4; over the two periods of 1996–2002 and 2003–2009 for the selected nine countries. It is evident that the change between share of hours worked by high-skilled persons engaged and the change in average annual growth rate of labour productivity are positive for six out of the nine countries and negative for the two countries; namely Korea, and Taiwan. The positive change supports the contention of increase in the growth of labour productivity with increase in the use of high-skill persons. On further analysis, it is found that the two countries where the relationship is not supported are the ones which had not only the highest average per capita income but also had the highest share of hours worked by high-skill persons engaged during the initial years of 1996–2002 and the maximum change in the share of high-skill persons engaged. It is an indication of their fast adaption of new technology and focus on developing the skills of their labour force. The case of Mexico is an exception where a decrease in both the share of high-skilled persons engaged and the growth in labour productivity between the two periods took place. It reflects that perhaps Mexico could not continue its earlier efforts in increasing the educational level of its labour force, possibly resulting into slow growth in labour productivity and employment in the second sub-period. One of the implications from the pattern observed in these nine selected countries could be that the potential of improvement

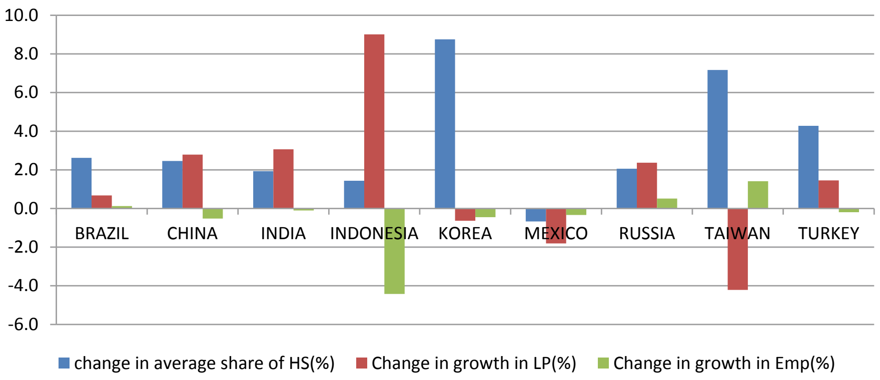

Fig. 4 Change in average share of hours worked by high-skill persons engaged, change in average growth in labour productivity and change in average growth in total employment between 1996–2002 and 2003–2009. *Source* Author's calculations based on data from WIOD data base (2014)

[12]It is observed that in all the selected nine countries, average labour productivity during 1995–2009 is higher in high capital intensive industries than the medium and low-skill intensive industries (Table 2).

in labour productivity by increase in skill levels of persons engaged may be higher for countries with low initial level of income and skills.

On the question of behaviour of growth in employment as a result of increase in the share of hours worked by high-skill persons and growth in labour productivity, the evidence of the selected nine countries in Fig. 4 does show a mixed result. Out of the six countries in which growth rate of labour productivity increased along with increase in the share of hours worked by high-skill persons engaged in the second sub-period, two countries namely Brazil, and Russia experienced a faster growth in employment in the second sub-period than the first sub-period. The experience of the other four countries—China, India, Indonesia and Turkey is, however, opposite and in these countries the growth rate in employment slowed down during the second sub-period as compared to the first sub-period. Of the remaining three countries, while in Taiwan the total employment grew at a faster average annual growth rate during 2003–2009 than during 1996–2002, the rate of growth is slower in the second period in Korea, and Mexico. There is thus no unique pattern between the changes in the three indicators.

4 Structure of the Economy: Contribution of High Capital Intensive Industries

With the evolving of technology at a fast pace since 1990s, it was expected that the firms in all the industries would adopt the new technology to improve their efficiency and to remain competitive. As a result of adoption of the new technology it was expected that two changes would simultaneously happen—first the firms and the industry would become more capital intensive; and second the firms may simultaneously displace some of the labour in the short term, but with improvements in efficiency and increase in demand due to increased incomes and/or lower prices for their products; may increase employment in the long term. As a result of these changes the contribution of capital intensive industries to total value added and employment was likely to increase. Figure 5 shows the contribution of high capital intensive industries in the real value added and in employment (total hours worked) for the selected countries. The figure shows that the share of high capital intensive industries to real value added and employment has increased in 2009 as compared to 1995 in Indonesia, Korea, and Taiwan; while the share increased in value added but decreased in employment in Brazil, and China. On the contrary, the share of high capital intensive industries to both value added and employment fell in India, Mexico, Russia and Turkey. The empirical evidence thus does not fully support the contention that with new technology over time, the high capital intensive industries would necessarily contribute more to value added and to employment. A plausible reason could be that within capital intensive industries the skill level distribution is not uniformly same. Some high capital intensive industries engage more of high-skill

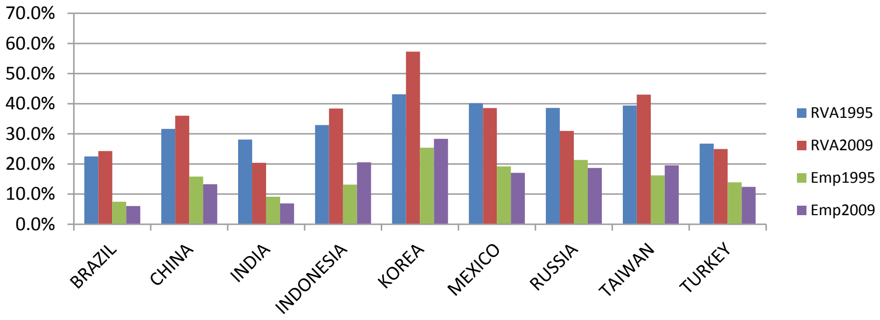

Fig. 5 Contribution of high capital intensive industries in real value added and employment in 1995 and 2009 for selected countries. *Source* Author's calculations based on data from WIOD data base (2014)

persons than others. The detailed analysis of growth in employment by skill level among high capital intensive industries is displayed in Fig. 6.

Figure 6 shows that in all the selected countries except Brazil and Mexico the average annual growth rate in high-skill persons engaged in high capital intensive industries; is different in different countries but is higher than that of medium-skill and low-skill persons engaged. The same trend is visible in Fig. 2 for the total non-agriculture economy. Thus, the trend at the disaggregate level is similar to the trend at the aggregate economy level.

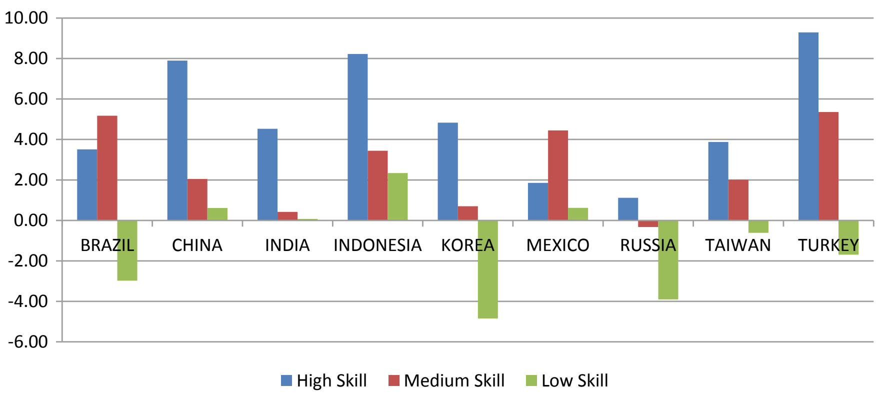

Fig. 6 Average annual growth rate of employment by skill level among high capital intensive industries (1995–2009). *Source* Author's calculations based on data from WIOD data base (2014)

Table 1 Fixed effect panel model estimates-1995–2009. Dependent variable: labour productivity

Explanatory variable	Coefficient	t-ratio
Capital labour ratio	3.53	19.71
Share of high-skill persons engaged	6822.38	6.45
constant	−1066.90	−7.76
No. of observations	135	
No. of groups	9	
F-value	369.77 (0.000)	
R-squared overall	0.946	

Source Author's estimates

5 Estimates of Econometric Model

As mentioned earlier, a simple econometric model has been estimated from the panel data of the selected nine countries for the period 1995–2009 (15 years) in which the relationship between labour productivity, capital labour ratio and the share of high-skill persons engaged in the total hours worked is obtained. For the purpose of this model, capital is defined as real gross fixed capital formation (real GFCF), labour is defined as total hours worked by persons engaged and output is real gross value added (real GVA). Labour productivity thus is defined as real gross value added (real GVA) per hour worked by persons engaged and capital—labour ratio as GFCF per hour worked by persons engaged. The results of the Fixed Effect panel model are presented in Table 1. It shows a significant and positive relationship of labour productivity with share of high-skill persons engaged, which is consistent with the postulated relationship. As expected, capital labour ratio is also found to be a significant determinant of labour productivity.

To confirm the results, the study also tested the relationship between Human capital index score given in The Human Capital Report 2016 (WEF 2016a), labour productivity and growth in employment for the selected eight countries.[13] It found a significant and positive relationship of Human capital score with labour productivity (correlation = 0.703) and GDP per capita (correlation = 0.852) but negative and insignificant correlation with growth in employment (−0.294). Similar results are also obtained from the correlations of score on 'Education and Training' given by Global Competitiveness Report: 2017–18 (WEF 2017) with the three variables of labour productivity, GDP per capita and growth in employment (Table 3).

[13] See Table 3. The score is not available for Taiwan.

Both the exercises in part I thus lead to the same conclusion that higher share of high-skill persons/higher human capital score generally has a positive relationship with higher labour productivity but not necessarily with higher growth in employment.

Part II: Skill, productivity and employment in the Organized and Unorganized Sectors in India (1999–00, 2004–05, and 2011–12)

6 Distribution of Employment by Skill in the Organized and Unorganized Sectors in India

The distribution of employment by skill in the organized and unorganized sector of the Indian economy for the three survey periods of 1999–00, 2004–05 and 2011–12 is presented in Fig. 7. Figure 7 shows that in the organized sector, the share of low-skill employed persons remained almost stagnant between 27 and 30% between 1999–00 and 2011–12. However, the share of medium-skill employed persons fell by 10 percentage points from 47 to 37% and that of high-skill persons employed increased by 8 percentage points from 25 to 33%. The increase in the share of high-skill workers in total employment could be partially due to the change in the nature of work in the organized sector due to fast changing technology requiring better skills. The other reason could be the general increase in the skill (education) level of the population and workers due to increased access and availability of education and training. The distribution of employment by skill in the unorganized sector in India is however very skewed towards low-skill and medium-skill employment. The

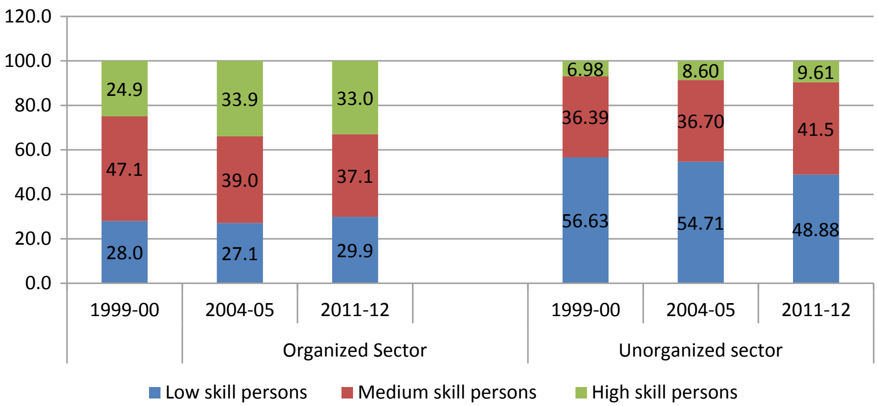

Fig. 7 Share of workers employed by skill in the Indian organized and unorganized sectors. *Source* Author's calculations based on data from different rounds of EUS

share of high-skill employment is very small at 9.6% in 2011–12 and was only 7% in 1999–00. The trend is partly the reflection of the nature of production activity and hence the skills required by the unorganized sector in India.

As a result of the basic difference in the nature of the production and skill requirements, one may also expect differences in the labour productivity between the two sectors. It is clear from Fig. 8 that not only the share of high-skill employment is higher in the organized sector; it is three times of the unorganized sector but the level of labour productivity (Rs. 0000) is also very high; 4–5 times higher in the organized sector as compared to the unorganized sector. However, we notice in Fig. 9

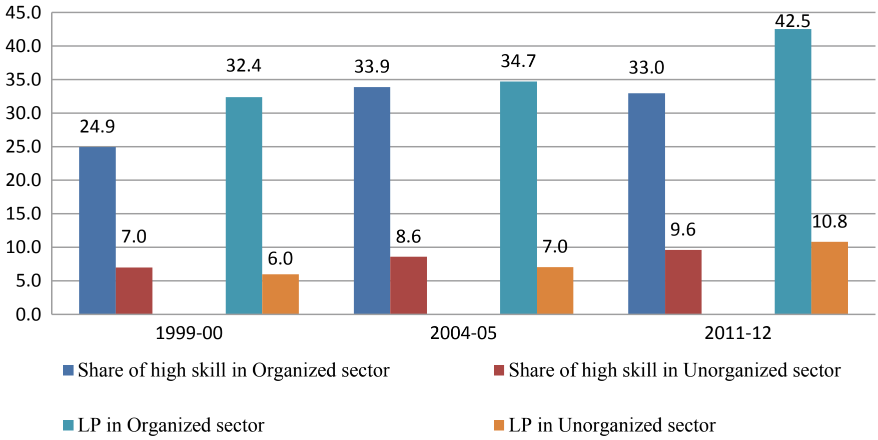

Fig. 8 Share of high-skill employment and labour productivity (LP) (Rs. 0000) in organized and unorganized sectors in India. *Source* Author's calculations

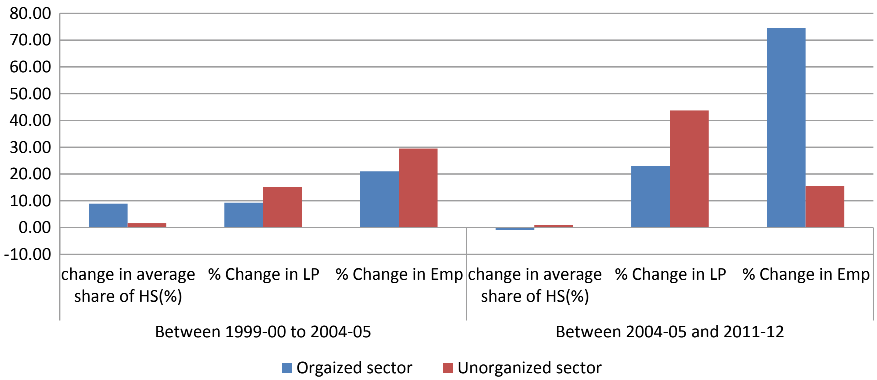

Fig. 9 Change in average share of high-skill persons employed, percentage change in average labour productivity and percentage change in average total employment between 1999–2004 and 2004–11. *Source* Author's calculations

that though the absolute level of labour productivity is higher in the organized sector but the percentage change in labour productivity between the two time periods of 1999–00 to 2004–05 and 2004–05 to 2011–12 is higher in the unorganized sector, thus catching up with the organized sector. However, the percentage change in employment is higher in the unorganized sector in the first period and in the organized sector in the second period. The important policy implication could be that a faster expansion of the organized sector in the Indian economy may help to accelerate the economy's growth.

7 Skill and Employment in the High Capital Intensive Industries in India

As is argued earlier that with capital-augmenting technological progress, the capital intensity of the industries would increase with increase in demand for high-skills and it is the high capital intensive industries that would be critical to the growth of the economy. The adoption of new technology leading to automation and increase in capital intensity of the firms in the organized sector in India is confirmed recently by Kapoor (2016) and was earlier concluded by Das et al. (2015) and Goldar (2000).

The analysis of the high capital intensive industries in Indian organized and unorganized industries begins with a look at their contribution in their respective total real value added and employment. It is noticed in Fig. 10 that high capital intensive industries have a more significant contribution in RVA and employment in the orga-

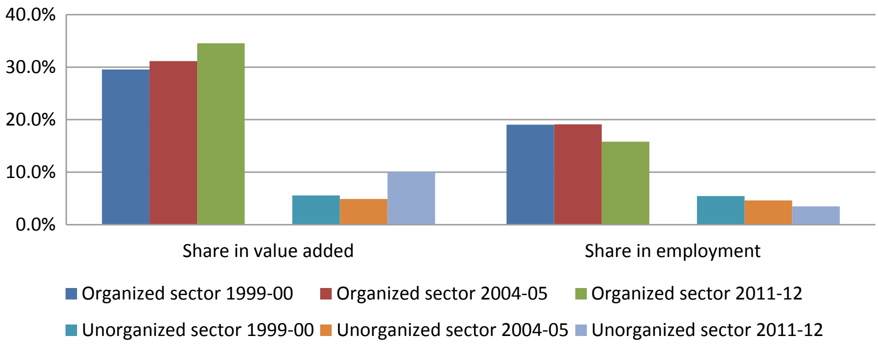

Fig. 10 Share of high capital intensive industry in Indian organized and unorganized sectors. *Source* Author's calculations

nized sector and in unorganized sector their contribution is rather small. However, the contribution in value added has been increasing but in employment it witnessed a declining trend. It is thus obvious that the high capital intensive industries will play a more important role in the growth of the Indian economy. But what kind of skills is used and how these are changing over the recent period in both the organized and unorganized sectors of the Indian economy is displayed in Fig. 11.

Figure 11 shows that among the high capital intensive industries, the growth in employment during 1999–00 and 2011–12 is highest in the low-skill employed persons in both the organized and unorganized sectors and is slower in medium-skill employed persons and moderate in high-skill employed persons. However, the growth of high-skill workers in the organized sector is much higher than the unorganized sector (where in fact it has declined), supporting the contention that it is the organized sector which might have more easily adopted and used the new technology requiring high skills. Kapoor[14] (2016) also finds support for the contention that firms with high capital intensity employed a higher share of skilled workers. The high growth in low-skill employment is partially the result of low access to education and training to the workers; both within the firm and outside the firms and is partly due to the increase in sub-contracting and informalization of the workers (Mehrotra et al. 2013; Goldar and Aggrawal 2012).

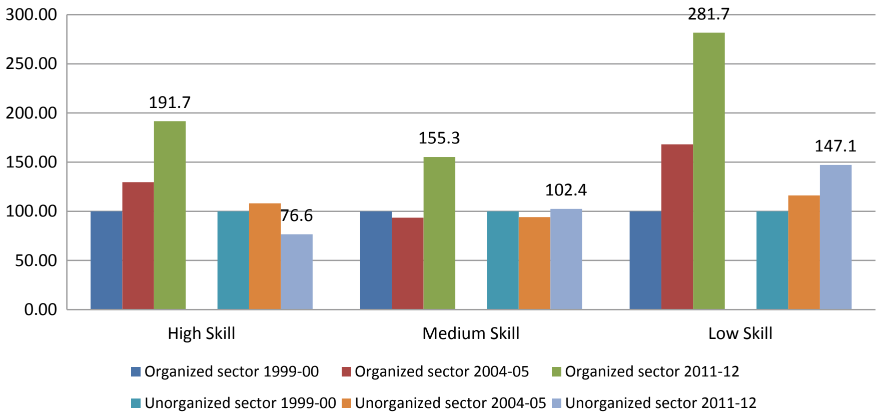

Fig. 11 Index of employment by skill level among high capital intensive industries in the Indian organized and unorganized sector (1999–2011). *Source* Author's calculations

[14]The author believes that it has led to a widening inequality of income between the high-skill and low-skill workers.

8 Summary and Conclusion

In a rapidly changing world with increased globalization, fast technical change, demographic transitions, migration and immigration have put pressure on the structure of skill requirements in most countries in recent decades. There is a growing concern that these changes are making many of the old skills redundant and there is a surge in some of the new skills which are in short supply. The costs of mismatch and shortages of skills are presumed to be substantial through its impact on productivity and income for individuals, employers, as well as society as a whole. However, the exact costs are hard to measure and some efforts are made to find the exact mismatch of the skills.

The current paper has just looked at the supply side of the skills whereby the changes in the supply of three different types of skills-high-skills, medium-skills, and low skills are examined in the first part of the paper for the selected countries and for the organized and unorganized sectors of the Indian economy in the second part. It is observed that generally the share of high–skill employed persons has increased over the period of the study. It is also evident that in the selected countries, the change in the share of high-skill workers is associated with a positive change in labour productivity and total employment with some exceptions. The share of high capital intensive industries in the value added and employment has also witnessed an increase in majority of the countries. The growth in employment of high-skill workers within high capital intensive industries is positive in all the selected countries. The econometric analysis also lends support to the positive association between the share of high-skill persons engaged and labour productivity.

The evidence from the Indian organized and unorganized sector supports the hypothesis that generally the share of high-skill employed persons and the level of labour productivity are higher in the organized sector than the unorganized sector. However, recently there seems to be some catching up of labour productivity by the unorganized sector. An interesting trend observed in the Indian organized and unorganized sector is that, while the share of high capital intensive industries in value added has increased over the period of 1999–2011, its share in employment has declined. The declining share in employment could be possible due to the labour displacing nature of capital intensive industries. One distinct feature observed within high capital intensive industries is that while employment of all the three skill levels increased in the organized sector; it is only the low-skill employment which grew in the unorganized sector. The growth of low-skill employment in the unorganized sector in India does not auger well for the future of economic growth in India because the unorganized sector is not only huge in terms of its contribution to total value added and total employment but the labour productivity in the sector is also very low. Thus, government intervention is required to promote the organized sector in the economy and also to improve the productivity of the unorganized sector. Based on the evidence, it may be argued that there is a close association between skills of the person employed and the labour productivity. The countries have to make serious efforts to improve the share of the (hours worked by) high-skill workers

Table 2 Index of labour productivity by capital intensity in selected countries

Country	Labour productivity in High Capital Intensive Industries	Labour productivity in Medium Capital Intensive Industries	Labour productivity in Low Capital Intensive Industries
Brazil	100	35.3	14.8
China	100	50.9	16.2
India	100	37.9	25.4
Indonesia	100	30.1	27.6
Korea	100	48.0	27.9
Mexico	100	68.3	18.6
Russia	100	56.4	44.6
Taiwan	100	45.4	26.1
Turkey	100	71.2	31.6

Source Author's calculation

to both improve their labour productivity and thus economic growth; as well as to quickly adapt to the 'fourth industrial revolution'. Efforts by individuals, firms and governments are required to minimize the mismatch in the demand and supply of skills by continuously updating the skills through education and training.

Appendix: Methodology of Estimating Organized and Unorganized Employment

Since 1999–00, NSSO surveys on employment and unemployment (EUS) provide information about the type of enterprises, the number of workers and whether the enterprise uses electricity. From these, one can discern the nature of enterprise, whether it belongs to organized or unorganized sector. Organized sector employment is defined as the workers employed in either (a) Government/Public sector enterprises (code 5) or in public/private limited company (code 6) or cooperative societies/trusts/other non-profit institutions (code 7), or (b) in other manufacturing enterprises employing 20 and more workers or using electricity and employing 10 or more than 10 workers (Sundaram 2008).

The methodology used in this study to estimate employment in the organized and unorganized sectors of the Indian economy is based on the above framework given by Sundaram (2008) (Tables 2 and 3).

Table 3 Relationship between Human capital score, labour productivity, GDP per capita and growth of employment

Country	Human Capital score 2016	Score on education and training—2016	Labour productivity per person employed in 2017 US$ (converted to 2017 price level with updated 2011 PPPs)	GDP per capita in 2017 US $ (converted to 2017 price level with updated 2011 PPPs)	Growth of employment (percentage change)
Brazil	64.51	4.2	30,810	15,399.169	1.802
China	67.81	4.8	27,628	15,378.107	−0.318
India	57.73	4.3	18,473	7,434.626	1.376
Indonesia	67.61	4.5	27,970	13,040.361	1.237
Mexico	69.25	4.1	46,235	20,088.396	0.845
Russia	77.86	5.1	58,010	27,966.140	0.688
South Korea	76.89	5.3	77,315	40,064.685	0.840
Taiwan	67.57	4.8	76,789	26,363.858	3.098
Correlation of Human Capital score	–		0.703	0.852	−0.294
p-value	–		0.0518	0.007	0.480
Correlation of Score on education and training	–	–	0.665	0.776	−0.184
p-value			0.0718	0.0236	0.6634

Source Author's calculation
Sources of data 1. Table 1: The Human Capital Index (WEF 2016a) for Human capital score which is not available for Taiwan. 2. The Global Competitiveness Report: 2017–18 (WEF 2017) for the score on education and training. 3. Total economy database (The Conference Board 2019) for other three variables

References

Das, D. K., Sen, K., & Das, P. C. (2015). Labour intensity in Indian manufacturing. In K. V. Ramaswamy (Ed.), *Labour, employment and economic growth in India*. Delhi: Cambridge University Press.

Fields, G. S. (1980). Education and income distribution in developing countries: A review of the literature [Electronic version]. In T. King (Ed.), *Education and income: A background study for world development* (pp. 231–315). Washington, DC: The World Bank.

Goldar, B. (2000). Employment growth in organised manufacturing in India. *Economic and Political Weekly, 35*(14), April 1–7.

Goldar, B., & Aggrawal, S. C. (2012). Informalization of industrial labor in India: Effects of labor market rigidities and import competition. *Developing Economies, 50*(2), 141–169.

Greatz, G., & Michaels, G. (2017). Is modern technology responsible for jobless recoveries? *American Economic Review Papers and Proceedings*.
Kapoor, R. (2016). Technology, jobs and inequality: Evidence from India's manufacturing sector (Working Paper 313). New Delhi: ICRIER.
Mehrotra, S., Parida, J., Sinha, S., & Gandhi, A. (2013). Explaining employment trends in the Indian economy: 1993–94 to 2011–12. *Economic and Political Weekly, 49*(32), 49–57.
NCEUS. (2007). *Report on conditions of Work and Promotion of Livelihoods in the Unorganized Sector*. National Commission for Enterprises in the Unorganized Sector, Government of India, New Delhi, 2007.
OECD. (2013). *OECD skills outlook 2013. First results from the survey of adult skills*. Paris: OECD.
OECD. (2015). *Getting skills right: Assessing and responding to changing skill needs*. Paris: OECD.
OECD. (2018). *OECD compendium of productivity indicators*. Paris: OECD.
Sastry, N. S. (2004). Estimating informal employment and poverty in India. Discussion Paper Series, 7, Human Development Resource Centre, UNDP, India.
Sundaram, K. (2008). Employment, wages and poverty in the non-agricultural sector: All-India, 2000–05. *Economic and Political Weekly, 43*(22), 91–99.
The Conference Board. (2019). *Total economy data base*.
The Economist Intelligence Unit Limited. (2018). *The automation readiness index: Who is ready for the coming wave of automation?*
Timmer, M. P., Dietzenbacher, E., Los, B., Stehrer, R., & de Vries, G. J. (2015). An illustrated user guide to the world input–output database: The case of global automotive production. *Review of International Economics, 23*, 575–605.
WIOD. (2012). *Socio Economic Accounts (SEA): Sources and methods*.
World Bank. (2018). *World economic indicators.*
World Development Report. (2019). *The changing nature of work.*
World Economic Forum. (2016a). *The human capital report 2016*.
World Economic Forum. (2016b). *Global competitiveness report: 2016–17*.
World Economic Forum. (2017). *Global competitiveness report: 2017–18*.