



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

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Introduction

Skills development is central to economic performance of the countries in the current milieu when ‘disruptive’ technology is evolving at a fast pace. The new technology- internet of things (IOT); artificial intelligence (AI); machine learning; neural networks; digitization of manufacturing; 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 will get created tomorrow which do not exist today. So there is a simultaneous creation and destruction of jobs. The net impact 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.

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 labor 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 percent 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 percent of workers report mismatch. In parallel, many employers report that they face recruitment problems due to skill shortages.” 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

ones 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 ICT and the opportunities for lifelong learning¹ 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 shortages².

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 Guy (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 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 skills³ 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.

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.

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

However, higher economic growth and income also in turn, helps 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 WEF report (2016) on The Human Capital Index 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, 2016)), 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 association between skills, productivity and employment has long been discussed and 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 in PPP). Global Competitiveness Report (2016) also points out the significance of skills (talent) in an economy to reap the benefits of the tech revolution and achieve higher productivity and employment.

The paper in part I explores this crucial linkage between skills distribution, (labor) productivity and growth in employment both at the national level as well 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 labor 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 section 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 section 5. In part II on the link for India's organized and unorganized sectors, section 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, section 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 is WIOD data base, 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 to 2009; a period of 15 years⁴. 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. The same grouping has been used in both the sections of the current study. In the first section, the analysis and the data is restricted to a small set of countries which include the BRIC countries along with few other emerging 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 labor 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 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 2011-12⁶. So mainly three rounds of the survey 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 defined as real gross fixed gross fixed capital formation per person engaged (K/L). It is expected that the industries with high capital labor ratio would generally be the ones using better (may be latest) technology and more skilled labor. 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 industries⁷. 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 labor productivity, labor productivity is calculated as real value added per

⁴ The short time period is a serious limitation of the study.

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

⁶ See Appendix 1 for details of methodology to estimate organized and unorganized employment.

⁷ Agriculture has been excluded from this exercise.

hour worked by persons engaged (OECD, 2018) in section I and as double deflated⁸ real value added per person employed in section II.

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

3. Pattern in the distribution of employment by skill

Over the years the labor 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 labor productivity and to growth of national income (WEF, 2016). The role of education in human capital is but too obvious. The challenges of new technology have made it more imperative to invest in human capital and develop the 'right' skills⁹. Now there is awareness among countries to invest in education of its population and its labor 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 labor force of the countries around the world. WEF (2016) has come out with The Human Capital Report highlighting differences in 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 of employment (hours worked) by skill

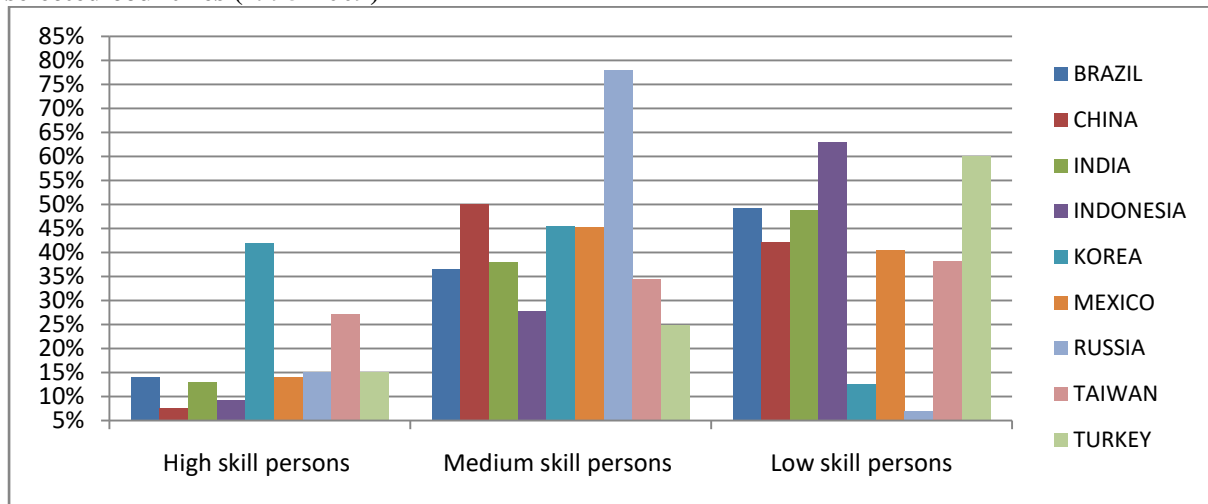
The average distribution of total hours worked in non-agriculture sector of the economies by skill of the persons engaged during 1995 -2009 is shown in Figure 1. It is seen from it that there are large variations in the average share of hours worked by high skill persons engaged among the selected nine countries. While the share is around 13-15 percent in Brazil, India, Mexico, Russia, and Turkey; the share is just 8-9 percent in China and Indonesia and is moderately high in Taiwan at 27 percent and significantly high in Korea at 42 percent. It seems this high skill advantage to Taiwan and Korea and relative disadvantage to other countries is partially reflected in their production pattern and international trade¹⁰. 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 percent in Indonesia and Turkey, it ranges between 35-40 percent for Brazil, India and Taiwan; and between 45-50 percent 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 percent) and a very low share of hours worked by low-skill persons engaged (just 7 percent). The share of hours worked by low-skill persons engaged is around 40-50 percent for majority of the selected countries- Brazil, China, India, Mexico and Taiwan; a high of 63 percent in Indonesia and significantly low in Korea (13 percent) and Russia (7 percent).

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

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.

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

Figure 1: Average Percentage distribution of hours worked by skill of the persons engaged in selected countries (1995-2009)



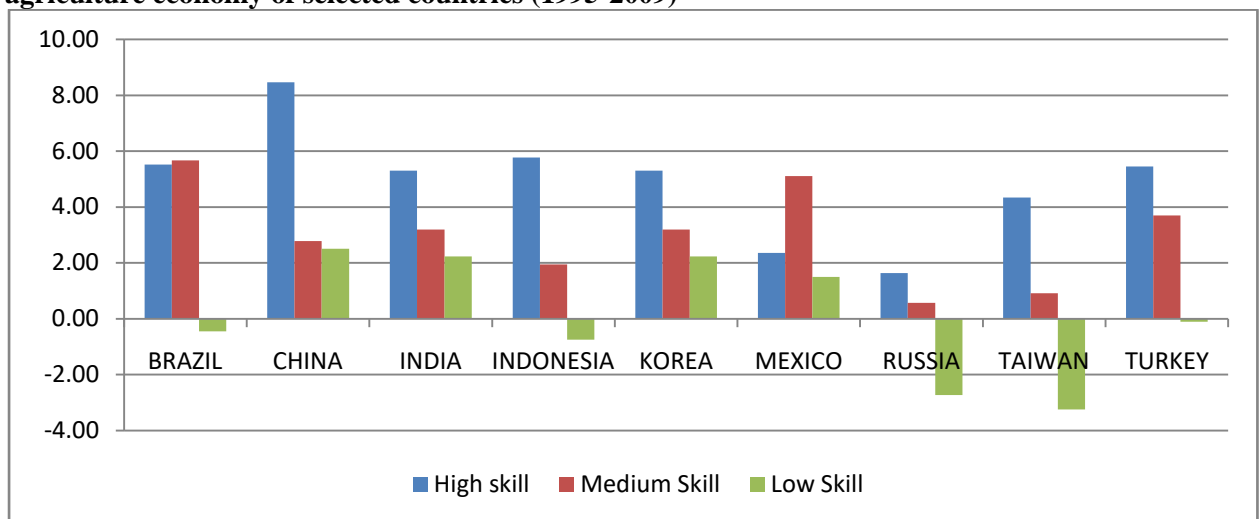
Source: Author's calculations

To add more clarity to the pattern of employment by skill, an analysis of growth of employment by skill is undertaken. In Figure 2, the average annual growth rate of hours worked during 1995-2009 by skill level of the persons engaged for non-agriculture sectors¹¹ of the economy is shown for all the selected countries. It shows that though the share of high-skill persons engaged as depicted in Figure 1 is low in majority of the countries, but the growth rate of high-skill persons engaged is higher (or almost same for Brazil) 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 recent changes in the nature of work where the technology induced new jobs now require significantly higher level of human capital (World Development Report, 2019).

The distribution and growth of skills of persons engaged reflects 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 does change in skill composition affects labor productivity and growth in employment. The answer to it is being attempted in the next section-3.2.

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

Figure 2: Average annual growth rate of hours worked by skill of the persons engaged in non-agriculture economy of selected countries (1995-2009)

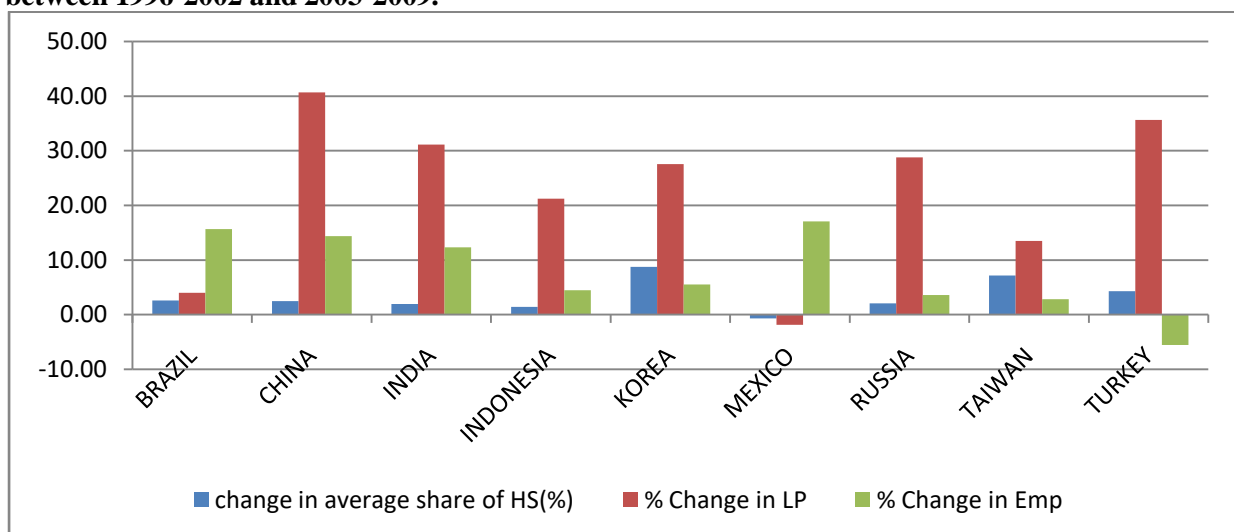


Source: Author's calculations

3.2 Skill composition, labor productivity and growth in employment

The relationship between skill composition and labor productivity can be viewed in two perspectives- either at the level of labor productivity or at the growth rate of labor productivity. The paper discusses the relationship at both the 'level' as well as at 'growth'. In Figure 3, the change in the average share of hours worked by high-skilled person engaged in total hours worked; the percentage change in the average level of labor 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.

Figure 3: Change in average share of hours worked by high-skill persons engaged, percentage change in average labor productivity and percentage change in average total employment between 1996-2002 and 2003-2009.



Source: Author's calculations

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 labor productivity has increased (in Mexico, both have reduced) between the two sub-periods. There is thus a positive association between change in average level of high-skill and change in average labor 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 collaborate the argument that increase in skill level may increase labor productivity and employment. However, one may argue that increase in labor productivity (and employment) may be induced by other factors like capital intensity¹² and not necessarily by change in the skill level. An econometric analysis using the panel data has been performed in Section 5 to validate the postulated relationship.

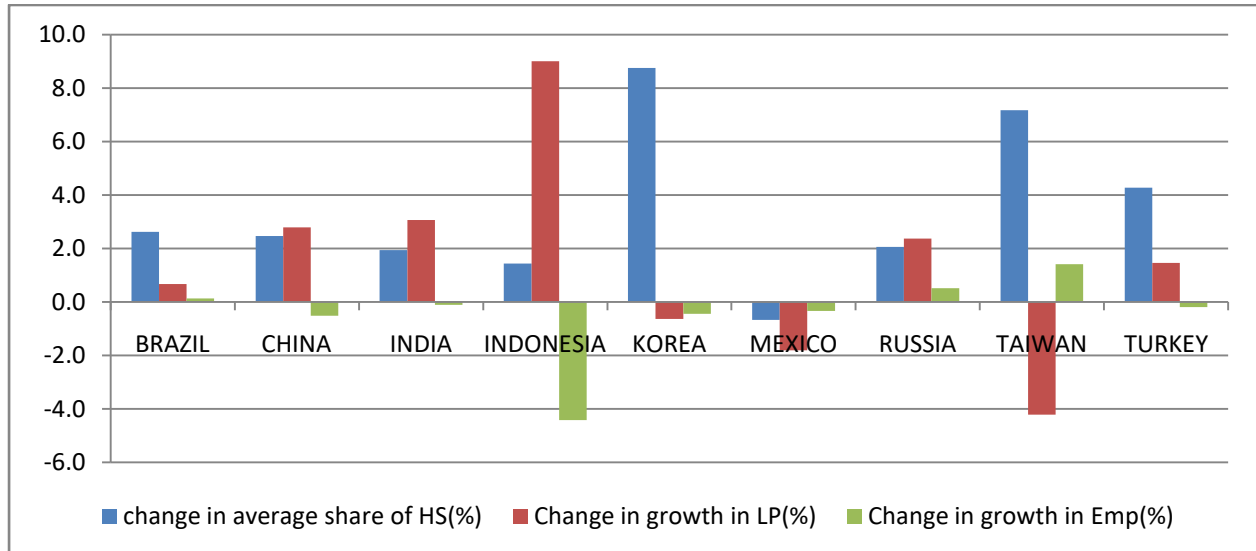
The relationship between the change in the share of hours worked by high-skill persons and change in the average growth rates of labor productivity and employment is presented in Figure 4; over the two periods of 1996-2002 and 2003-2009 for the selected nine countries. It is evident that the change between share of hours worked by high-skilled persons engaged and the change in average annual growth rate of labor 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 growth of labor 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 in indication of their fast adaption of new technology and focus on developing the skills of their labor force. The case of Mexico is an exception where a decrease in both the share of high-skilled persons engaged and the growth in labor 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 labor force, possibly resulting into slow growth in labor 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 in labor 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 behavior of growth in employment as a result of increase in the share of hours worked by high-skill persons and growth in labor productivity, the evidence of the selected nine countries in Figure 4 does show a mixed result. Out of the six countries in which growth rate of labor 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,

¹² It is observed that in all the selected nine countries, average labor productivity during 1995-2009 is higher in high capital-intensive industries than the medium and low skill intensive industries (Appendix Table 1)

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.

Figure 4: Change in average share of hours worked by high-skill persons engaged, change in average growth in labor productivity and change in average growth in total employment between 1996-2002 and 2003-2009



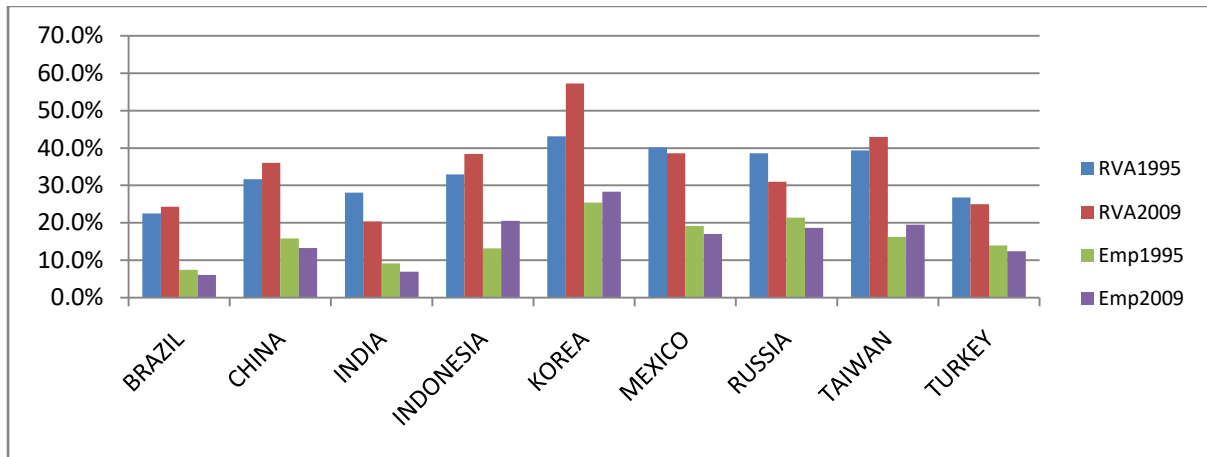
Source: Author's calculations

4. Structure of the economy: contribution of high capital intensive industries

With the evolving of technology at a fast pace since 1990's, 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 labor 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 persons

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

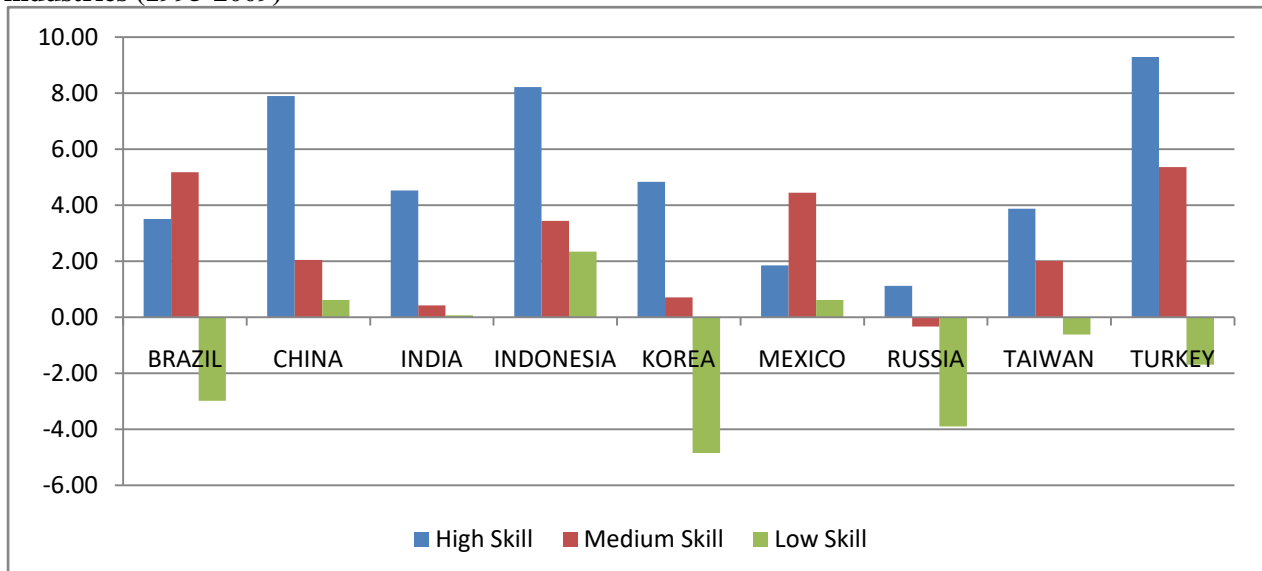
Figure 5: Contribution of high capital intensive industries in real value added and employment in 1995 and 2009 for selected countries



Source: Author's calculations

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 though is different in different countries but is higher than that of medium-skill and low-skill persons engaged. The same trend is visible in Figure 2 for the total non-agriculture economy. Thus, the trend at the disaggregate level is not much different than the aggregate economy level.

Figure 6: Average annual growth rate of employment by skill level among high capital intensive industries (1995-2009)



Source: Author's calculations

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 labor productivity, capital labor 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), labor is defined as total hours worked by persons engaged and output is real gross value added (real GVA). The results are presented in Table 1. It shows a significant and positive relationship of labor productivity with share of high-skill persons engaged, which is consistent with the postulated relationship. As expected, capital-labor ratio is also found to be a significant determinant of labor productivity.

Table 1: Panel Data Model Estimates-1995-2009

Dependent variable: labor productivity

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

To confirm the results, the study also tested the relationship between The Human capital index score given by The Human Capital Index (WEF, 2016), labor productivity and growth in employment for the selected eight countries¹³. It found a significant and positive relationship of Human capital score with labor 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 (WEF, 2017-18) with the three variables of labor productivity, GDP per capita and growth in employment (Appendix Table 2).

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 labor 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

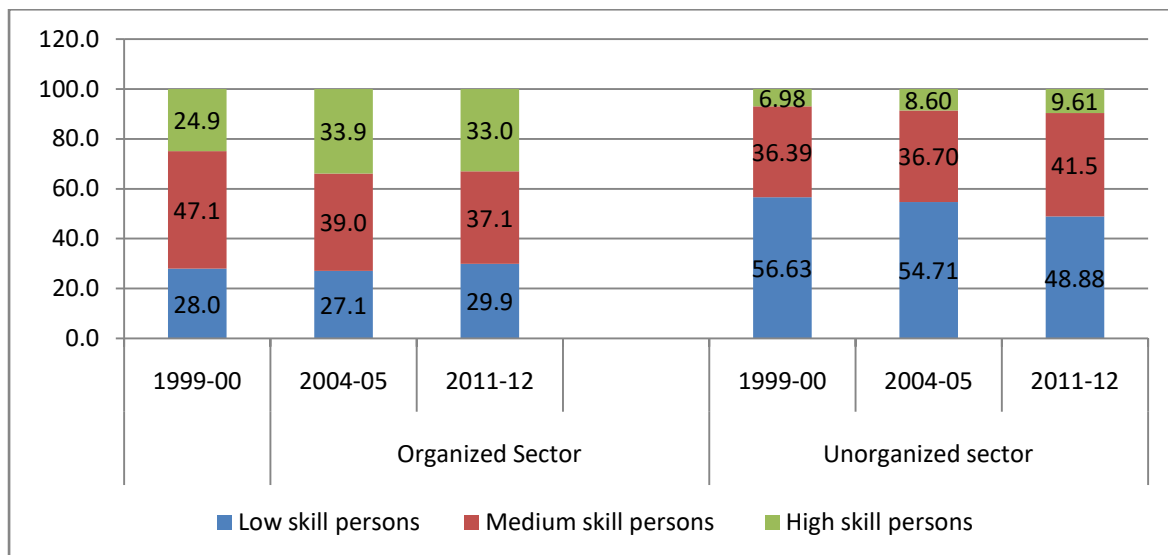
The distribution of employment by skill in the organized and unorganized sector of the Indian economy for the three survey periods of 1999-00, 2004-05 and 2011-12 is presented in Figure 7. Figure 7 shows that in the organized sector, the share of low-skill employed persons remained almost stagnant between 27 to 30 percent between 1999-00 and 2011-12. However, the share of medium-skill employed persons fell by 10 percentage points from 47% to 37%

¹³ See Appendix Table 2. The score is not available for Taiwan.

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 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.

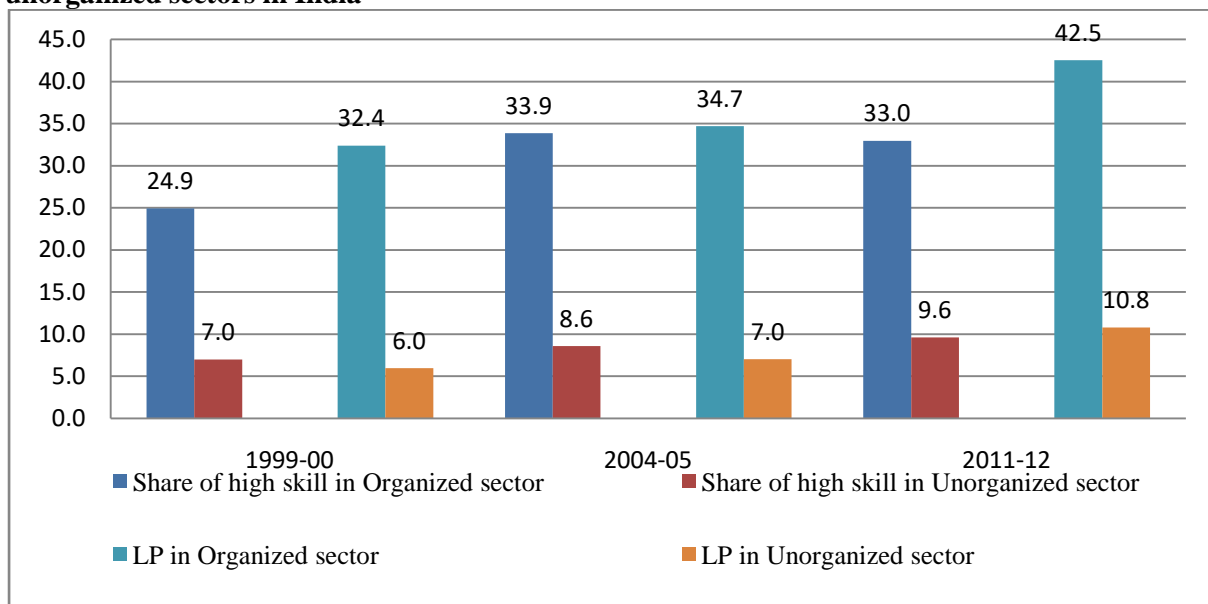
As a result of the basic difference in the nature of the production and skill requirements, one may also expect differences in the labor productivity between the two sectors. It is clear from Figure 8 that not only the share of high-skill employment is higher in the organized sector; it is three times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

Figure 7: Share of workers employed by skill in the Indian organized and unorganized sectors



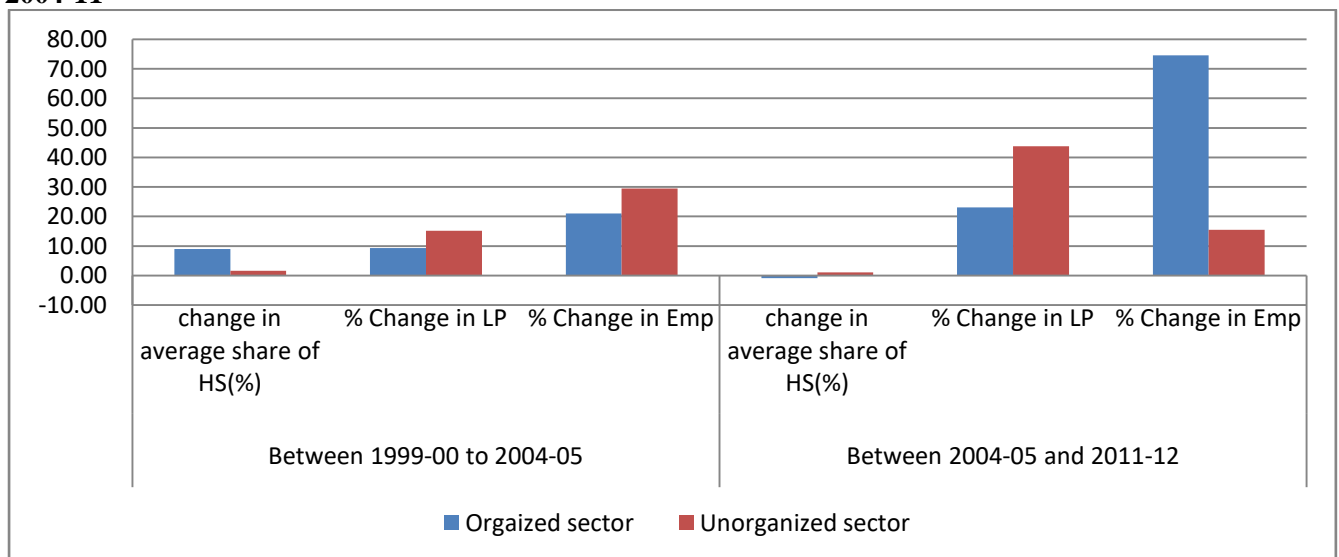
Source: Author's calculations

Figure 8: Share of high-skill employment and labor productivity (LP) in organized and unorganized sectors in India



Source: Author's calculations

Figure 9: Change in average share of high-skill persons employed, percentage change in average labor productivity and percentage change in average total employment between 1999-2004 and 2004-11



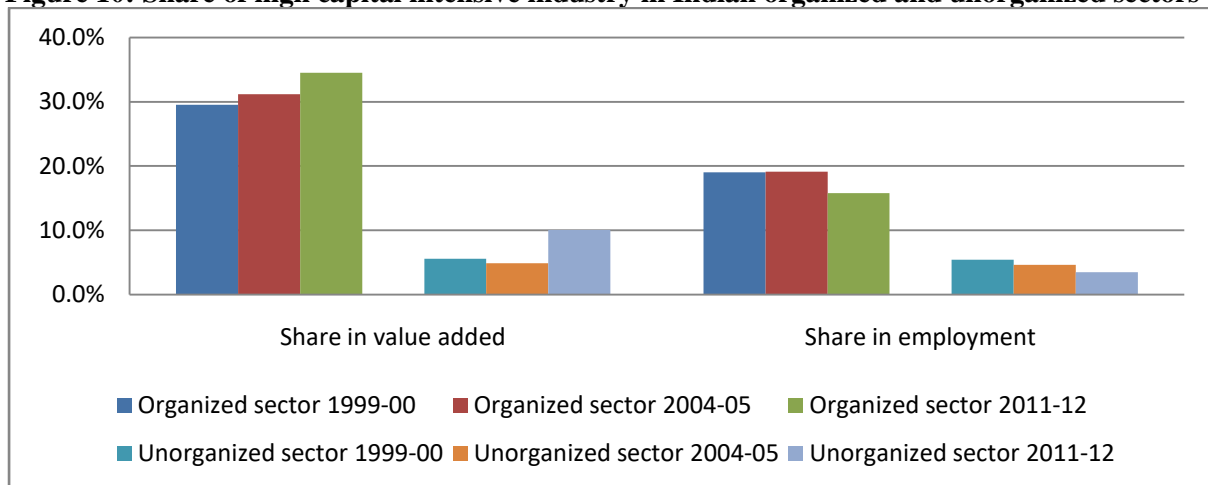
Source: Author's calculations

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).

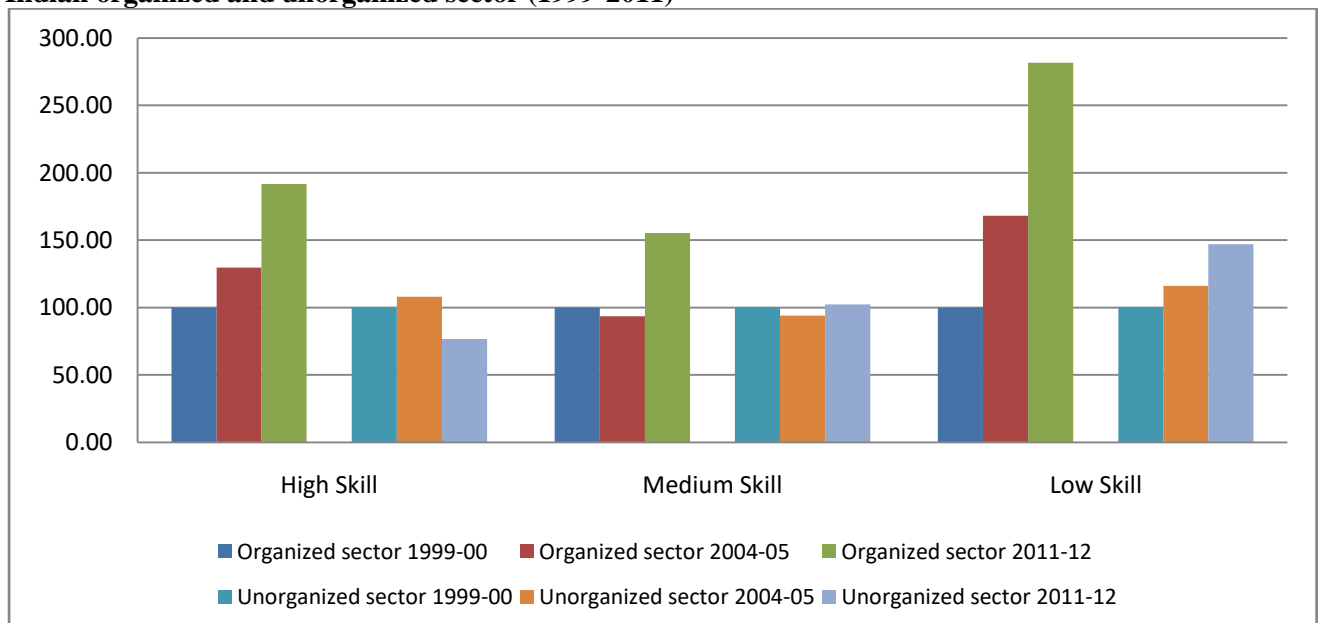
The analysis of the high capital intensive industries in Indian organized and unorganized industries begins with a look at their contribution in their respective total real value added and employment. It is noticed in Figure 10 that high capital intensive industries have a more significant contribution in RVA and employment in the organized sector and in unorganized sector their contribution is rather small. But while 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 would 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 Figure 11.

Figure 10: Share of high capital intensive industry in Indian organized and unorganized sectors



Source: Author's calculations

Figure 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

Figure 11 shows that among the high capital intensive industries, the growth in employment 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. Kapoor¹⁴(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 Aggarwal, 2012).

8. 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 recent 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 is examined in the first part 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 labor 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 labor productivity.

The evidence from the Indian organized and unorganized sector supports the hypothesis that generally the share of high-skill employed persons and also labor productivity is higher in the organized sector than the unorganized sector. However, recently there seems to be some catching up of labor 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 to 2011, its share in employment has declined. The declining share in employment could be possible due to the labor displacing nature of capital intensive industries. One distinct feature observed within

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

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 labor productivity in the sector is also very low. So 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 labour productivity. The countries have to make serious efforts to improve the share of the (hours worked by) high-skill workers to both improve their labor 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 skills demand and supply by continuously updating the skills through education and training.

Appendix 1: Methodology of estimating Organized and Unorganized Employment

Since 1999-00, NSSO surveys provide information about the type of enterprises, the number of workers and whether the enterprise uses electricity. From these, one can discern about 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 the formal and informal employment within the organized sector of manufacturing is based on the definition given by NCEUS (2007) and the framework given by Sastry (2004), which is similar to the ILO framework. As per this framework, informal worker includes all the workers in the proprietary and partnership firms except the regular and salaried workers with social security.¹⁵ It also includes all other unpaid family workers, all casual workers, and any other worker without social security working in Government/public sector (code 5), public/private limited company (code 6) and Cooperative societies/trust/other non- profit institutions (code 7). So, formal workers by the ILO framework include only workers who have social security and are working in Government/public sector (code 5), public/private limited company (code 6) and Cooperative societies/trust/other non- profit institutions (code 7) and are (i) own account workers (code 11); (ii) employers (code 12); (iii) regular employees (code 31) in any type of enterprises.

¹⁵ The information on Social security in the 55th round is available from coverage under the Provident fund. So, those regular employees with PF coverage are included as formal employees. In the 68th round, the information is available about the type of job contract and the availability of social security contribution.

Appendix Table 1: Index of labor productivity by capital intensity in selected countries

Country	Labor productivity in High Capital Intensive Industries	Labor productivity in Medium Capital Intensive Industries	Labor 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

Appendix Table 2: relationship between Human capital score, labor productivity, GDP per capita and growth of employment

Country	Human Capital score 2018	Score on education and training - 2016*	Labor 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, percent 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. The Human Capital Index, WEF, 2016 for Human capital score which is not available for Taiwan. 2. The Global competitiveness Report, 2017-18 for the score on education and training. 3. **Total economy data base** for other three variables.

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