Trends in Employment and Wages of Female and Male Workers in India: A Task-Content-of-Occupations Approach

Shruti Sharma

This paper uses the task-content-of-occupations framework to analyze trends in employment and wages of female and male workers in the Indian labor market from 1994 to 2017. Workers are classified into four main occupational categories: nonroutine cognitive, routine cognitive, nonroutine manual, and routine manual. Decomposing the changes in employment shares into *between-industry* changes and *within-industry* changes across occupational categories reveals that within-industry employment changes have increasingly played an important role, suggesting the growing importance of using the task-content framework to analyze labor market trends. The biggest increase in employment shares is for nonroutine cognitive occupations for both female and male workers. The wage analysis reveals that, on average, the gender wage gap has been lowest in routine cognitive occupations for most of the period of analysis. However, the analysis finds no consistent, significant changes in wages based on occupational specialization during the period of analysis.

Keywords: employment, gender, occupations, wages, tasks

JEL codes: J20, J24, J30, J31

Shruti Sharma: Department of Social Sciences, Human Services and Criminal Justice, Borough of Manhattan Community College, City University of New York. Email: shsharma@bmcc.cuny.edu. Support for this project was provided by a PSC-CUNY Award, jointly funded by The Professional Staff Congress and The City University of New York. I am grateful to the participants of the Faculty Fellowship Publication Program 2020 (City University of New York), the managing editor, and two anonymous referees for very helpful suggestions on this paper.

Asian Development Review, Vol. 39, No. 1, pp. 169–199
DOI: 10.1142/S0116110522500020

I. Introduction

Labor markets in both developed and developing countries have been significantly impacted by technological innovations and advancements (James 1999; Autor, Levy, and Murnane 2003; Bruckner, LaFleur, and Pitterle 2017). India, since its economic reforms in the 1990s, has also experienced an increase in technological adoption brought about by substantial growth of its technology sector (Kapur 2002, Heeks 2015) as well as trade-induced technological transfers (Goldberg et al. 2010, Topalova and Khandelwal 2011, Bas and Berthou 2012, Sharma 2018). It is therefore important to incorporate the likely impacts of such technological developments in analyzing India's labor market.

Traditional literature that examines the impact of technology on workers focuses on the skills of workers, hypothesizing that the impact of technological advancement on the labor force should be skill biased (Tinbergen 1974, 1975, Bound and Johnson 1992, Katz and Murphy 1992). However, Acemoglu and Autor (2011) develop a framework that focuses on tasks involved in various occupations. These are distinguished along two dimensions—whether they are routine or not (which captures the differential effects of technology adoption), and whether they are cognitive or not (which captures the effects of skills or education). Accordingly, they divide occupations into four categories—routine manual, routine cognitive, nonroutine manual, and nonroutine cognitive. The hypothesis is that technology is likely to displace routine tasks, whether these are cognitive or not. In their paper, they find evidence of job polarization for the United States (US)—a decline in the share of "middle-skilled" occupations, which are mainly routine occupations, both cognitive and manual, while the share of workers in nonroutine cognitive and nonroutine manual occupations increased. This framework performs better than previous models in explaining the trends in employment and wages of US workers in recent decades (Acemoglu and Autor 2011, Autor and Dorn 2013).

While the Indian context is very different compared to a developed country such as the US when it comes to technological adoption, it is nonetheless useful to understand labor market trends from the perspective of the task content of various occupations given the increase in technological adoption and advancement in India in the period after liberalization (Kapur 2002, Heeks 2015). This paper applies the task-content-of-occupations framework to analyze the Indian labor market separately for female and male workers and to examine the differences between them. One can expect technology adoption (captured by whether occupations are routine or nonroutine) and education (captured by whether occupations are cognitive or noncognitive) to impact gender inequality in labor markets. There is empirical evidence that adoption of technology can reduce gender wage gaps. Juhn, Ujhelyi, and Villegas-Sanchez (2014) show that technological adoption through trade liberalization in Mexico reduced the demand for "brawn-intensive skills" and favored employment of blue-collar female workers. There is also evidence that female workers with cognitive skills earn higher wages and suffer from lower gender wage gaps than those with noncognitive skills, although education does not entirely reduce the gender wage gap (Gunewardena, King, and Valerio 2018). This paper studies the trends in employment and wages of female and male workers separately to capture the differences in average trends that emerge from using a task-content-of-occupations framework.

To examine these trends, the paper uses data on India's labor force for the years 1994, 2000, 2005, 2008, and 2012 from the National Sample Survey of India, and for the year 2017 from the Periodic Labor Force Survey. The data provide detailed information on the principal activity, occupational code, wages, gender, age, education, region, and industry of workers. To create occupational categories, as in Acemoglu and Autor (2011), information on the task content of each occupation was obtained from the Occupational Network (O∗NET) database and merged onto the main worker-level dataset.

Employment analysis reveals that, on average, for both female and male workers, the share of nonroutine cognitive occupations increased the most during the period of analysis, mainly at the cost of the share of occupations in nonroutine manual occupations. This was followed by an employment decomposition exercise, which further revealed interesting findings. Examining whether changes in employment shares are mainly driven by changes in industrial structure (referred to as "between-industry" changes hereinafter) or by changes in the occupational shares within industries (referred to as "within-industry" changes hereinafter), I find that in the more recent decade (2005–2017), within-industry changes in occupational shares primarily influenced total changes across all occupational categories. In the previous decade (1994–2005), however, changes in industrial structure played a more important role in determining total change in employment shares. This shows that within-industry changes in occupational categories are becoming increasingly important in determining changes in employment shares of occupations, which suggests that the demand and supply of workers performing certain tasks within industries have been increasingly responsible for shifts in employment trends. In particular, within-industry changes in nonroutine cognitive shares increased significantly between the two periods and contributed to an overall increase in the employment share for both female and male workers. However, there are some differences across female and male workers across occupational categories. During 2005–2017, while within-industry declines in employment shares for male routine manual workers was the primary factor behind the changes in total employment shares, the same was not true for female workers in routine manual occupations. In fact, the employment share of routine manual female workers increased whereas male workers experienced a decline in this category. This could be indicative of the fact that routinization, especially in manual occupations, affects male workers more severely and could serve to reduce the perceived differences between the abilities of female and male workers. Overall, these findings emphasize the importance of within-industry changes in occupational structures in determining trends in employment and occupational structures in India.

Examining trends in wages across occupational categories also yield interesting findings. Average real wages and relative wages (measured as the ratio of average wages earned by female workers to male workers) increased during the period of analysis. Workers in nonroutine cognitive occupations earned the highest wages throughout the period, followed by those employed in routine cognitive occupations, for both male and female workers. The analysis also reveals that average wages earned by routine manual workers are higher than those of nonroutine manual workers. When considering relative wages, the gender wage gap on average is lowest for almost the entire period for routine cognitive occupations, followed by nonroutine cognitive occupations. However, examining how wages have changed over time based on the occupational specialization of the workers after controlling education, age, and region fixed effects reveals that there have been no significant changes in trends across all occupational categories. This could be possible because within-industry occupational shares in employment have only recently started playing an important role. Thus, these changes might become more prominent in the future.

The paper is divided into six sections. A description of the datasets used in the analysis and the task-content model is described in Section II. Section III presents summary statistics and trends in employment and wages of workers after classifying them into four categories based on the task-content model. A decomposition of the percentage change in employment across these categories into between-industry and within-industry changes can be found in Section IV. An analysis of changes in wages of male and female workers based on their occupational category is presented in Section V. Section VI concludes.

II. Data

This paper uses data from the employment-unemployment rounds of the National Sample Survey (NSS) of India and the Periodic Labor Force Survey (PLFS). These are household-level datasets that provide information on the activities of all household members. This includes whether they are employed, their occupation, industry of employment, wages, age, educational qualification, gender, and the region they are employed in. Both datasets use a sampling methodology that is representative of the Indian labor force, and they are available as repeated cross sections. Data for years 1994, 2000, 2005, 2008, and 2012 are from the NSS, and data for the year 2017 are from the PLFS. The last NSS employment-unemployment round available is from the year 2012, and labor force data are only available in the form of the PLFS since then. All the rounds used in this study are thick rounds.[1] Occupation data are reported using a three-digit National Classification of Occupations (NCO) code, and industry data are reported using a four-digit National Industrial Classification (NIC) code. For the purpose of the study, any member who reported an occupation code as a current employment activity is considered employed. Workers who did not report an industry of employment have been dropped from the analysis.[2] The data include both full-time and part-time workers as well as workers from both the formal and informal sectors. Salaried as well as self-employed workers and wage laborers are included. The industry classifications change over time—NIC-1987 for the year 1994, NIC-1998 for the years 2000 and 2005, NIC-2004 for the year 2008, and NIC-2008 for the years 2012 and 2017, and concordances used from the Ministry of Statistics and Programme Implementation were used to map all classifications to the NIC-2004 classification. The occupation classifications also change over time—NCO-1968 for the years 1994, 2000, and 2005, and NCO-2004 for the years 2008, 2012, and 2017, and a concordance from the Ministry of Labor and Employment was used to map NCO-1968 to NCO-2004 classification.

Data on wages are reported as weekly wages in Indian rupees. Real wages are obtained by using a deflator from the consumer price index data of the Organisation

---

[1]Thick rounds consider a large sample of households (which ranges from roughly 100,000 to 125,000 in this dataset) and are conducted approximately every five years. Thin rounds, on the other hand, consider 35% to 40% of thick round samples and are conducted in the intervening years.

[2]As a result, a total of 1.2% workers were dropped over six years. Of the workers excluded from the analysis, 43% were in routine manual occupations whereas 50% were in nonroutine manual occupations. Of the workers dropped in routine manual occupations, 73% were male workers while 27% were female. For nonroutine manual workers, this breakdown was 87% male workers and 13% female workers.

for Economic Co-operation and Development (OECD 2021). I consider the wages reported for the current activity of the workers for each year of the survey.[3]

To obtain the task content of occupations, this paper follows Acemoglu and Autor (2011). The O∗NET database version 20.3 from April 2016 is used to obtain this information. This dataset provides the task content of occupations using various descriptors—variables that describe various tasks involved in each occupation—with values assigned along different scales for each occupation. I consider a subset of descriptors to classify O∗NET occupations into nonroutine cognitive, routine cognitive, nonroutine manual, and routine manual occupations. The descriptors are based on the abilities, skills, work context, and work activities used for each occupational category.

The descriptors used in this study are provided in Table A1 of Appendix.[4] The value for the "importance" of each descriptor for all occupations is normalized, and the values across all descriptors for each occupational category are added up to obtain a score. This score is then normalized, and each occupation is classified as belonging to an occupational category based on which occupational category has the highest normalized score for that occupation code. For instance, a high normalized value for the descriptor "the amount of time spent making repetitive motions" would suggest that an occupation is intensive in routine manual tasks, whereas a high normalized value for the descriptor "thinking creatively" would mean that an occupation is intensive in nonroutine cognitive tasks. Once we obtain this classification, data from O∗NET are then merged onto the NSS data. This is accomplished by first using a concordance from the O∗NET occupation classification to the ISCO-1988 occupation codes (which is the same classification used by NCO-2004). For years in which NSS data report occupations using NCO-1968 codes, a concordance between NCO-1968 and NCO-2004 is used. Table A2 of Appendix shows a mapping between the one-digit NCO division and the percentage of three-digit NCO occupations in that division classified as either routine manual, nonroutine manual, routine cognitive, or

[3]The wages are reported as weekly earnings. I use the "principal activity" occupation code specified for individual persons in the dataset to classify the workers in their occupational categories. The wages are reported for the "current activity" of a person, which could have multiple entries. In 97% of the cases, there is only one current activity for a person, and in all these cases, it matches the principal activity. For the remaining 3% of the cases where there are multiple entries for the current activity, I sum up the wages for all the current activities. These are mainly workers classified as "Agriculture and Fishery workers" or as "Elementary occupations." However, all current activities for these workers fall within nonroutine manual occupations.

[4]Unlike Sharma (2016), which uses an interaction of level and importance values reported to obtain the score for each task category, I consider only the "importance" of each occupational category based on Acemoglu and Autor (2011) to match their analysis. This explains why Sharma (2016) finds only three main occupational categories, whereas this study finds four main occupational categories.

nonroutine cognitive. This can provide an understanding of how one-digit NCO codes roughly match occupational categories.

The following section describes the trends in employment and wages for female and male workers based on this classification of occupations.

III. Summary Statistics

In analyzing the trends in female and male workers in India, it is important to first understand the labor force participation rates. Figure 1 shows the labor force participation rates from 1994 to 2017. Labor force participation rate for male workers was 84.7% in 1994 and declined to 83% in 2017. For female workers, the labor force participation rate was 30.5% in 1994 and declined to 22.2% in 2017.

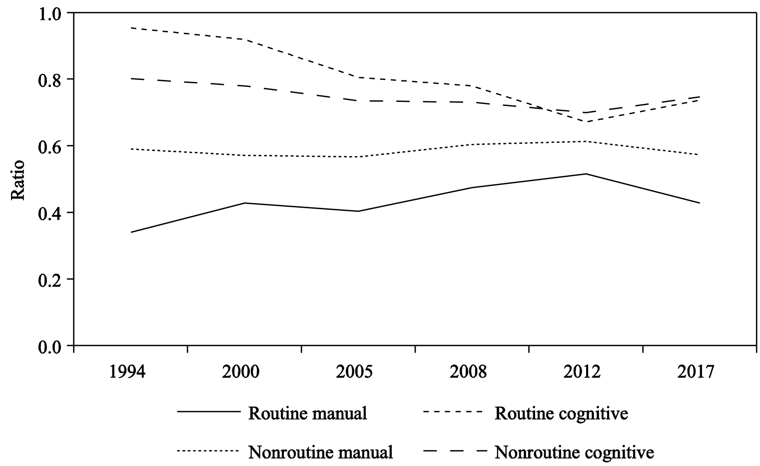
In terms of gender composition of the workforce, Figure 2 shows that female workers comprised 19% of the workforce in 2017, down from 23% in 1994, whereas the share of male workers increased to 81% in 2017 from 77% in 1994.

The next set of statistics is based on examining the task content of occupations, which would help identify occupations that are experiencing the biggest changes in employment shares.

Table 1 reports summary statistics for employment of all workers and male and female across all occupational categories. I compute the shares of workers in nonroutine manual, nonroutine cognitive, routine manual, and routine cognitive occupations for both male and female workers (Table A3). Figure 3 presents the trends in employment obtained from this classification. I find that for both male and female workers, the share of workers employed in nonroutine manual occupations[5] is the highest, although it has been decreasing over time. For male workers, this share declined from 81% in 1994 to 72% in 2017, whereas for female workers, the share declined from 80% in 1994 to 65% in 2017. For both female and male workers, the biggest increase in employment shares is for nonroutine cognitive workers. For routine cognitive occupations, on the other hand, the share of male workers employed in this category decreased from 5% in 1994 to 4% in 2017, while for female workers, this share increased from 2% in 1994 to 3% in 2017. Finally, for routine manual occupations, employment shares in this category increased from 18% in 1994 to 21%

[5]Unlike Acemoglu and Autor (2011), I do not drop occupations in the agriculture sector, all of which classified as nonroutine occupations, to be able to provide an analysis of all possible sectors. Mechanization in the agriculture sector is not properly captured in the classification of occupations as routine and nonroutine, which might explain why this analysis presents a decline in the share of nonroutine manual occupations.

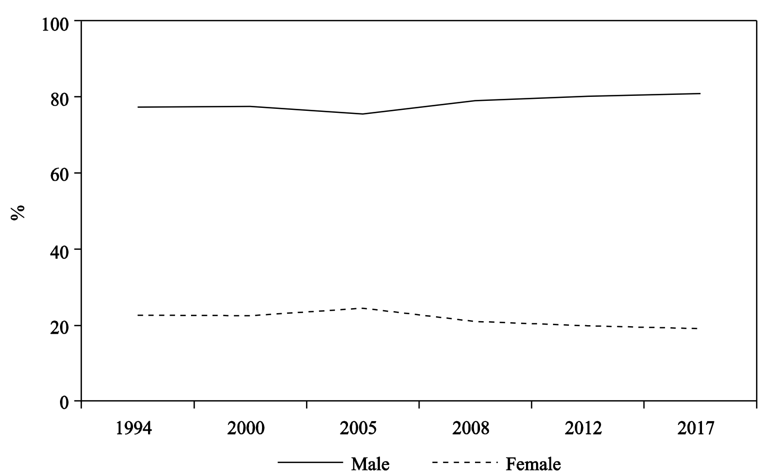
Figure 1. **Labor Force Participation Rate**



Source: Author's calculations using data from the National Sample Survey of India (1994, 2000, 2005, 2008, 2012) and the Periodic Labor Force Survey (2017).

in 2017 for female workers; however, for male workers, this share declined from 12% in 1994 to 10% in 2017. This reflects the share in the economy and growth of India's manufacturing sector (Sharma and Singh 2013) where most routine manual occupations are concentrated.

Figure 2. **Share of Employment by Gender**



Source: Author's calculations using data from the National Sample Survey of India (1994, 2000, 2005, 2008, 2012) and the Periodic Labor Force Survey (2017).

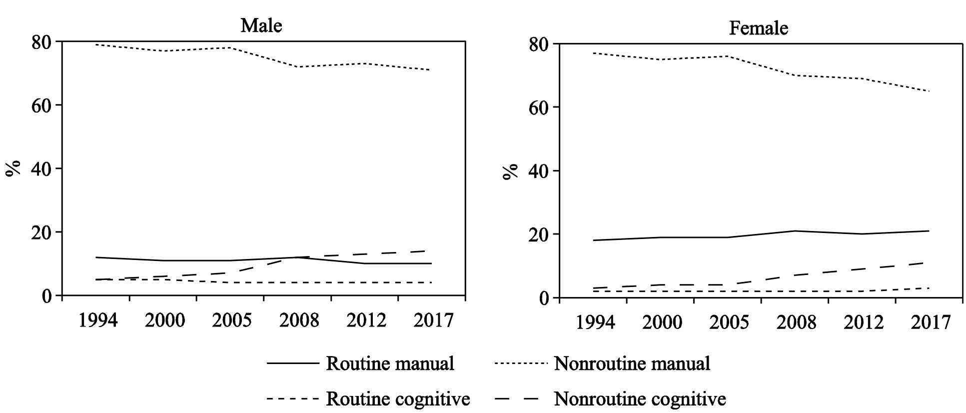
Table 1. **Summary Statistics: Employment (million)**

	1994	2000	2005	2008	2012	2017
All						
Male	151.0	186.0	215.0	214.0	227.0	250.0
Female	45.1	54.2	70.0	57.1	56.6	59.5
Routine manual						
Male	14.0	21.3	24.6	25.6	23.5	25.7
Female	6.9	10.5	13.1	11.9	11.5	12.5
Routine cognitive						
Male	7.4	8.8	8.4	9.3	9.0	10.2
Female	0.84	1.1	1.3	1.1	1.2	1.6
Nonroutine manual						
Male	122.0	144.0	168.0	154.0	166.0	179.0
Female	36.0	40.5	52.9	40.0	39.0	38.8
Nonroutine cognitive						
Male	7.4	11.8	14.0	25.4	28.8	35.7
Female	1.4	2.1	2.7	4.1	4.9	6.7

Source: Author's calculations using data from the National Sample Survey of India (1994, 2000, 2005, 2008, 2012) and the Periodic Labor Force Survey (2017).

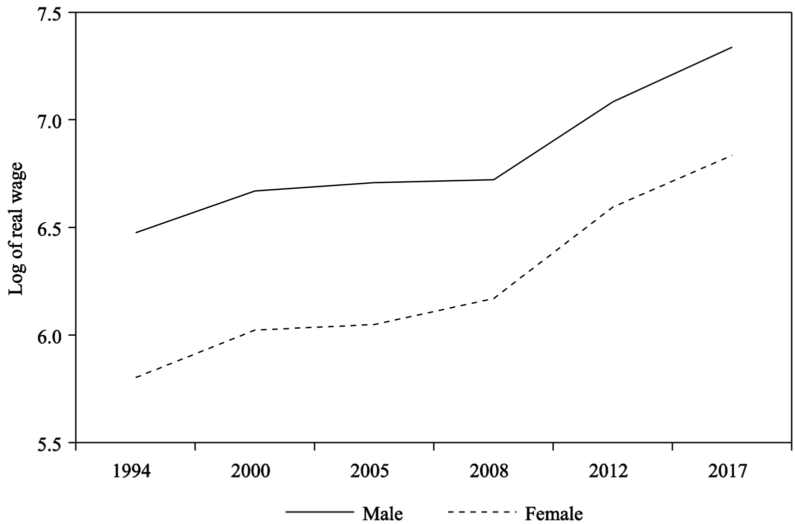
The next set of summary statistics considers trends in average and relative wages. Wages are weekly and in Indian rupees, and have been deflated using the consumer price index (OECD 2021). Figure 4 shows that average real wages for both male and female workers increased from 1994 to 2017, and Figure 5 shows that relative wages

Figure 3. **Share of Employment across Occupational Categories**



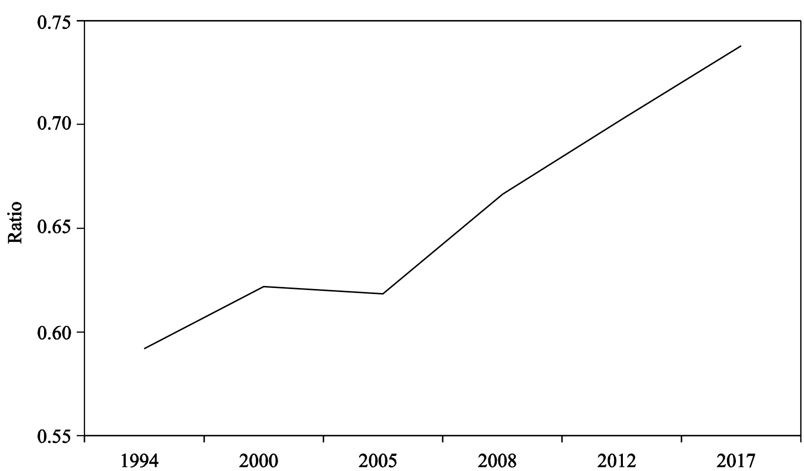
Source: Author's calculations using data from the National Sample Survey of India (1994, 2000, 2005, 2008, 2012) and the Periodic Labor Force Survey (2017).

Figure 4. **Average Wage by Gender**



Source: Author's calculations using data from the National Sample Survey of India (1994, 2000, 2005, 2008, 2012) and the Periodic Labor Force Survey (2017).

Figure 5. **Relative Wage**



Note: Relative wage is measured as the ratio of the average wage of female workers to the average wage of male workers.
Source: Author's calculations using data from the National Sample Survey of India (1994, 2000, 2005, 2008, 2012) and the Periodic Labor Force Survey (2017).

(measured as the ratio of average wages of female workers to average wages of male workers) have also increased for the period of analysis.

Table 2 presents the summary statistics for the average weekly real wages earned by all workers, male workers, and female workers. This is provided for the entire labor

Table 2. **Average Weekly Real Wages across Occupational Categories (₹)**

	All	**Male (M)**	**Female (F)**	**Relative Wage (F/M)**
1994				
All	858.96	948.92***	565.13***	0.60
	(2.93)	(3.41)	(5.16)	
Routine manual	956.09	1,031.77***	362.99***	0.35
	(5.79)	(6.14)	(8.55)	
Routine cognitive	1,314.12	1,321.55**	1,264.80**	0.96
	(7.65)	(8.13)	(22.44)	
Nonroutine manual	427.42	488.19***	285.08***	0.58
	(1.56)	(1.99)	(1.82)	
Nonroutine cognitive	2,011.37	2,113.09***	1,698.37***	0.80
	(10.07)	(11.62)	(18.93)	
2000				
All	1,096.38	1,203.20***	748.24***	0.62
	(4.03)	(4.68)	(7.36)	
Routine manual	1,180.30	1,241.38***	530.80***	0.43
	(7.59)	(8.00)	(14.51)	
Routine cognitive	1,730.15	1,748.76***	1,606.92***	0.92
	(10.85)	(11.49)	(32.28)	
Nonroutine manual	512.30	588.28***	335.62***	0.57
	(2.09)	(2.70)	(2.33)	
Nonroutine cognitive	2,759.63	2,939.71***	2,290.82***	0.78
	(14.77)	(17.25)	(26.80)	
2005				
All	1,135.25	1,246.88***	771.20***	0.62
	(4.27)	(4.96)	(7.77)	
Routine manual	1,075.50	1,138.43***	459.45***	0.40
	(7.04)	(7.50)	(11.27)	
Routine cognitive	1,632.09	1,682.04***	1,353.21***	0.80
	(10.73)	(11.59)	(27.56)	
Nonroutine manual	518.76	598.94***	339.27***	0.57
	(2.27)	(2.96)	(2.57)	
Nonroutine cognitive	2,671.22	2,883.88***	2,117.64***	0.73
	(14.71)	(16.97)	(27.13)	

Continued.

Table 2. *Continued.*

	All	Male (M)	Female (F)	Relative Wage (F/M)
2008				
All	1,135.48	1,228.93***	819.10***	0.67
	(4.24)	(4.91)	(7.95)	
Routine manual	1,163.70	1,210.86***	574.10***	0.47
	(7.60)	(8.00)	(15.01)	
Routine cognitive	1,740.20	1,799.45***	1,402.27***	0.78
	(11.64)	(12.55)	(29.96)	
Nonroutine manual	556.38	625.92***	378.06***	0.60
	(2.00)	(2.52)	(2.45)	
Nonroutine cognitive	2,845.78	3,102.36***	2,264.87***	0.73
	(16.83)	(20.23)	(27.93)	
2012				
All	1,599.33	1,701.22***	1,195.20***	0.70
	(6.48)	(7.30)	(13.38)	
Routine manual	1,286.59	1,335.65***	688.38***	0.52
	(8.43)	(8.90)	(16.57)	
Routine cognitive	2,048.36	2,166.66***	1,453.69***	0.67
	(16.40)	(17.95)	(36.90)	
Nonroutine manual	828.41	920.14***	563.47***	0.61
	(3.88)	(4.77)	(4.89)	
Nonroutine cognitive	3,309.58	3,609.05***	2,523.94***	0.70
	(20.40)	(23.56)	(37.14)	
2017				
All	1,859.17	1,940.36***	1,431.70***	0.74
	(4.70)	(5.05)	(12.10)	
Routine manual	1,606.90	1,708.99***	730.83***	0.43
	(7.52)	(7.86)	(15.12)	
Routine cognitive	2,005.17	2,095.45***	1,542.80***	0.74
	(10.15)	(11.05)	(24.09)	
Nonroutine manual	1,283.83	1,364.15***	781.53***	0.57
	(5.04)	(5.48)	(9.71)	
Nonroutine cognitive	2,684.02	2,848.47***	2,127.55***	0.75
	(11.90)	(13.31)	(24.97)	

₹ = Indian rupee.

Notes: Standard errors in parentheses. ** and *** indicate that the means of weekly real wages for male and female workers are significantly different at $p < 0.05$ and $p < 0.01$, respectively.

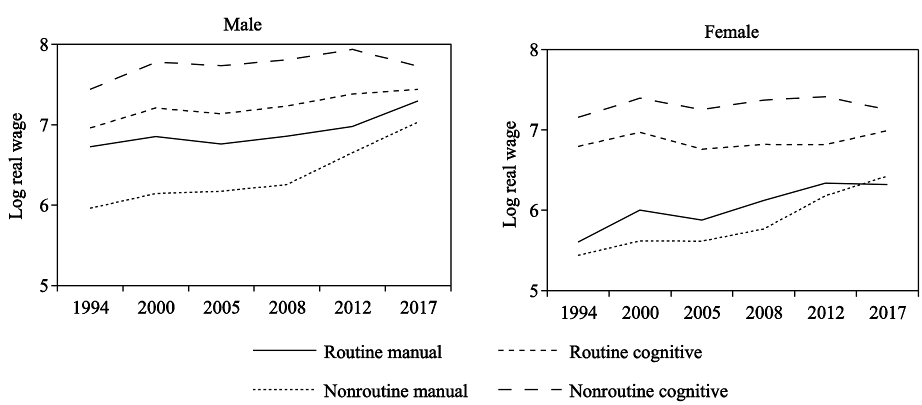
Source: Author's calculations using data from the National Sample Survey of India (1994, 2000, 2005, 2008, 2012) and the Periodic Labor Force Survey (2017).

force as well as by occupation type. The data show that there exists a gender wage gap on average and across all occupation types, with wages earned by male workers significantly higher than that of female workers across all years.

Figure 6 presents the average log real wages for female and male workers across occupational categories. For both female and male workers, average trends reveal that wages are highest for workers in nonroutine cognitive occupations, followed by routine cognitive occupations. The lowest average wages are earned by workers in nonroutine manual occupations.

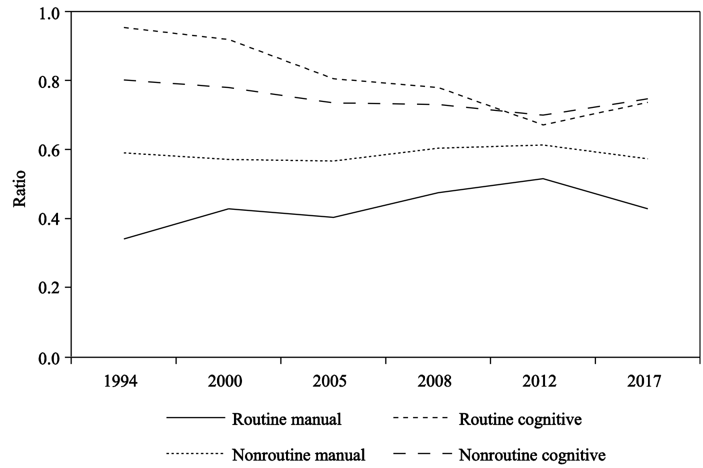
The relative wages shown in Figure 7 are a ratio of average weekly real wages of female workers to the average weekly real wages of male workers. The figure shows that relative wages are highest for female workers in nonroutine cognitive and routine cognitive occupations. However, these wages have been declining over time. On the other hand, gender wage inequality is higher in manual occupations but has been exhibiting a decreasing trend over time. It is also interesting to note that gender wage inequality for the most part has been lowest in routine cognitive occupations. The fact that the gender wage gap is lower for cognitive occupations is not surprising. Evidence from Gunewardena, King, and Valerio (2018) shows that obtaining cognitive skills reduces the gender wage gap for female workers. Sections IV and V delve into these trends in employment and wages in more detail.

Figure 6. **Average Wage by Gender and across Occupation Types**



Source: Author's calculations using data from the National Sample Survey of India (1994, 2000, 2005, 2008, 2012) and the Periodic Labor Force Survey (2017).

Figure 7. **Relative Wage by Occupation Type**



Note: Relative wage is measured as a ratio of average weekly real wage of female workers to the average weekly real wage of male workers.
Source: Author's calculations using data from the National Sample Survey of India (1994, 2000, 2005, 2008, 2012) and the Periodic Labor Force Survey (2017).

IV. Employment Decomposition

It is important to examine whether changes in employment shares in the four categories of occupations obtained in this paper are mainly driven by a change in industrial structure or by changes in employment shares within occupations. This enables us to understand whether, for example, an increase in employment shares in nonroutine cognitive occupations is mainly driven by an expansion of industries that predominantly employ nonroutine cognitive workers or an increase in the share of nonroutine cognitive workers within industries. Following Acemoglu and Autor (2011), I use the given shift-share instrument to determine the total change in employment shares:

$$\Delta E_{jt} = \Delta E_t^B + \Delta E_t^W. \tag{1}$$

Changes in employment shares of occupations between industries, ΔE_t^B, or changes in occupation shares within-industry, ΔE_t^W, can explain the total change in the share of employment ΔE_{jt}, where j is the occupation and t is the time. I can further express this as follows:

$$\Delta E_{jt} = \sum_k \Delta E_{kt} \lambda_{jk} + \sum_j \Delta \lambda_{jkt} E_k. \tag{2}$$

ΔE_{kt} represents the change in industry k's share over the period under consideration, whereas E_k represents the average employment share. Similarly, $\Delta\lambda_{jkt}$ gives the change in occupation j's share of industry k's employment over the period under consideration, whereas λ_{jk} gives the average share. The industries in this analysis are at the NIC four-digit level.

Table 3 reports the decomposition of changes in employment shares, in percentage points, of the four main occupation categories for all workers, male workers, and female workers. I divided the data into roughly 2 decades to examine

Table 3. **Employment Decomposition (Percentage Points)**

	1994–2005	**2005–2017**	**1994–2017**
All			
Routine manual			
Total Δ	2.55	−0.94	1.61
Between industry Δ	2.22	−0.06	1.88
Within industry Δ	0.33	−0.88	−0.27
Routine cognitive			
Total Δ	−0.80	0.44	−0.36
Between industry Δ	−1.00	0.72	−0.50
Within industry Δ	0.20	−0.28	0.14
Nonroutine manual			
Total Δ	−3.10	−7.32	−10.42
Between industry Δ	−4.58	−1.66	−7.68
Within industry Δ	1.48	−5.66	−2.74
Nonroutine cognitive			
Total Δ	1.35	7.82	9.17
Between industry Δ	0.36	2.86	3.39
Within industry Δ	0.99	4.96	5.78
Male			
Routine manual			
Total Δ	2.13	−1.20	0.93
Between industry Δ	1.93	−0.23	1.49
Within industry Δ	0.20	−0.97	−0.56
Routine cognitive			
Total Δ	−0.98	0.20	−0.78
Between industry Δ	−1.18	0.49	−0.97
Within industry Δ	0.20	−0.29	0.19
Nonroutine manual			
Total Δ	−2.75	−6.73	−9.48
Between industry Δ	−4.33	−0.87	−6.23
Within industry Δ	1.58	−5.86	−3.25

Continued.

Table 3. *Continued.*

	1994–2005	2005–2017	1994–2017
Nonroutine cognitive			
Total Δ	1.60	7.73	9.33
Between industry Δ	0.41	2.57	3.18
Within industry Δ	1.19	5.16	6.15
Female			
Routine manual			
Total Δ	3.47	2.21	5.68
Between industry Δ	2.65	2.60	5.25
Within industry Δ	0.82	−0.39	0.43
Routine cognitive			
Total Δ	−0.05	0.84	0.79
Between industry Δ	−0.26	1.12	0.60
Within industry Δ	0.21	−0.28	0.19
Nonroutine manual			
Total Δ	−4.13	−10.46	−14.59
Between industry Δ	−5.44	−5.57	−14.02
Within industry Δ	1.31	−4.89	−0.57
Nonroutine cognitive			
Total Δ	0.72	7.40	8.12
Between industry Δ	0.50	3.44	3.53
Within industry Δ	0.22	3.96	4.59

Δ = change in employment shares in percentage points.
Source: Author’s calculations using data from the National Sample Survey of India (1994, 2000, 2005, 2008, 2012) and the Periodic Labor Force Survey (2017).

how this decomposition has been changing over time, in addition to reporting the decomposition for the entire period under consideration. One can expect differences over time because technological adoption and advancements have increased significantly in India since 1990. For instance, the output of the IT sector alone increased from \$2.21 billion in 1994–1995 to \$123.22 billion in 2014–15. While the IT sector’s output increased by about \$26 billion in the first decade of the analysis, it increased by almost quadruple that amount in the following decade (Heeks 2015).

I find that within-industry changes in employment shares of occupations became more important in the second period (2005–2017) when there was likely greater technological adoption compared to the first period (1994–2005). For instance, within-industry changes accounted for only 12.9% of the total change in routine manual occupations in 1994–2005, but increased to 93.6% in 2005–2017. In fact, within-industry changes contributed to a slight increase in the employment share of these occupations in the first period but caused the employment share to shrink in the second period. The growing importance of within-industry shifts over time is consistent across almost all occupational categories and for both female and male workers. This highlights the need for following a task-content-of-occupations approach to understand changes in employment structures, especially with greater technological advances and adoption over time.

The results from the analysis suggest that routinization could be causing a decline in within-industry employment shares in routine occupational categories. For instance, for both male and female workers, the contribution of within-industry employment share to the total change in employment shares for routine manual occupations went from positive in 1994–2005 to negative in 2005–2017. It is interesting to note, however, that in the period 2005–2017 for male workers in routine manual occupations, within-industry declines accounted for 80% of the total decline in employment shares, whereas for female workers this decline was much smaller than the positive increase in employment share between industries. Similarly, for routine cognitive occupations for male workers, within-industry changes during 2005–2017 accounted for the larger percentage of the total change in employment shares, whereas this change was smaller for female workers. This might suggest that routinization has differential impacts on female and male workers, affecting the employment of male workers more adversely than that of female workers. Mechanization and technological adoption, while automating jobs, also reduces the perceived differences in female and male workers (Juhn, Ujhelyi, and Villegas-Sanchez 2014).

It is also interesting to note that while within-industry employment shares of nonroutine cognitive occupations have been increasing as expected, the within-industry employment shares for nonroutine manual occupations have been declining. The latter runs counter to the hypothesis that automation should be increasing the relative demand for workers in nonroutine occupations. This could be explained by the fact the task-content framework does not capture mechanization that can occur within the agriculture sector, which is primarily categorized as nonroutine manual in the occupational categorization. Also, there may be supply-side effects with workers moving to cognitive occupations as they gain greater access to education. In fact, Acemoglu and Autor (2011) drop the agriculture sector from their analysis. Table A4 of Appendix shows the employment decomposition after leaving out the agriculture sector from the analysis. Compared to Table 3, Table A4 shows a smaller decline in the employment shares of nonroutine manual occupations, and a bigger decline in the employment of routine occupations, which is more in line with expectations. Table A5 provides an employment decomposition at the one-digit

NCO for female workers to provide a description of each occupational type. For instance, technicians and associate professionals experienced the biggest increase in the share of employment overall, and also the largest within-industry increase in employment shares.

An important concern is whether the between-industry changes in employment shares could be a result of the changing classification of NIC codes over the years. Table A6 of Appendix reports the share of employment in the data that is affected by these changes in classification. Table A7 then reports the results of the employment decomposition exercise without the employment data that have changed because of changes in industrial classification. This change does not affect the analysis significantly, and the main inferences stay the same.

V. Wage Analysis

In this section, I analyze whether routinization of tasks has impacted the returns to workers based on their occupational specialization. To do so, I follow Acemoglu and Autor (2011) in examining how wages of workers have changed over time depending on their occupational specialization. They divide workers into three main categories: workers performing routine tasks, those in nonroutine cognitive tasks, and those in occupations intensive in nonroutine manual tasks. The main hypothesis is that increased routinization leads to a decline in wages of workers in occupations intensive in routine tasks. This should be reflected in a relative increase in wages of workers in both nonroutine cognitive and nonroutine manual occupations.

To estimate this, Acemoglu and Autor first create demographic groups based on gender, education, age, and region and then construct employment shares of workers in routine occupations, nonroutine cognitive occupations, and nonroutine manual occupations at the beginning of the period of their analysis, with the assumption that workers self-select into each of these categories based on their comparative advantage or task specialization. I similarly create these demographic groups and then construct γ^{R}_{sejk}, $\gamma^{\mathrm{NRM}}_{sejk}$, and $\gamma^{\mathrm{NRC}}_{sejk}$, which are the shares of workers employed in routine occupations (including both routine manual and routine cognitive), nonroutine manual occupations, and nonroutine cognitive occupations in each demographic group, respectively, for the year 1994, which is the first year of the analysis. The age and education buckets used for creating these cohorts are presented in Appendix in Tables A8 and A9, respectively. NSS state-region codes (125 codes) were used for the region category. The variables gender, education, age, and region are denoted by s, e, j, and k, respectively. Then based on Acemoglu and Autor's analysis, I estimate the following:

$$\Delta w_{sejkt} = \beta_0 + \beta_1 * \gamma_{sejk}^{\mathrm{NRM}} * t_i + \beta_2 * \gamma_{sejk}^{\mathrm{NRC}} * t_i + t_i + \theta_e + \theta_j + \theta_k + \epsilon_{sejkt}. \quad (3)$$

γ_{sejk}^{R} was dropped from the regression because by construction $\gamma_{sejk}^{R} + \gamma_{sejk}^{\mathrm{NRM}} + \gamma_{sejk}^{\mathrm{NRC}} = 1$. The education, region, and age fixed effects are denoted by θ_e, θ_j, and θ_k, respectively, and t_i is the time (year) dummy where t stands for time. Δw_{sejkt} stands for the change in mean log wages for each demographic group in the analysis. The difference in this analysis compared to Acemoglu and Autor (2011) is that the change in wages is not within a decade but across the various time periods available for this analysis.

The estimation results are presented in Table 4. Model 1 reports the estimates for male workers without fixed effects, which are included in Model 2. Similarly, Model 3 reports the results for female workers without fixed effects, which are then included in Model 4. There are more male workers than female workers in the survey, which is reflected in the total number of observations for each.

Table 4. **Wage Analysis**

	Male without Fixed Effects	**Male with Fixed Effects**	**Female without Fixed Effects**	**Female with Fixed Effects**
	(1)	**(2)**	**(3)**	**(4)**
Nonroutine manual				
2000 share × 2000 time dummy	−0.210**	−0.288***	−0.156	−0.0863
	(0.0902)	(0.0985)	(0.131)	(0.135)
2005 share × 2005 time dummy	0.212**	0.134	−0.108	−0.0380
	(0.103)	(0.108)	(0.137)	(0.137)
2008 share × 2008 time dummy	0.0343	−0.0434	0.118	0.188*
	(0.0797)	(0.0864)	(0.0989)	(0.107)
2012 share × 2012 time dummy	−0.0191	−0.0968	−0.191*	−0.121
	(0.0830)	(0.0898)	(0.110)	(0.113)
2017 share × 2017 time dummy	0.314***	0.237***	−0.106	−0.0364
	(0.0795)	(0.0849)	(0.119)	(0.123)
Nonroutine cognitive				
2000 share × 2000 time dummy	−0.181	−0.158	0.106	0.198
	(0.114)	(0.119)	(0.177)	(0.186)
2005 share × 2005 time dummy	0.159	0.182	−0.244	−0.152
	(0.112)	(0.116)	(0.166)	(0.173)
2008 share × 2008 time dummy	0.0388	0.0620	−0.00166	0.0903
	(0.0993)	(0.109)	(0.128)	(0.146)
2012 share × 2012 time dummy	−0.0639	−0.0408	−0.235*	−0.143
	(0.0865)	(0.0931)	(0.140)	(0.155)
2017 share × 2017 time dummy	−0.240**	−0.217**	−0.172	−0.0797
	(0.0970)	(0.101)	(0.152)	(0.163)

Continued.

Table 4. *Continued.*

	Male without Fixed Effects	Male with Fixed Effects	Female without Fixed Effects	Female with Fixed Effects
	(1)	**(2)**	**(3)**	**(4)**
2000 year dummy	0.424***	0.550***	0.347***	0.286**
	(0.0659)	(0.0873)	(0.0888)	(0.140)
2005 year dummy	−0.387***	−0.261***	−0.235**	−0.296**
	(0.0700)	(0.0884)	(0.0988)	(0.145)
2008 year dummy	0.191***	0.317***	0.181***	0.119
	(0.0567)	(0.0796)	(0.0671)	(0.129)
2012 year dummy	0.124**	0.250***	0.227***	0.165
	(0.0594)	(0.0840)	(0.0748)	(0.130)
2017 year dummy	−0.0552	0.0711	0.0608	−0.000817
	(0.0580)	(0.0812)	(0.0866)	(0.144)
Region fixed effect	No	Yes	No	Yes
Education fixed effect	No	Yes	No	Yes
Age fixed effect	No	Yes	No	Yes
Observations	3,165	3,165	2,005	2,005
R^2	0.239	0.259	0.124	0.152

Notes: Standard errors in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Models 1−4 in each column present a separate ordinary least squares regression of stacked changes in mean log weekly real wages by cohort and year, where cohorts are created using sex, age group (Table A8), education group (Table A9), and state (125 State-region codes are reported in NSS) of the workers in the National Sample Survey (1994, 2000, 2005, 2008, 2012) and Periodic Labor Force Survey (2017) data. Occupation shares are calculated for each demographic group in 1994 and interacted with decade dummies. Occupations are grouped into three categories: (1) nonroutine cognitive; (2) nonroutine manual; and (3) routine—both cognitive and manual. The routine group is the omitted category in the regression models. For the year dummy variables, the reference year is 1994.
Source: Author's calculations using data from the National Sample Survey of India (1994, 2000, 2005, 2008, 2012) and the Periodic Labor Force Survey (2017).

The results obtained are mixed. Relative to routine occupations, male workers in nonroutine manual occupations experienced a significant decline in their wages in 2000, which is robust to the inclusion of fixed effects. These relative returns however increased significantly in 2017 for both Models 1 and 2. This provides some support for the fact that returns to workers specialized in nonroutine manual tasks have been increasing recently relative to routine occupations. On the other hand, while wages of male workers in nonroutine cognitive occupations did not change significantly relative to workers in routine occupations in most years, a significant decline is observed for 2017, which runs counter to expectations. Female workers in nonroutine manual and nonroutine cognitive occupations, on the other hand, for most years, did not experience any significant changes in wages relative to those in routine occupations during the period of analysis. One exception is an increase in the wages of female workers in nonroutine manual occupations to those in routine occupations for 2008.

The coefficients of the time dummies in this analysis provide an estimate of the wage trends of workers specializing in routine occupations at the beginning of the analysis. For female workers in routine occupations, wages increased significantly in 2000 and then declined significantly in 2005, which is consistent with the hypothesis that the returns to these occupations should decline over time. For male workers in routine occupations, on the other hand, the results are not consistent—wages initially increase significantly in 2000, then decline significantly in 2005, and then increase thereafter.

This analysis is a preliminary exercise in determining how returns to workers in various occupational specializations are evolving over time. While there is some evidence of a decline in returns to workers in routine occupations over time, especially for female workers, this is not strongly corroborated. Given that a developing country such as India is still lagging in terms of technological adoption compared to the US, one might observe these effects on wages becoming more prominent as technological adoption increases in the future. The fact that changes in within-industry employment shares have only recently become prominent in impacting overall changes in employment across occupational categories also suggests that we can probably expect these results to be stronger in the future.

VI. Conclusion

This paper uses a task-content-of-occupations approach to analyze trends in employment and wages of male and female workers in India from 1994 to 2017. This approach provides a better framework to take into account the impact of technological advancements and automation while analyzing these labor market trends. Accordingly, it classifies male and female workers into four occupational categories: routine cognitive, nonroutine cognitive, routine manual, and nonroutine manual. The paper considers the trends in male and female workers separately to understand how technological advancements on average might be impacting these two groups of workers differently.

Analyzing the employment trends I find that, on average, the share of workers in nonroutine manual work is highest for both male and female workers but declining over time, whereas the share of nonroutine cognitive workers is increasing. An employment decomposition exercise, which uses a shift-share instrument to determine the extent to which changes in employment shares across occupations are due to changes in industrial structure compared to changes in within-industry occupational shares, reveals interesting results. I find that in the more recent decade, changes in within-industry employment shares are more important in determining the overall change in occupational shares. This suggests that using the task-content framework to understand changes in employment trends is becoming more important in the Indian context. I find that, as expected, there is a decline in within-industry shares of employment for routine cognitive and routine manual occupations. This decline in occupational shares in routine occupations is the main factor driving the overall changes in employment shares of male workers, while the same is not true for female workers. This suggests that routinization might not be impacting female workers as adversely as male workers. Within-industry employment shares of nonroutine cognitive occupations for both female and male workers have been increasing, in line with expectations.

I also examine average trends in wages across all occupational categories. For both male and female workers, average wages are highest for nonroutine cognitive occupations, followed by routine cognitive occupations and then routine manual occupations, with the lowest wages for nonroutine manual occupations. The gender wage gap is lowest in cognitive occupations—with routine cognitive occupations recording the lowest gap for most of the period of analysis. A wage analysis that considers changes in wages for workers specializing in a certain occupational category at the beginning of the period, however, finds that there are no consistent, significant changes in the earnings of workers of nonroutine occupations compared to those in routine occupations.

The paper highlights the importance of using a task-content framework in analyzing trends in employment and wages of workers by showing that changes in employment shares across occupational categories are increasingly driven by within-industry changes in occupational shares. Nonroutine cognitive occupations experienced the biggest increases in employment shares—both between and within industries—and we can expect the employment shares of workers in routine occupations to decline over time. Labor market policies need to take these findings into account as policy makers prepare for the future of the Indian workforce.

References

Acemoglu, Daron, and David Autor. 2011. “Skills, Tasks and Technologies: Implications for Employment and Earnings.” In *Handbook of Labor Economics*, Volume 4, edited by Orley Ashenfelter and David Card, 1043–171. Amsterdam: Elsevier-North Holland.

Autor, David, Frank Levy, and Richard J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *The Quarterly Journal of Economics* 118 (4): 1279–333.

Autor, David H., and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review* 103 (5): 1553–97.

Bas, Maria, and Antoine Berthou. 2012. "The Decision to Import Capital Goods in India: Firms' Financial Factors Matter." *The World Bank Economic Review* 26 (3): 486–513.

Bound, John, and George Johnson. 1992. "Changes in the Structure of Wages in the 1980's: An Evaluation of Alternative Explanations." *American Economic Review* 82 (3): 371–92.

Bruckner, Matthias, Marcelo LaFleur, and Ingo Pitterle. 2017. "Frontier Issues: The Impact of the Technological Revolution on Labor Markets and Income Distribution." United Nations Department of Economic and Social Affairs.

Goldberg, Pinelopi Koujianou, Amit Kumar Khandelwal, Nina Pavcnik, and Petia Topalova. 2010. "Imported Intermediate Inputs and Domestic Product Growth: Evidence from India." *The Quarterly Journal of Economics* 125 (4): 1727–67.

Gunewardena, Dileni N., Elizabeth M. King, and Alexandria Valerio. 2018. "More Than Schooling: Understanding Gender Differences in the Labor Market When Measures of Skill Are Available." The World Bank Policy Research Working Paper Series 8588.

Heeks, Richard. 2015. "Indian IT/Software Sector Statistics: 1980–2015 Time Series Data." Retrieved from Reserve Bank of India. https://ict4dblog.wordpress.com/2015/04/28/indian-itsoftware-sector-statistics-1980-2015-time-series-data/ (accessed 31 May 2021).

James, Jeffrey. 1999. "New Technologies, Employment and Labor Markets in Developing Countries." In *Globalization, Information Technology and Development*, 116–54. London: Palgrave Macmillan UK.

Juhn, Chinhui, Gergely Ujhelyi, and Carolina Villegas-Sanchez. 2014. "Men, Women, and Machines: How Trade Impacts Gender Inequality." *Journal of Development Economics* 106 (C): 179–93.

Kapur, Devesh. 2002. "The Causes and Consequences of India's IT Boom." *India Review* 1: 91–110.

Katz, Lawrence F., and Kevin M. Murphy. 1992. "Changes in Relative Wages, 1963–1987: Supply and Demand Factors." *The Quarterly Journal of Economics* 107 (1): 35–78.

Organisation for Economic Co-operation and Development (OECD). 2021. Consumer Price Index: All Items for India [INDCPIALLMINMEI]. Retrieved from FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/INDCPIALLMINMEI (accessed 14 May 2021).

Sharma, Shruti. 2016. "Employment, Wages and Inequality in India: An Occupations and Tasks Based Approach." *The Indian Journal of Labor Economics* 59 (4): 471–87.

_____. 2018. "Heterogeneity of Imported Intermediate Inputs and Labor: Evidence from India's Input Tariff Liberalization." *Applied Economics* 50 (11): 1171–87.

Sharma, Shruti, and Nirvikar Singh. 2013. "Information Technology and Productivity in Indian Manufacturing India Policy." *India Policy Forum* 9 (1): 189–238.

Tinbergen, Jan. 1974. "Substitution of Graduate by Other Labor." *Kyklos* 27 (2): 217–26.

_____. 1975. *Income Differences: Recent Research*. Amsterdam: North-Holland Publishing Company.

Topalova, Petia, and Amit Khandelwal. 2011. "Trade Liberalization and Firm Productivity: The Case of India." *The Review of Economics and Statistics* 93 (3): 995–1009.

Appendix

Table A1. **Classification of Occupations Based on Tasks**

Occupation Type	Tasks
Routine manual	4.C.3.d.3 Pace determined by speed of equipment
	4.A.3.a.3 Controlling machines and processes
	4.C.2.d.1.i Spend time making repetitive motions
Routine cognitive	4.C.3.b.7 Importance of repeating the same tasks
	4.C.3.b.4 Importance of being exact or accurate
	4.C.3.b.8 Structured vs. unstructured work (reverse)
Nonroutine manual	4.A.3.a.4 Operating vehicles, mechanized devices, or equipment
	4.C.2.d.1.g Spend time using hands to handle, control, or feel objects, tools, or controls
	1.A.2.a.2 Manual dexterity
	1.A.1.f.1 Spatial orientation
	2.B.1.a Social perceptiveness
Nonroutine cognitive	4.A.2.a.4 Analyzing data/information
	4.A.2.b.2 Thinking creatively
	4.A.4.a.1 Interpreting information for others
	4.A.4.a.4 Establishing and maintaining personal relationships
	4.A.4.b.4 Guiding, directing, and motivating subordinates
	4.A.4.b.5 Coaching/developing others

Source: Acemoglu and Autor (2011)

Table A2. **Classification of Occupations**

Division	**Dominant Category**	**Total 3-Digit Occupations**	**% Routine Manual**	**% Routine Cognitive**	**% Nonroutine Manual**	**% Nonroutine Cognitive**
Legislators, senior officials, and managers	Nonroutine cognitive	7	0	0	0	100
Professionals	Nonroutine cognitive	18	0	0	0	100
Technicians and associate professionals	Nonroutine cognitive	20	0	40	5	55
Clerks	Routine cognitive	7	0	100	0	0
Service workers	Routine cognitive	8	37	50	13	0
Skilled agriculture and fishery workers	Nonroutine manual	6	0	0	100	0
Crafts and trades-related workers	Routine manual	16	56	0	44	0
Plant and machine operators and assemblers	Routine manual	20	80	0	20	0
Elementary occupations	Nonroutine manual	9	33	11	45	11

Source: Author's calculations using data from the National Sample Survey of India (1994, 2000, 2005, 2008, 2012) and the Periodic Labor Force Survey (2017).

Table A3. **Share of Workers across Occupation Types (%)**

	1994	2000	2005	2008	2012	2017
All						
Routine manual	11	13	13	14	12	12
Routine cognitive	4	4	3	3	4	4
Nonroutine manual	81	77	78	72	72	70
Nonroutine cognitive	4	6	6	11	12	14
Male						
Routine manual	9	11	11	12	10	10
Routine cognitive	5	5	4	4	4	4
Nonroutine manual	81	78	78	72	73	72
Nonroutine cognitive	5	6	7	12	13	14
Female						
Routine manual	15	19	19	21	20	21
Routine cognitive	2	2	2	2	2	3
Nonroutine manual	80	75	75	70	69	65
Nonroutine cognitive	3	4	4	7	9	11

Source: Author's calculations using data from the National Sample Survey of India (1994, 2000, 2005, 2008, 2012) and the Periodic Labor Force Survey (2017).

Table A4. **Employment Decomposition without Agriculture**

	1994–2005	2005–2017	1994–2017
All			
Routine manual			
Total Δ	1.39	−5.08	−3.69
Between industry Δ	0.87	−3.39	−2.76
Within industry Δ	0.52	−1.69	−0.93
Routine cognitive			
Total Δ	−2.66	−0.25	−2.91
Between industry Δ	−2.96	0.30	−2.94
Within industry Δ	0.30	−0.55	0.03
Nonroutine manual			
Total Δ	0.08	−3.95	−3.87
Between industry Δ	−2.28	3.47	0.88
Within industry Δ	2.36	−7.42	−4.88
Nonroutine cognitive			
Total Δ	1.18	9.30	10.48
Between industry Δ	−0.68	2.65	1.73
Within industry Δ	1.86	6.65	8.75

Continued.

Table A4. *Continued.*

	1994–2005	**2005–2017**	**1994–2017**
Male			
Routine manual			
Total Δ	0.85	−3.85	−3.00
Between industry Δ	0.59	−2.15	−1.73
Within industry Δ	0.26	−1.70	−1.27
Routine cognitive			
Total Δ	−3.04	−0.40	−3.44
Between industry Δ	−3.31	0.15	−3.53
Within industry Δ	0.27	−0.55	0.09
Nonroutine manual			
Total Δ	0.88	−4.97	−4.09
Between industry Δ	−1.42	2.52	1.24
Within industry Δ	2.30	−7.49	−5.33
Nonroutine cognitive			
Total Δ	1.31	9.23	10.54
Between industry Δ	−0.75	2.59	1.51
Within industry Δ	2.06	6.64	9.03
Female			
Routine manual			
Total Δ	2.46	−8.66	−6.20
Between industry Δ	0.61	−7.17	−5.30
Within industry Δ	1.85	−1.49	−0.90
Routine cognitive			
Total Δ	−0.75	0.28	−0.47
Between industry Δ	−1.26	1.02	−0.48
Within industry Δ	0.52	−0.74	0.01
Nonroutine manual			
Total Δ	−2.39	−1.07	−3.46
Between industry Δ	−5.11	6.22	−0.88
Within industry Δ	2.72	−7.29	−2.58
Nonroutine cognitive			
Total Δ	0.67	9.47	10.14
Between industry Δ	0.32	2.77	2.48
Within industry Δ	0.35	6.70	7.66

Δ = change in employment shares in percentage points.
Source: Author's calculations using data from the National Sample Survey of India (1994, 2000, 2005, 2008, 2012) and the Periodic Labor Force Survey (2017).

Table A5. **Employment Decomposition for Female Workers at One-digit NCO Divisions**

	1994–2005	2005–2017	1994–2017
Legislators, senior officials, and managers			
Total Δ	0.64	3.33	3.97
Between industry Δ	0.22	0.70	1.00
Within industry Δ	0.42	2.63	2.97
Professionals			
Total Δ	0.51	4.11	4.62
Between industry Δ	0.32	3.43	2.91
Within industry Δ	0.19	0.68	1.71
Technicians and associate professionals			
Total Δ	0.48	4.54	5.02
Between industry Δ	−0.08	4.16	1.23
Within industry Δ	0.56	0.38	3.79
Clerks			
Total Δ	−0.11	0.77	0.66
Between industry Δ	−0.15	1.00	0.55
Within industry Δ	0.04	−0.23	0.11
Service workers			
Total Δ	0.92	3.02	3.94
Between industry Δ	0.61	3.44	3.41
Within industry Δ	0.31	−0.42	0.53
Skilled agriculture and fishery workers			
Total Δ	−5.79	−16.33	−22.12
Between industry Δ	−5.85	−14.53	−21.50
Within industry Δ	0.06	−1.80	−0.62
Crafts and trades related workers			
Total Δ	2.46	−0.45	2.01
Between industry Δ	2.03	1.09	2.85
Within industry Δ	0.43	−1.54	−0.84
Plant and machine operators and assemblers			
Total Δ	0.64	−0.84	−0.20
Between industry Δ	0.10	−0.20	0.20
Within industry Δ	0.54	−0.64	−0.40

Continued.

Table A5. *Continued.*

	1994–2005	2005–2017	1994–2017
Elementary occupations			
Total Δ	0.25	1.83	2.08
Between industry Δ	0.27	2.47	2.68
Within industry Δ	−0.02	−0.64	−0.60

Δ = change in employment shares in percentage points, NCO = National Classification of Occupations.
Source: Author's calculations using data from the National Sample Survey of India (1994, 2000, 2005, 2008, 2012) and the Periodic Labor Force Survey (2017).

Table A6. **Industries and their Share of Employment**

Year	Total Number of Industries	Number of New Industries	Employment Share of New Industries (%)	Number of Industries Leaving	Employment Share of Industries Leaving (%)
1994	238	—	—	—	—
2000	302	65	4.35	1	0.01
2005	305	5	0.09	2	0.01
2008	300	2	0.002	7	0.01
2012	303	7	0.01	4	0.11
2017	307	4	0.02	0	0.00

— means data not available.
Source: Author's calculations using data from the National Sample Survey of India (1994, 2000, 2005, 2008, 2012) and the Periodic Labor Force Survey (2017).

Table A7. **Employment Decomposition without the Effects of Changes in Industrial Classification**

	1994–2005	2005–2017	1994–2017
All			
Routine manual			
Total Δ	2.65	−0.55	2.10
Between industry Δ	2.67	0.36	2.71
Within industry Δ	−0.02	−0.91	−0.61
Routine cognitive			
Total Δ	−1.35	0.24	−1.11
Between industry Δ	−1.15	0.42	−0.72
Within industry Δ	−0.20	−0.18	−0.39

Continued.

Table A7. *Continued.*

	1994–2005	2005–2017	1994–2017
Nonroutine manual			
Total Δ	−1.68	−6.56	−8.24
Between industry Δ	−1.52	−1.12	−2.91
Within industry Δ	−0.16	−5.44	−5.33
Nonroutine cognitive			
Total Δ	0.39	6.87	7.26
Between industry Δ	0.02	1.95	2.70
Within industry Δ	0.37	4.92	4.56
Male			
Routine manual			
Total Δ	2.15	−0.92	1.23
Between industry Δ	2.30	0.08	2.09
Within industry Δ	−0.15	−1.00	−0.86
Routine cognitive			
Total Δ	−1.54	−0.04	−1.58
Between industry Δ	−1.32	0.19	−1.22
Within industry Δ	−0.22	−0.23	−0.36
Nonroutine manual			
Total Δ	−1.30	−5.97	−7.27
Between industry Δ	−1.07	−0.38	−1.64
Within industry Δ	−0.23	−5.59	−5.63
Nonroutine cognitive			
Total Δ	0.70	6.93	7.63
Between industry Δ	0.13	1.83	2.58
Within industry Δ	0.57	5.10	5.05
Female			
Routine manual			
Total Δ	3.75	3.60	7.35
Between industry Δ	3.22	4.33	7.35
Within industry Δ	0.53	−0.73	0.00
Routine cognitive			
Total Δ	−0.58	0.82	0.24
Between industry Δ	−0.48	0.80	0.44
Within industry Δ	−0.10	0.02	−0.20
Nonroutine manual			
Total Δ	−2.75	−10.06	−12.81
Between industry Δ	−2.95	−5.19	−8.89
Within industry Δ	0.20	−4.87	−3.92

Continued.

Table A7. *Continued.*

	1994–2005	2005–2017	1994–2017
Nonroutine cognitive			
Total Δ	−0.42	5.64	5.22
Between industry Δ	0.00	1.63	2.32
Within industry Δ	−0.42	4.01	2.90

Δ = change in employment shares in percentage points.
Source: Author's calculations using data from the National Sample Survey of India (1994, 2000, 2005, 2008, 2012) and the Periodic Labor Force Survey (2017).

Table A8. **Age Buckets**

Age Bucket	Age Range (years)
1	< 18
2	18–24
3	25–34
4	35–44
5	45–54
6	55–64
7	65+

Source: Author's categories.

Table A9. **Education Buckets**

Education Bucket	Label	Years of Education
1	Below middle school	Up to grade 8
2	Secondary/higher secondary	Grade 9 to grade 12
3	Higher education	College or more

Source: Author's categories.