ARE TECHNOLOGY TRANSFERS SKILL BIASED?

Abstract

A growing consensus suggests that absorption of new technology has a bias towards skilled labour. We investigate the relationship between technology change and demand for skilled workers by taking into account an array of tests to find evidence if technology has important effects on skill premium. The paper adopts an exploratory approach. Using a panel data for Indian manufacturing industries over the 2001-02 and 2013-14 period, the paper depicts the rising trend of skilled workers, decomposes the trend into within and between industries, suggests capital-skill complementarity as an important factor behind increasing skill demand, and identifies whether skill biased technology change (SBTC) is the key determinant of the trend observed. Our results show that not enough evidence can be found in favour of SBTC in case of India, a pattern comparable to 1990s as shown by previous studies. The study contributes as a good starting point to understand what accounts for the relative changes in industrial skill intensity.

Keywords: Skill biased technology change; Within & between industry decomposition; Capital-skill complementarity; Technology indicators; Services oriented industries

JEL Classification: J23, J24, E22**,** F66, O33

I. INTRODUCTION – BACKGROUND, KEY OBJECTIVES AND MOTIVATION

Human capital plays a twofold role in the process of economic growth – (i) as a stock of skills it is a factor of production that coordinates with physical capital and with raw (unskilled) labour; and (ii) as a stock of knowledge it is a source of innovation that is the basic source of economic growth. Human capital comprises of the knowledge, education, skills and characteristics of the members of an organization. It incorporates the abilities of the organizational performers to undertake skilful action and thereby produce value for the industry (Kianto et al., 2010). Therefore, an increase in skill intensity essentially means or implies an increased acquisition of human capital. In other words, skilled workers are bearers of human capital. The essential idea of this study is to look at the human capital adjustments to the pace of technological change and search for evidences for the same. Does a more rapid technical change bring about a greater utilization of human capital? This is because more educated or skilled labour can deal effectively with a rapid changing environment or with a temporary disequilibria resulting from technology change. Further, skilled people or workers make good innovators, so that an increase in skill intensity speeds the process of technological diffusion.

A more rapid pace of technological progress should induce increased inputs of human capital by making their acquisition more profitable. Relation between technological change and human capital is therefore complementary. Also, technical change is more complementary with human capital than with raw (unskilled) labour. There is evidence that the absorption of new technologies into production process is skill intensive, it creates skill biased labour demand and increases the relative wage of skilled to unskilled labour (Mincer, 1989; Nelson and Phelps, 1966; Eicher, 1996; Bartel and Lichtenberg, 1987). Therefore, there is an interaction between technological change and incentives to accumulate human capital, or growth of human capital is a consequence of exogenous accumulation of physical capital.

A growing consensus among economists is that the lead factor in increasing the demand for education, in the US for example, is the bias of technological change toward more educated workforce, in other words skill biased technology change (SBTC) (Berman et al., 2005). SBTC implies that new technologies drive employers' increased demand for skilled workers relative to less skilled. Under standard assumptions, skilled biased technology change results in decline in demand for less skilled workers from industries, and depresses their relative wages by lowering the relative prices of goods intensive in less skilled labour. This is consistent with increased wage premium for skilled workers. To put it differently, skilled workers can easily adopt to a new technology as it is less costly for them to learn additional knowledge (Violante, 2008).

How does SBTC affect relative wages of skilled labour in open economies such as India? Berman et al. (1998) argue that at recent levels of international trade and openness, it is difficult to imagine that major technological changes could occur in one country without rapid adoption by similar industries in other countries, given that one believes technology transfers across borders. This is called pervasiveness of SBTC. And more pervasive the SBTC, greater is the potential to impact relative wages.

The hypothesis or the central theme of our paper hence runs as a sequence looking at the following objectives:

- To identify a shift in skill demand across Indian manufacturing industries for the period 2001-02 and 2013-14.
- To decompose the changes in proportion of skilled workers in order to identify what accounts for the shift – can the increase in demand for skills be attributed to technology changes, or is it mainly explained by higher capital-output ratio and increased capital-skill complementarity?
- To test whether India provides evidence for pervasive SBTC, i.e. (i) are the shifts concentrated in same industries as the US, and (ii) is skill intensity correlated with technology indicators of high income countries.

Another important point to look at is whether the technology biased skilled intensity is more visible in case of services oriented industries. These industries are heavily reliant on knowledge work, individual skills and capabilities. The role of human capital as a part of the 'Intellectual Capital', comprising of managers/ skilled workers/ R&D personnel/ non-wage oriented labour, is likely to be especially important in case of services. The services oriented industries require more attention to be paid to employee characteristics, such as knowledge, skills etc, as these industries have a large impact on consumer's perceived value (Kianto et al., 2010). The importance of human capital is more pronounced among service industries/ firms as they rely on 'personnel' to generate and produce the output 'services'. We therefore try to demark these industries because expecting that they would observe relatively higher levels of technology diffusion. The reason being that services are more human capital intensive and technological change is driven by human capital embedded in labour. Also international mobility of factors is high in services oriented industries, and increased specialization in services promotes diffusion of technology from where it originated to other markets.

The motivation for our analysis comes from the recent trend observed for India's economic growth that seems to have benefitted industries with more skilled workers and capital in contrast to those industries that rely on unskilled workforce (Kapoor, 2015). This raises concerns as increasing skill and capital intensity of manufacturing sector could result in fewer workers being employed. Further, substantial empirical evidence has supported a simultaneous increase in globalisation and wage inequality in developing countries, with international flow of capital as a factor behind (Goldberg and Pavcnik, 2007). Hence, as a starting point, it is important to understand what mainly accounts for the increase in skill demand. Also the paper draws attention from similar studies done in the past, for instance Berman et al. (2005), that look at the case of Indian manufacturing in the 1990s and test whether SBTC arrived in India during 1990s and how much was contributed by international transfer of technology.

The paper is original in several respects and contributes by (i) extending the period of study to 2000s, (ii) carrying out a series of tests to analyse the linkage between skill composition and technology process for Indian manufacturing at industry level, (iii) analysing whether Indian manufacturing industries showed signs of pervasive SBTC in 2000s, and (iv) giving a greater focus to services oriented industries.

Our conclusions are best stated at the outset: we find that Indian manufacturing observed a shift in favour of higher skill composition in the 2000s, and there appears to be a cross industry correlation, particularly in case of skilled wages. The trend also suggests a rise in capital-labour and capital-skill ratios. Decomposing the increase in skill demand, we find that majority of these changes can be attributed to within industries' shift. However, testing what results in such a movement towards greater skill demand, the outcomes suggest that, during 2000s, capital-skill complementarity along with a higher capital-output ratio are good predictors of skill upgrading within Indian manufacturing rather than changes or transfers in technology. In other words, not enough evidence can be found in favour of SBTC.

The paper is in 5 sections of which this is the first. In section II we briefly summarise the trend and stylized facts for 26 Indian manufacturing industries over the 2001-02 and 2013-14 period to build our discussion for the changing skill composition. Section III decomposes what accounts for the changes in skill demand. Section IV discusses whether there is a common pattern between India's increasing skill intensity and that of US; and whether there is a correlation between India's rising skill composition and technology indicators of high income countries. Conclusions and implications are drawn in section V.

II. DATA AND TREND

India's labour force is growing rapidly and will soon surpass China to become world's largest. However, the country is struggling to generate opportunities for its workforce. Workers have faced risks of redundancy or failed to find jobs. As reported by McKinsey firm, machines could eliminate around 52 percent of jobs if technology spreads across board (Economist, 2017). In the midst of rising mechanization workplaces must look for greater levels of efficiency, and this has different implications for different categories of workers. For instance, machines largely substitute unskilled labour and complement skilled labour (Kapoor, 2016). Further, over the 1983-1999 period wage inequality has risen in India. Rate of wage increase has been much faster for the higher wage group than lower. Of the 60% increase in real wages in 1999 compared to 1983, the least skilled workers have gained 40%

but most skilled workers' real wages doubled (Kijima, 2006). And this accelerating skill premium has been due to an increase in demand for skilled labour.

Before demarking the factors attributing to the shifts in skilled workers' demand (wages and employment), we look at some stylized facts in this section. We use the 'Principal Characteristics by Major Industry Group' data obtained from India's Annual Survey of Industries (ASI) for the period 2001-02 to 2013-14. The Annual Survey of Industries (ASI) is the principal source of industrial statistics in India, and extends its coverage to the entire country. It is the main survey conducted by Central Statistics Office (CSO) Industrial Statistics (IS) wing. ASI framework, scope and coverage are detailed in this document: http://www.csoisw.gov.in/cms/cms/Files/690.pdf.

The data is disaggregated at 2 digit National Industrial (Activity) Classification (NIC). NIC plays a very vital role in maintaining standards of data collection, processing and presentation along with its wide range of applications in policy formulation and analysis. This classification is used in all types of censuses and sample surveys conducted in India. The Central Statistical Organisation (CSO) in the Ministry of Statistics and Programme Implementation is the nodal authority for bringing out the NIC in India. The first classification was NIC-62 followed by NIC-70, NIC-87 and NIC-98, NIC-2004. The latest and sixth classification NIC-2008 has been developed and released by CSO, and can be found here: http://www.csoisw.gov.in/cms/cms/Files/856.pdf. We use the NIC-2008 classification, and adjust the pre 2008 data (based on NIC-1998 and NIC-2004) to reflect the adoption of the new industrial classification system in 2008.

We classify 26 manufacturing industries, out of which seven are identified as services oriented industries. The list of services oriented industries includes: Pharmaceuticals; Machinery, Equipment & Repairs; Motor Vehicles, Trailers & Semi Trailers; Electrical Equipment; Computer, Electronic & Optical Products; Printing & Reproductions of Recorded Media; and Publishing Activities.

A full list of all the variables used and their definitions is given in Table 1 below.

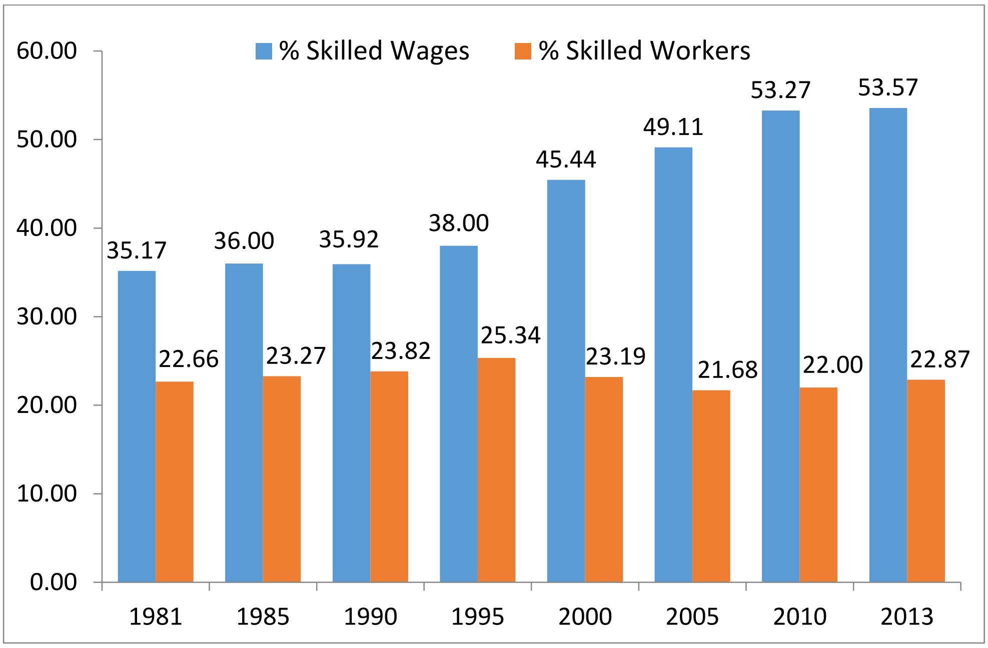
Table 1: Variable Definitions

Variable name	**Definition**
Skilled workers	Difference between total persons engaged and total number of workers (non manual workers).
Skilled wages	Difference between total emoluments and wages to workers.
Total persons engaged	All persons engaged by the factory whether for wages or not, in work connected directly or indirectly with the manufacturing process.
Total number of workers	Includes all persons employed directly, informally or formally or through contractor on payment of wages or salaries and engaged in any manufacturing process.
Total emoluments	Defined in the same way as wages but paid to all employees, plus imputed value of benefits in kind and also includes profit sharing.
Wages to workers	Includes all remuneration capable of being expressed in monetary terms and also paid more or less regularly in each pay period to workers as compensation for work done during the accounting year. It includes direct wages and salary, overtime, bonuses etc.
Capital	Represents the depreciated value of fixed assets owned by the factory as on the closing day of the accounting year. It would include land, building, plant and machinery, transport equipment etc.
Value added (Net)	Obtained by deducting the value of total input and depreciation from gross output.

Note: Detailed description can be found in this document:
http://www.csoisw.gov.in/cms/cms/Files/243.pdf

Over the past years, 1981-2013, India has experienced a widening skill wage gap along with a shift in favour of skilled workers' employment. Figure 1 shows the all India trend for percentage of skilled workers employed and skilled wages over the 1981-2013 period. Tables 2 and 3 give a more disaggregated industry wise trend and confirm a generally rising demand for skills but with variations across industries.

Figure 1: Changes in skill intensity over the period 1981-2013 – All Industries



Note: Figures are calculated by finding the percentage share of skilled wages to total emoluments, and by finding the percentage share of skilled workers to total persons engaged for the particular year.

Table 2: % Skilled Workers – Industry wise

	2013-14	2012-13	2010-11	2009-10	2008-09	2007-08	2006-07	2005-06	2004-05	2003-04	2001-02
BASIC METALS	23.28	23.03	24.09	22.07	22.54	22.41	23.24	24.15	25.30	25.79	26.09
COKE AND REFINED PETROLEUM PRODUCTS	25.76	25.69	25.40	22.26	20.33	20.86	23.39	23.23	24.44	25.76	24.94
CHEMICALS AND CHEMICAL PRODUCTS	30.23	26.83	25.85	26.32	27.61	31.57	32.36	32.05	31.71	32.80	33.03
PHARMACEUTICALS, MEDICINAL CHEMICAL AND BOTANICAL PRODUCTS	39.24	38.27	38.81	38.29	37.23	33.33	29.45	31.42	31.67	33.97	35.26
FOOD PRODUCTS & BEVARAGES	22.23	22.00	21.79	21.08	21.48	21.70	22.58	21.50	21.36	22.48	22.78
TEXTILES	15.27	14.86	14.73	14.87	14.75	14.85	27.36	14.63	14.86	15.14	15.00
MACHINERY AND EQUIPMENT N.E.C. & REPAIRS	31.67	31.34	31.42	31.13	42.46	30.82	30.75	32.19	31.93	33.90	34.96
MOTOR VEHICLES, TRAILERS AND SEMI-TRAILERS	23.74	22.61	21.87	22.57	22.91	21.84	22.58	23.32	24.22	25.45	27.70
OTHER NON-METALLIC MINERAL PRODUCTS	18.71	18.83	20.04	18.87	18.31	18.14	17.77	18.53	19.41	20.62	19.90
RUBBER AND PLASTICS PRODUCTS	21.02	21.95	21.73	21.36	23.00	23.43	22.93	23.39	24.87	24.45	25.29
ELECTRICAL EQUIPMENT	27.99	26.14	25.75	25.31	27.34	26.90	28.47	27.21	28.90	30.88	32.39
FABRICATED METAL PRODUCTS, EXCEPT MACHINERY AND EQUIPMENT	22.82	22.36	21.52	22.30	21.82	22.25	22.21	22.18	23.74	24.65	25.74
WEARING APPAREL	15.82	14.30	14.71	14.12	14.80	16.22	13.88	13.60	13.90	13.62	14.05
OTHER TRANSPORT EQUIPMENT	21.11	19.19	19.52	19.88	20.54	21.41	19.46	22.42	22.99	23.59	25.01
COMPUTER, ELECTRONIC AND OPTICAL PRODUCTS	31.52	32.63	29.45	51.23	32.43	37.66	30.12	34.02	41.42	43.44	37.12
TOBACCO PRODUCTS	4.30	5.08	4.72	4.95	4.96	4.97	5.23	5.61	4.96	4.98	6.17
PAPER AND PAPER PRODUCTS	22.33	21.73	21.18	20.89	21.01	16.97	20.72	21.95	22.47	21.78	21.73
CROP & ANIMAL PRODUCTION, HUNTING & RELATED SERVICE ACTIVITIES	25.08	22.22	18.98	21.54	18.18	18.18	16.22	17.39	15.77	18.43	17.93
LEATHER AND RELATED PRODUCTS	14.58	14.42	14.09	14.41	15.21	14.50	14.67	15.63	15.53	19.05	16.21
PRINTING AND REPRODUCTION OF RECORDED MEDIA	35.85	38.96	35.20	31.99	33.65	26.80	30.47	32.71	32.94	35.53	36.37
PUBLISHING ACTIVITIES	50.89	51.23	51.99	55.51	54.71	37.81	37.58	36.32	38.88	37.48	38.22

MANUFACTURE OF FURNITURE & OTHER MANUFACTURING	23.19	23.19	21.76	21.44	22.95	20.32	22.09	22.65	21.76	22.34	24.73
WOOD AND PRODUCTS OF WOOD AND CORK, EXCEPT FURNITURE	23.99	24.78	23.07	24.13	24.00	22.99	22.44	24.15	24.91	24.07	25.35
WASTE COLLECTION, TREATMENT & DISPOSAL ACTIVITIES; MATERIALS RECOVERY	22.87	24.02	19.67	17.95	18.03	18.25	19.59	17.78	13.45	16.82	26.55
OTHER MINING AND QUARRYING	11.02	11.17	12.19	13.84	10.25	9.46	13.09	12.25	8.03	10.19	12.11
OTHER INDUSTRIES	36.19	37.07	36.20	35.46	35.76	37.54	37.60	35.30	33.92	33.25	34.02

Note: Figures are calculated by finding the percentage share of skilled workers to total persons engaged.

Table 3: **% Skilled Wages - Industry wise**

	2013-14	2012-13	2010-11	2009-10	2008-09	2007-08	2006-07	2005-06	2004-05	2003-04	2001-02
BASIC METALS	48.53	49.13	53.14	51.34	52.31	50.02	48.68	47.17	45.51	45.81	40.34
COKE AND REFINED PETROLEUM PRODUCTS	52.28	54.25	51.53	52.08	50.00	45.54	47.86	45.97	45.62	46.18	43.23
CHEMICALS AND CHEMICAL PRODUCTS	61.27	61.11	60.31	60.99	65.07	63.38	63.53	62.42	60.84	60.11	54.88
PHARMACEUTICALS, MEDICINAL CHEMICAL AND BOTANICAL PRODUCTS	70.85	70.77	70.87	71.85	69.66	68.09	59.76	59.15	59.01	64.71	58.21
FOOD PRODUCTS & BEVARAGES	49.05	50.37	47.72	48.72	48.10	47.37	46.67	45.53	44.24	44.46	40.36
TEXTILES	36.73	36.78	36.80	37.66	37.03	36.57	36.20	33.21	32.80	32.38	26.10
MACHINERY AND EQUIPMENT N.E.C. & REPAIRS	64.08	63.17	64.59	63.40	62.25	61.16	58.46	58.99	56.05	55.55	53.98
MOTOR VEHICLES, TRAILERS AND SEMI-TRAILERS	54.96	54.44	53.17	52.58	53.84	52.71	50.94	50.23	48.46	50.41	44.67
OTHER NON-METALLIC MINERAL PRODUCTS	48.21	49.61	49.55	51.16	49.23	48.05	43.93	44.75	44.38	44.96	38.10
RUBBER AND PLASTICS PRODUCTS	50.33	49.20	50.58	51.88	53.17	51.36	47.80	47.37	47.89	47.09	42.54
ELECTRICAL EQUIPMENT	60.04	58.55	60.00	56.37	61.02	60.22	57.36	54.95	53.39	54.71	50.45
FABRICATED METAL PRODUCTS, EXCEPT MACHINERY AND EQUIPMENT	51.94	49.96	48.88	52.34	52.04	52.20	51.61	48.95	46.80	45.83	44.46
WEARING APPAREL	41.77	38.47	40.34	39.27	40.96	39.00	38.21	37.05	37.58	35.52	32.26
OTHER TRANSPORT EQUIPMENT	50.55	48.74	47.55	48.72	50.05	48.67	44.68	48.37	47.70	47.44	43.55
COMPUTER, ELECTRONIC AND OPTICAL PRODUCTS	71.30	70.41	68.78	59.96	72.39	71.75	68.46	71.32	74.13	73.90	72.63
TOBACCO PRODUCTS	29.79	28.79	25.07	26.93	25.13	24.23	24.34	23.97	21.76	22.10	16.94
PAPER AND PAPER PRODUCTS	47.85	49.73	48.36	46.25	45.88	43.47	44.23	43.33	42.34	42.48	37.59
CROP & ANIMAL PRODUCTION, HUNTING & RELATED SERVICE ACTIVITIES	48.24	45.71	43.49	39.77	30.14	31.54	26.27	30.76	24.41	27.42	23.41
LEATHER AND RELATED PRODUCTS	40.34	37.23	36.69	41.00	41.57	36.13	36.48	34.90	35.81	39.88	29.72
PRINTING AND REPRODUCTION OF RECORDED MEDIA	61.16	64.50	66.75	61.27	62.04	64.51	64.28	66.17	66.02	64.46	61.68
PUBLISHING ACTIVITIES	77.19	78.03	74.61	78.79	80.05	68.03	64.68	65.07	63.76	61.59	57.63
MANUFACTURE OF FURNITURE & OTHER MANUFACTURING	49.09	51.24	49.61	49.15	49.19	41.21	43.23	43.08	39.73	39.99	40.30

WOOD AND PRODUCTS OF WOOD AND CORK, EXCEPT FURNITURE	46.77	49.58	47.35	47.62	47.29	44.65	41.61	44.30	41.51	41.11	38.65
WASTE COLLECTION, TREATMENT & DISPOSAL ACTIVITIES; MATERIALS RECOVERY	44.05	44.42	42.60	38.75	42.02	38.73	54.93	31.63	22.15	31.04	41.04
OTHER MINING AND QUARRYING	29.12	29.85	31.76	31.97	31.85	24.97	31.26	27.06	17.51	27.17	15.47
OTHER INDUSTRIES	60.28	60.19	60.49	63.62	60.65	59.49	59.81	55.23	53.73	50.62	50.03

Note: Figures are calculated by finding the percentage share of skilled wages to total emoluments.

Focusing on the seven identified services oriented industries, we calculate the cross industry correlation for skilled wages and employment to check whether similar skill upgrading is observed in same sort of industries. Table 4 shows the cross industry correlations for percentage of skilled wages. There seems to be a cross industry correspondence with most industries showing positive and significant pair wise correlations: 11 out of 21 pair wise correlations are positive and 10 of them are statistically significant. Mainly two industries, namely Computer, Electronic & Optical Products and Printing & Reproduction of Recorded Media, give contrary results. However, such clustering is not significantly visible in case of percentage of skilled workers' employment: 13 positive out of 21 pair wise correlations but only 2 statistically significant, as shown in Table 5.

Table 4: Cross Industry Correlation of Percentage of Skilled Wages in Services Oriented Industries

	Pharmaceuticals	Machinery, equipment & repairs	Motor vehicles, trailers & semi-trailers	Electrical equipment	Computer, electronic & optical products	Printing & reproduction of recorded media	Publishing activities
Pharmaceuticals	1						
Machinery, equipment & repairs	0.87***	1					
Motor vehicles, trailers & semi-trailers	0.85***	0.90***	1				
Electrical equipment	0.77***	0.85***	0.92***	1			
Computer, electronic & optical products	- 0.43	- 0.51	- 0.29	- 0.16	1		
Printing & reproduction of recorded media	- 0.29	- 0.12	- 0.07	- 0.02	0.29	1	
Publishing activities	0.88***	0.92***	0.87***	0.77***	- 0.48	- 0.29	1

Note: *** denotes significance at 1% level.

Table 5: Cross Industry Correlation of Percentage of Skilled Workers in Services Oriented Industries

	Pharmaceuticals	Machinery, equipment & repairs	Motor vehicles, trailers & semi-trailers	Electrical equipment	Computer, electronic & optical products	Printing & reproduction of recorded media	Publishing activities
Pharmaceuticals	1						
Machinery, equipment & repairs	0.17	1					
Motor vehicles, trailers & semi-trailers	- 0.12	0.25	1				
Electrical equipment	- 0.37	0.24	0.92***	1			
Computer, electronic & optical products	- 0.01	- 0.11	0.23	0.08	1		
Printing & reproduction of recorded media	0.54	0.17	0.42	0.21	- 0.19	1	
Publishing activities	0.87***	0.25	- 0.41	- 0.62	- 0.02	0.35	1

Note: *** denotes significance at 1% level.

Another important trend to observe is the rising levels of Capital-Worker and Capital-Skill ratios as shown in Tables 6 and 7 respectively for all industries taken together and also for the seven services oriented industries. The trend confirms that a rising capital intensity of production in the manufacturing sector is evident, and raises the question whether there could be a potential link to a shift towards skill intensive production methods. In other words, the central question of the paper is emphasized, i.e. is growth of skill demand a consequence of accumulation of physical capital or technology change?

Table 6: Capital – Worker Ratio

	2001-02	2003-04	2004-05	2005-06	2006-07	2007-08	2008-09	2009-10	2010-11	2012-13	2013-14
Pharmaceuticals	5.19	5.17	5.96	4.64	4.59	6.24	17.79	19.89	19.44	21.09	23.05
Machinery, equipment & repairs	4.89	5.43	5.29	6.30	5.99	7.19	8.29	10.09	10.94	13.55	14.70
Motor vehicles, trailers & semi- trailers	12.11	9.39	3.29	9.53	9.65	12.54	17.30	16.83	17.49	20.84	24.09
Electrical equipment	6.28	5.85	11.96	5.44	5.83	6.70	8.76	9.57	10.67	12.86	12.42
Computer, electronic & optical products	10.94	24.98	20.52	21.25	17.35	17.53	13.77	12.66	14.26	15.06	24.56
Printing & reproduction of recorded media	10.21	16.95	14.11	15.35	15.13	12.97	11.68	10.52	13.08	13.67	13.61
Publishing activities	4.91	5.69	6.18	7.81	9.07	10.58	29.70	25.32	29.74	31.98	26.11
All Industries	7.25	7.78	7.77	8.51	9.07	10.31	12.03	14.77	16.23	21.69	22.77

Note: Capital worker ratio is calculated as the ratio of capital to total number of workers.

Table 7: Capital – Skilled Worker Ratio

	2001-02	**2003-04**	**2004-05**	**2005-06**	**2006-07**	**2007-08**	**2008-09**	**2009-10**	**2010-11**	**2012-13**	**2013-14**
Pharmaceuticals	9.52	10.05	12.86	10.14	10.99	12.48	30.00	32.05	30.64	34.02	35.69
Machinery, equipment & repairs	9.09	10.60	11.27	13.28	13.49	16.13	11.23	22.32	23.88	29.68	31.72
Motor vehicles, trailers & semi- trailers	31.59	27.50	10.30	31.36	33.10	44.87	58.20	57.74	62.50	71.30	77.42
Electrical equipment	13.10	13.09	29.42	14.57	14.65	18.20	23.28	28.24	30.76	36.34	31.94
Computer, electronic & optical products	18.54	32.52	29.02	41.22	40.25	29.02	28.70	12.06	34.16	31.10	53.38
Printing & reproduction of recorded media	17.86	30.74	28.73	31.57	34.52	35.40	23.04	22.38	24.07	21.42	24.36
Publishing activities	7.94	9.50	9.71	13.70	15.07	17.39	24.58	20.30	27.47	30.44	25.19
All Industries	24.10	26.54	27.67	30.72	29.21	37.49	41.40	51.33	57.54	75.22	76.78

Note: Capital skilled workers ratio is calculated as the ratio of capital to number of skilled workers.

In the remainder of the paper we consider these trends and try to explore the factors that account for such shifts and whether technology that complements skilled labour has transferred across borders to affect the skill intensity in case of India.

III. SHIFTS IN SKILL DEMAND – WHAT ACCOUNTS FOR IT?

1. Framework

The traditional method of defining technological change was introduced by Solow (1957). It suggested change in total factor productivity (TFP) as a measure of economy wide technical change. In other words, it is a form of factor neutral technical change that can be quantified residually and leaves marginal rates of transformations untouched for given inputs. For instance, an illustrative production function would be: $Y = A\,K^{\alpha}L^{1-\alpha}$, where Y denotes the total output, K is capital, L is labour and A denotes the TFP.

However, given the more recent changes in relative quantities, movement along the production curve is not a sufficient argument to support factor price changes. This is because neutral technical change does not incorporate changes in relative factor prices (Violante, 2008). Hence the concept of factor biased technical change becomes more relevant for our study. Violante (2008) decomposed total labour into skilled and unskilled labour and used a constant elasticity of substitution (CES) function to show that TFP does not appear in explaining technical change. Let L be a CES function of skilled labour (L_s) and unskilled labour (L_u), and A_s and A_u be the respective factor productivities. $L = [(A_sL_s)^{\sigma} + (A_uL_u)^{\sigma}]^{1/\sigma}$, σ≤1. The marginal rate of transformation (MRT) between two labour inputs is: $MRT_{s,u} = \sigma Ln\frac{A_s}{A_u} + (1-\sigma)Ln\frac{L_u}{L_s}$. Now a change in ratio $\frac{A_s}{A_u}$ is a form of factor biased technical change as it modifies MRT at a given input ratio, and TFP doesn't appear. Technical change is skill biased if $\frac{A_s}{A_u}$ increases (Violante, 2008).

A simple explanation of factor biased technological change would be to look at the rate at which elasticity of output with respect to a factor of production changes with time (Berman et al., 2005). Looking at the production function: $Y = f(K, S, L, t)$, where Y is total output, K is capital, S is skilled workforce, L is unskilled labour, and t is time, the variable t appears to allow for technical change. If the second order partial derivative of elasticity of output with respect to skilled workforce (S) changes with time and is strictly positive, we could suggest that technological change is skill biased:

$$\frac{\delta^2 LnY}{\delta LnS \delta Lnt} = \gamma_s > 0$$

...........(1)

This forms the logical argument behind our evidence based approach in characterizing what accounts for a rise in skill demand.

2. Within and between industry decomposition

A number of studies have documented within sector shifts in the skill composition of employment. For instance, Machin and Van Reenen (1998), Berman et al. (1998) found evidences for within industry substitution towards skilled labour in manufacturing sector of the OECD economies. These studies point that within industry shifts reveal that majority of the industry upgrading is due to SBTC. Further, as pointed by Berman et al. (2005), a shift in composition of skill may not be only due to skill biased technology, but also due to trade, shifts in taste or scale etc. Hence a useful approach to diagnose what accounts for the shift in skill intensity is to decompose the changes into within and between industry components. The within component would indicate shift in demand within industries and could be attributed to SBTC, whereas the between component would reflect shifts due to changes in industrial distribution. Therefore, we decompose the aggregate shift in skill demand into two components – upgrading or change within industries as compared to between industries.

We first define the wage bill share of skilled workers as below, where S is skilled and U is unskilled:

$$S_n = \frac{W_s S}{W_s S + W_u U}$$

………..(2)

Hence the decomposition of changes in wage bill shares into within and between components is as follows:

$$\Delta S_n = \sum_i \Delta S_{ni} \bar{P}_i + \sum_i \Delta P_i \bar{S}_{ni}$$

………..(3)

In the above equation, i is for industry and a bar denotes time mean. The weights, P, measure the relative size of i industry, i.e. industry's share in total manufacturing skilled wage bill. The first term is the within industry component and the second is the between industry component. Each term is summed across all 26 industries under consideration. A number of studies, such as Berman et al. (2005), Berman and Machin (2000a, 2000b), Berman et al. (1998), have used this decomposition to show that bulk of changes is due to within component.

We carry out this exercise for skilled wages. Table 8 gives the percentage changes attributed to within and between industries. The bulk of aggregate changes can be attributed to shifts within industries. In other words, some industries show faster rates of skill upgrading than others – an essential prerequisite for skill biased technology change (Berman et al., 1994; Berman et al., 1998; Berman and Machin, 2000a).

Table 8: Decomposition for Skilled Wages

Year	% Within	% Between
2003-04	90.81	-30.92
2004-05	-15.56	-17.37
2005-06	37.90	4.60
2006-07	26.19	1.36
2007-08	27.73	-10.49
2008-09	57.35	1.57
2009-10	-18.14	0.07
2010-11	10.12	5.57
2012-13	11.97	8.10
2013-14	-0.42	-4.17

Note: The decomposition uses the following equation, where the first term denotes within industry component and the second denotes between industry component:

$$\Delta S_n = \sum_i \Delta S_{ni}\bar{P}_i + \sum_i \Delta P_i \bar{S}_{ni}$$

3. Can we relate shifts in skill demand to observable measures of technology?

Though the previous section shows that within industry decomposition is consistent with SBTC, it does not provide sufficient evidence for relating increase in skill demand to technology changes. A possible reason behind increased demand for skill is capital-skill complementarity along with increased capital-output ratio, where capital-skill complementarity is defined as the elasticity of substitution between capital and skilled labour being lower than that between capital and unskilled labour (Krusell et al., 2000). Table 9 below gives the descriptive statistics of the variables used here to establish a relationship between capital intensity and skill premium. Note that during 2001-02 and 2013-14 period the capital/value added ratio increased by more than 50 percent annually.

Table 9: Descriptive Statistics – Manufacturing Industries 2001-02 – 2013-14

	Mean	**Std. Dev.**	**Min**	**Max**	**No. of Observations**
Skilled share in wage bill (S)	0.4858	0.1277	0.1547	0.8005	286
Ln Capital	14.0338	1.9429	7.0379	17.8049	286
Ln Value Added	13.4754	1.8236	6.3852	16.3413	286
Ln (Capital/ValueAdded)	0.5584	0.5998	- 1.2821	2.0505	286

Note: (i) Skilled share in wage bill (S) is calculated as the ratio of skilled wages to total emoluments; (ii) Capital/ValueAdded is defined as the ratio of fixed capital to net value added.

Looking at a causation estimation to test for capital-skill complementarity we study the following equation using a fixed effects (FE) estimator for a balanced panel:

$$LnS_{it} = \alpha + \beta Ln(\frac{K}{Y})_{it} + \gamma LnY_{it} + \varepsilon_{it}$$

………..(4)

Here S is share of skilled workers in wage bill, K is capital, Y is value added, i includes 26 manufacturing industries, t is the time period from 2001-02 to 2013-14, and ε gives the error term. Table 10 below gives the results. We observe that the coefficient of K/Y is positive and significant, indicating that capital-skill complementarity could well explain the increased demand for skilled workers and hence a rise in the wage bill share. Also, positive and significant coefficient of value added suggests that industries that grew faster showed signs of increased skill demand. Though the result gives a weak explanatory power (overall R^2), but the goodness of fit is slightly stronger than that observed during 1990s (Berman et al., 2005). Hence, in case of India during 2000s, capital-skill complementarity and higher capital-output ratio could well account for a shift in skill demand rather than the latter happening due to observable shifts or changes in technology.

Table 10: Causation estimation, Dependent Variable – Skilled share in wage bill (Ln S)

	Fixed Effects
Ln (Capital/ValueAdded)	0.0605* (0.0327)
Ln Value Added	0.0811*** (0.0181)
Constant	- 1.8879*** (0.2391)
R^2 within **R^2 between** **R2 overall**	0.3234 0.2109 0.2260
No. of observations	286

Note: (i) *** denotes significance at 1% level; * denotes significance at 10% level; (ii) Parentheses give standard errors – robust to heteroscedasticity; (iii) Skilled share in wage bill (S) is calculated as the ratio of skilled wages to total emoluments.

IV. CORRELATION WITH TECHNOLOGY INDICATORS – IS THERE A COMMON PATTERN OF CHANGE?

We now try to test whether and to what extent skill upgrading in India can be attributed to the international pattern of SBTC? Berman et al. (1998) argue that SBTC is pervasive. In other words, an increased demand for skilled workers due to technology changes in one country affects the skill composition of wages and employment throughout the world. Liberalization, openness, international communication and trade are factors behind this. International trade has important effects on skill premium. This is because capital equipment may be produced in a small group of countries and imported by others, hence linking changes in wages of skilled and unskilled workers (Burstein et al., 2013). An integrated world economy responds to technology changes affecting relative wages and employment (Krugman, 1995). Pervasiveness of SBTC drives up the relative price of skill intensive goods and this in turn induces an increase in skill premium.

1. Any similarity in direction of upgrading compared to US skill composition?

Most of the skill biased technological change literature has looked for common trends, i.e. whether skill upgrading displays similar pattern in both developing and developed countries. For instance, Berman & Machin (2000a) show positive correlation between US-UK and US-Korea reflecting faster skill upgrading in same type of industries across countries. Hence, if SBTC is assumed to be pervasive then increased skill intensity in US must be evident in other parts of the world, i.e. if technology transfers across borders, then SBTC cannot be present in the US and absent elsewhere.

We therefore analyse whether skill upgrading occurs in same industries in India and the US? We look at the pattern of percentage of skilled wages in India for the seven identified services oriented industries and correlate with the percentage of skilled wages for the same set of industries in the US over the 2001-02 – 2013-14 period. The data for US industries is obtained from OECD.Stat STAN Industrial Analysis. Table 11 summarises the correlations. Skill upgrading in Indian industries seems to be correlated mainly for industries like Pharmaceuticals and Machinery, Equipment & Repairs, otherwise there appears to be a weak correlation. Appendix gives the year wise paired scatter plots for each industry, depicting the direction of relationship between skilled wages (%) for India and the US.

This result is similar to Berman et al. (2005) that predicted a weak evidence for correlation between skill upgrading in Indian and US industries in the 1990s. Thus, India's participation in international SBTC or pervasiveness of SBTC seems to be limited, even during 2000s, suggesting that increased demand for skills is primarily related to increased output and greater capital-skill complementarity as shown in the previous section. It could be the case that India experienced indigenous SBTC such that technology evolved according to its own pattern of progress rather than just imitation of OECD or US experience. Further, studies such as Verhoogen (2008) point that quality upgrading induced by the exchange-rate shock could be a factor behind increased within-industry wage inequality. Also, a shift of export shares towards most skill intensive goods may also be a cause for rising wage inequality (Zhu & Trefler, 2005). Hence, factors other than SBTC must be explored and are a question of a further research.

Table 11: Correlation with US Skill Upgrading

Industry	Correlation
Pharmaceuticals	0.77***
Machinery, equipment & repairs	0.60*
Motor vehicles, trailers & semi-trailers	- 0.05
Electrical equipment	0.34
Computer, electronic & optical products	0.07
Printing & reproduction of recorded media	0.31
Publishing activities	- 0.01

Note: *** denotes significance at 1% level, * denotes significance at 10% level

2. Any evidence of industry skill upgrading correlated with technology indicators?

Another implication of SBTC, if present, is that India's skill upgrading could be predicted by technology change elsewhere or R&D intensity in high income countries. In order to test this, we estimate the correlation of four technology indicators with skilled wages and employment shares for all the Indian manufacturing industries taken together and separately for the seven services oriented industries. The technology indicators we use are: OECD gross domestic expenditure on R&D (GERD) % of GDP, OECD business enterprise expenditure on R&D (BERD) % of GDP, US GERD % of GDP, and US BERD % of GDP. The data for these indicators is gathered from OECD.Stat Science Technology and Industry Outlook 2014. A well-established literature (Berman & Machin, 2000b) supports that indicators of technology change in high income countries should influence skill upgrading within the developing countries, hence the use of these indicators is justified.

Table 12 & 13 below give the statistics for skilled wages and employment respectively. There is an indication, positive and significant coefficients, of a strong correlation between skill biased technology transfer and wages for most industries, but two industries, namely Computer, Electronic & Optical products and Printing, give contrary results. In case of skill mix of employment, apart from Pharmaceuticals and Publishing industries, there isn't much evidence that technology indicators have a positive and significant correlation, even at all industries aggregated level. This implies that technology changes in the US and OECD countries are not sufficient indicators to explain skill upgrading in India. Once again these outcomes point a similarity with what was observed in 1990s (Berman et al., 2005), indicating that the increase in demand for skills in Indian manufacturing is still very much qualitatively different from other OECD, developed and developing countries that depicted a common pattern. In other words, our study supports that India in the 2000s produced comparable pattern to what happened in the 1990s in the manufacturing sector.

Table 12: Correlation of Skilled Wages with Technology Indicators

	OECD BERD % GDP	**US BERD % GDP**	**OECD GERD % GDP**	**US GERD % GDP**
Pharmaceuticals	0.8632***	0.8599***	0.9028***	0.9229***
Machinery, equipment & repairs	0.8866***	0.8166***	0.9171***	0.8565***
Motor vehicles, trailers & semi-trailers	0.8614***	0.7301**	0.8225***	0.7277**
Electrical equipment	0.8132***	0.7206**	0.7100**	0.6730**
Computer, electronic & optical products	- 0.3970	- 0.5159	- 0.5264*	- 0.5946*
Printing & reproduction of recorded media	- 0.4803	- 0.6184**	- 0.4243	- 0.4910
Publishing activities	0.9114***	0.8852***	0.9299***	0.9121***

All Industries	0.8696***	0.7882***	0.8531***	0.8015***

Note: *** denotes significance at 1% level; ** denotes significance at 5% level; * denotes significance at 10% level.

Table 13: Correlation of Skilled Employment with Technology Indicators

	OECD BERD % GDP	**US BERD % GDP**	**OECD GERD % GDP**	**US GERD % GDP**
Pharmaceuticals	0.7265**	0.7556***	0.8392***	0.8571***
Machinery, equipment & repairs	0.1051	0.2658	- 0.0220	0.1843
Motor vehicles, trailers & semi-trailers	- 0.5552*	- 0.4672	- 0.5231*	- 0.4794
Electrical equipment	- 0.6297**	- 0.5764*	- 0.6786**	- 0.6433**
Computer, electronic & optical products	- 0.2629	- 0.0518	- 0.1532	0.0196
Printing & reproduction of recorded media	0.1271	0.0183	0.2645	0.1467
Publishing activities	0.8195***	0.8668***	0.9018***	0.9453***
All Industries	0.0628	0.0557	0.0120	- 0.0323

Note: *** denotes significance at 1% level; ** denotes significance at 5% level; * denotes significance at 10% level.

V. Conclusion and Implications

Following the pattern of 1990s, in 2000s, Indian manufacturing industries witnessed an increase in demand for skilled workers along with a skill premium in the wages. In this study, we try to find evidence in support of factors that contribute to the shift towards skill intensity. It is apparent that bulk of shifts can be attributed to shifts within industries, and capital-skill complementarity appears as a good predictor of skill upgrading. However, there has not been enough evidence to suggest that the increase in skilled workers' employment and wages is due to SBTC or pervasive SBTC.

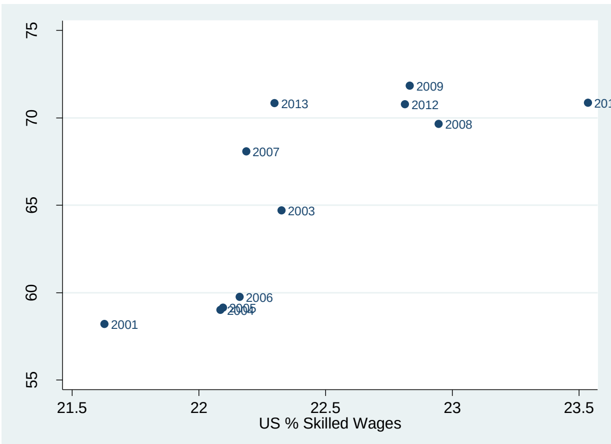
Even though the ongoing pervasive SBTC throughout much of the developed and developing world suggests that changes in skill composition are attributed to technology advancements or transfers, this may not be the only explanation behind increasing demand for skilled workers in India. In other words, India's participation in pervasiveness of SBTC is limited. A number of other factors, for instance capital-output ratio and capital-skill complementarity have been identified to account for increased skill demand. Moreover, decline in investment rate, long term decline in agricultural employment, faulty education system reduces the proportion of Indians who hold proper jobs (Economist, 2017). Hence in the midst it may seem that percentage of skilled workforce is actually increasing. Such aspects must therefore be taken into account and need to be explored. Data on types of investments, including indigenous, in technology is necessary to understand why demand for skills has increased in some industries and not in others.

The effects of new technologies in terms of increase in relative demand and wage premium for skilled workers is of explicit interest for developing countries such as India and has a number of implications. A shift in skill demand along with rapidly rising workforce in India can be a cause for concern as employment opportunities seem to be limited for the unskilled workers, in particular, the implications of increase in income inequality may be severe. Also, if new technologies are skill biased and result in increased demand for skilled workers then it has an effect on private and public investment in education (Harrison, 2008). Further, if present, skill biased technology change may help to explain why conditional convergence of per capita income across countries is slow. As estimated by Berman (2000), only a country with twice the capital and skill per less skilled worker enjoys 1.4 to 1.8% faster growth in annual total factor productivity.

The study therefore contributes as a good starting point to understand what accounts for the relative changes in industrial skill intensity, and raises an important question of what could explain the narrow contribution of manufacturing sector to employment generation but a greater to income inequality – a topic of further research.

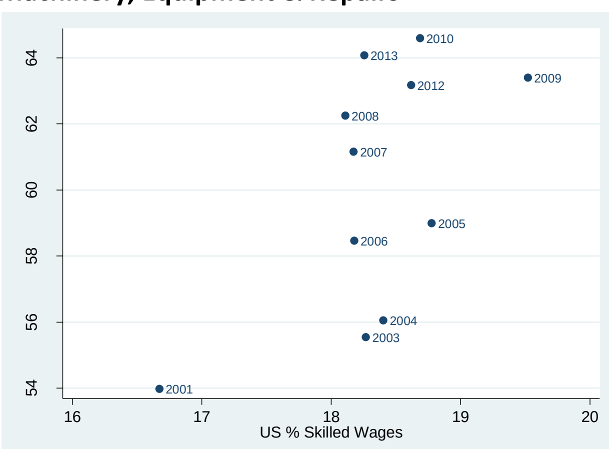
Appendix: Scatter plots depicting direction of relationship between skilled wages (%) for India and US (2001-2013)

Pharmaceuticals



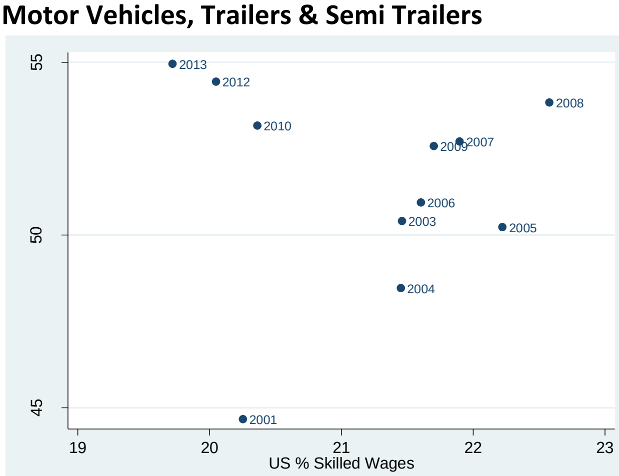
Electrical Equipment

Machinery, Equipment & Repairs

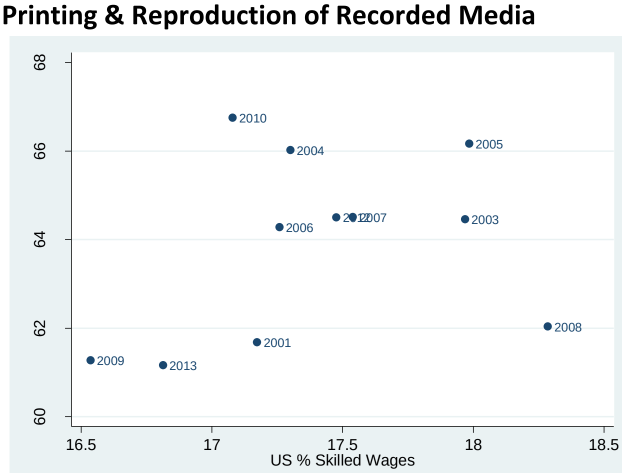


Computer, Electronic & Optical Products

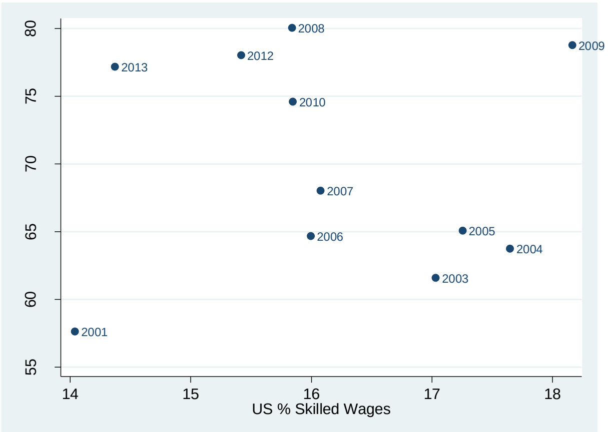
Motor Vehicles, Trailers & Semi Trailers



Printing & Reproduction of Recorded Media



Publishing


80
75
70
65
60
55
2008
2009
2013
2012
2010
2007
2005
2006
2004
2003
2001
14
15
16
17
18
US % Skilled Wages

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