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THE DIFFERENTIAL EFFECTS OF TECHNOLOGY AND TRADE ON FEMALE AND MALE WORKERS IN INDIA

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Abstract

This paper uses the task content model of occupations to investigate whether technology and trade have had differential effects on male and female workers in India. It describes trends in employment shares and wages for female and male workers based on whether they have routine manual, routine cognitive, or non-routine cognitive occupations. It finds that, though there are some similarities in the broad trends for both female and male workers, such as the fact that those with routine cognitive occupations for both categories have the smallest employment shares, there are also important differences. An investigation into the changes in employment shares reveals that female workers suffer less of a decline in routine cognitive jobs within industry than male workers. Furthermore, male workers experience a bigger increase in demand than female workers due to more jobs within industries that intensively employ workers in non-routine cognitive occupations. The findings in this paper have important implications for labor market policies that target skill development in developing countries.

Keywords: occupational choice, tasks, wages, employment, skills, economics of gender

JEL Classification: J21, J24, J16, O14

Contents

1. INTRODUCTION

Our understanding of the impact of technology, automation, and trade on the workforce has changed significantly over the past few years. Previously, this was mainly a debate on how technology differentially affected workers based on their skills (typically using training and education as proxies), and the literature focused on the displacement of production workers with technological and trade advancement and whether all countries were experiencing the phenomenon of skill-biased technological change. The evidence was mixed, and recent developments in the literature have shed some light on why that may be the case. Autor, Levy, and Murname (2003) took a different approach to understanding how computerization affected the demand for skilled workers based on whether the jobs were routine or non-routine and further whether they were manual, cognitive, analytic, or interactive. Their main findings reflected that what mattered for displacement was whether the job was routine or non-routine. Computers would mainly displace workers in routine jobs, even if they were cognitive in nature. Following this, many studies considered this classification of routine and non-routine occupations when analyzing the impact of technology and trade.

Recent evidence that accounts for this indicates that the advancement of technology, trade, and automation has been changing labor markets in the developed world in unpredicted ways. Research has documented the displacement of jobs that require education, skills, and training but are suitable for routinization as a phenomenon called "job polarization" (Acemoglu and Autor 2011; Autor and Dorn 2013). There is evidence of shrinking of all jobs that it is possible to routinize—manual or cognitive—for various developed countries in the OECD (Michaels et al. 2013) and various parts of Europe (Goos and Manning 2007; Dustmann, Ludsteck, and Schönberg 2009; Asplund and Barth 2011). Empirical investigations into whether these trends are also observable in the developing country context have not been as extensive. Sharma (2016) investigated this question in the South Asian context, focusing on India's labor market, and found some evidence of job polarization for all workers. This study extends the same analysis by determining whether the effects of technology, trade, and automation are different for female and male workers in India.

The case of India, which is representative of large developing economies, is distinct from that of any developed country in that it has a significant population of skilled workers in the service and manufacturing sectors while also having a large workforce of unskilled workers. While India has much to achieve in terms of automation, its information technology sector has grown significantly over the past two decades and various industries have widely adopted information technology. Even in a country like India, where manpower is significantly cheaper than investments in capital, technology has provided alternatives that are cheaper than hiring skilled workers. Additionally, better educational opportunities and the improvements in transport and technology have allowed more women to enter the labor force, especially in the service sector. Trade liberalization has also provided access to better technologies through high-quality imported intermediate inputs, which has affected the skill composition of plants in the Indian labor force (Sharma 2018a). Similarly, policies that encourage higher inward foreign direct investment in India have had positive spillover effects through the transfer of technology and skills in the regions that have received these inflows for a sustained period of time (Sharma 2018b). This paper investigates how changes in technology might have affected the employment and wages of female and male workers in India differently, creating opportunities for both in very different kinds of tasks.

To examine these trends, this study used two important datasets. The first is a worker-level dataset from the National Sample Survey of India, which provides detailed information on the principal activity of the workers through a three-digit code—the National Code of Occupations (NCO 2004) and the industry of occupation, along with data on employment, wages, hours of work, gender, and other relevant information on each worker. The study used the data for the years 2005, 2006, 2008, 2010, and 2012. The second is the Occupational Network (ONET) database, which the study used to measure the task content of each occupation category. It merged information about the task content of occupations from the ONET database with the NSS dataset. It further categorized occupations based on their task content into three main groups: non-routine manual, routine cognitive, and non-routine cognitive.

The study found evidence of job polarization for both female and male workers in the period under investigation, that is, 2005–12. For female workers, the number working in routine manual jobs fell by 11 percentage points, whereas for male workers it fell by roughly 6 percentage points. Changes in the shares of female and male workers with non-routine cognitive jobs also display a similar trend; while this share increased by roughly 10 percentage points for female workers, it increased by 8 percentage points for male workers. Over this period, while both female and male workers had the smallest share of employment in routine cognitive occupations, female workers registered a slight increase of about 0.4 percentage points, but for male workers it decreased by roughly 2 percentage points. A breakdown of these shares by education reveals that, as one would expect, both male and female workers with high levels of education mainly occupy non-routine cognitive jobs, whereas those with low levels of education are mainly engaged in routine manual tasks.

Further, a decomposition of these employment shares into “changes within industry,” referring to changes in employment shares due to changing task intensities within occupations, and “changes between industry,” that is, changes in employment shares due to changes in the size of industries that are typically intensive in certain occupational categories, reveals differential trends across male and female workers. For routine cognitive occupations, male workers experience a much bigger decline of 2.15% in “within-industry” employment shares than female workers, for whom this decline is 0.96%. However, as far as non-routine cognitive jobs are concerned, a significant increase in employment shares for male workers came from an increase in the demand for male workers “within industry,” which accounts for 47% of the total increase, while it was responsible for only 7% of the increase for female workers. For female workers, the main increase in employment for non-routine cognitive occupations stemmed from the fact that industries that are intensive in the employment of this occupation category have been expanding, contributing roughly 93% of the total change.

Following this, the study conducted an analysis of the trends in the returns to these occupations, which it measured using the average wages that workers earn in each occupational group. On average, over the period of investigation, female and male workers across all three categories of occupations experienced an increase in average wages, ranging from 142.7% for male workers in non-routine cognitive occupations to 338% for female workers in routine manual occupations. However, in an empirical exercise that controlled for these workers’ characteristics, such as age, education, region, and industry of occupation, I found that the wages of both male and female workers engaged in non-routine cognitive and routine cognitive occupations rose faster than the wages of workers engaged in routine manual occupations. For male workers, the returns to non-routine cognitive tasks were higher than those to routine cognitive tasks for most years. In the case of female workers, on the other hand, for most years, routine cognitive tasks yielded greater returns than non-routine cognitive tasks.

One possible explanation for the trends in employment shares and wages for female workers with routine cognitive jobs could be that, as technology makes work easier in routine cognitive jobs, there is less discrimination between men and women in terms of the perception of the skills required to carry out a particular task (Becker 1957). In addition, because of the possible differences in wages, it might be cheaper to hire female workers than male workers for these routinized tasks. Finally, with increased outsourcing of such tasks to developing countries like India, there are greater opportunities for women to join the workforce. Thus, even with easy automation in routine cognitive jobs, the decline in the employment shares within industry is smaller for female workers than for male workers. On the other hand, with increased globalization and an increase in the requirement for management of multinational firms in India, there has been an increased demand for workers in non-routine cognitive occupations. It is harder for technology to automate non-routine cognitive jobs, and, again, based on Becker's model of gender discrimination, it is possible that there are significant differences in the perception of abilities between female and male workers, favoring the employment of male workers. Thus, I found a significantly larger "within-industry" increase in employment shares for male workers than for female workers.

This paper proceeds as follows. Section 2 presents a description of the data and the method employed for categorizing workers into occupational categories. Section 3 provides the employment trends for female and male workers as well the differences across educational and industrial sectors. Following this, Section 4 analyzes the average wage trends for female and male workers. Section 5 carries out an investigation into whether changes across industries or changes in the demand for occupations within industries play a bigger role in the changes in employment shares for female and male workers. Section 6 determines how returns differ across female and male workers in various occupational specializations defined by task content and how these change over time, then Section 7 concludes.

2. DATA

The main dataset that this paper used is from the employment and unemployment rounds of the National Sample Survey of India. This is a worker-level dataset that contains, among other details, information on the workers' occupation, industry of employment, educational qualifications, and gender. The years that the data consider are 2005, 2006, 2008, 2010, and 2012, respectively. This dataset, combined with the 2010 revision of the O*NET database, provides the task content of these occupations. I used the ONET content model, which contains 277 descriptors—variables that describe various aspects of a job—to which a value is assigned along different scales for each occupation. The ONET scales of reference describe about 30 types of scales.

First, I multiplied the normalized value for each scale to obtain a score between zero and one for each descriptor. I then took a subset of descriptors based on Acemoglu and Autor (2011) and determined whether they represent non-routine cognitive, routine cognitive, and routine manual tasks. For instance, I included the descriptor "the amount of time spent making repetitive motions" in routine manual tasks, whereas the descriptor for "thinking creatively" counted toward non-routine cognitive tasks. Then, for each task type, I added the measures up and standardized the scores to a mean of zero and a standard deviation of one. Based on this exercise, and with reference to Autor and Dorn (2013), I divided all the occupations into routine manual, routine cognitive, and non-routine cognitive categories based on their task content. I could not include the non-routine manual category in this exercise because of a lack of observations.

To map this onto the NSS worker-level data, I first used the concordance between the ONET occupation classification and the ISCO 1988 occupation classification. Further, the NCO 2004 classification, which the NSS dataset uses, is based on the ISCO classification, and I was thus able to merge the obtained scores with the worker-level data. For certain rounds, such as 61 and 62, I used NCO 1968 codes, as they are based on the ISCO 1968 classification. To achieve this, I used a concordance between ISCO 1968 and ISCO 1988, which allowed me to merge the values of the task content for these data. Using this information, I could obtain scores for the task content of occupations in the NSS worker-level data set and categorize each worker as having a routine manual, routine cognitive, or non-routine cognitive intensive occupation. The following sections examine the trends in employment and wages for male and female workers, respectively.

3. TRENDS IN EMPLOYMENT FOR FEMALE AND MALE WORKERS

Using the categorization that Section 2 detailed, I first present the share of female workers and male workers in each of these categories from 2005 to 2012. When considering the share of female workers with employment in routine manual, routine cognitive, and non-routine cognitive occupations, the share of women working in routine manual jobs is the largest but shows a declining trend from 2005 to 2012 (Figure 1)—it dropped from 55.6% to 46.6%. This is followed by the share of women with non-routine cognitive jobs, which increased from 35.5% in 2005 to 45.2% in 2012. The share of women with routine cognitive jobs is the smallest at around 8% (there was a marginal increase from 7.9% in 2005 to 8.3% in 2012).

Similarly, when analyzing the shares for male workers, as Figure 2 presents, I found a similar trend—the share of male workers engaged in routine manual tasks is the largest (51.7% in 2005 and 45.4% in 2012), followed by the share of workers with non-routine cognitive tasks (32.2% in 2005 and 40.2% in 2012), with those working in routine cognitive jobs comprising the smallest share (16.1% in 2005 and 14.4% in 2012). For both male and female workers, I found evidence of job polarization. If it is possible to consider workers in routine manual jobs as low skilled, those with routine cognitive jobs as middle skilled, and finally those with non-routine cognitive jobs as highly skilled, I can say that the share of workers in middle-skilled occupations is the smallest. I explored this in more detail when I considered the educational qualifications of male and female workers. There is, however, one small difference between the two categories of workers. While the share of male workers in routine cognitive jobs from 2005 to 2012 clearly declined, the share of female workers in routine cognitive jobs, while remaining almost stagnant, seems to have marginally increased.

Figure 1: Share of Female Workers in Routine Manual, Routine Cognitive, and Non-routine Cognitive Occupations

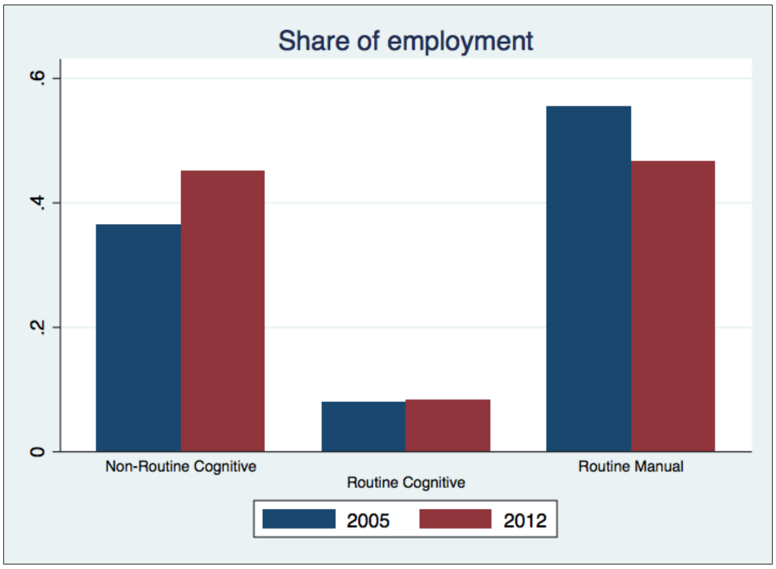
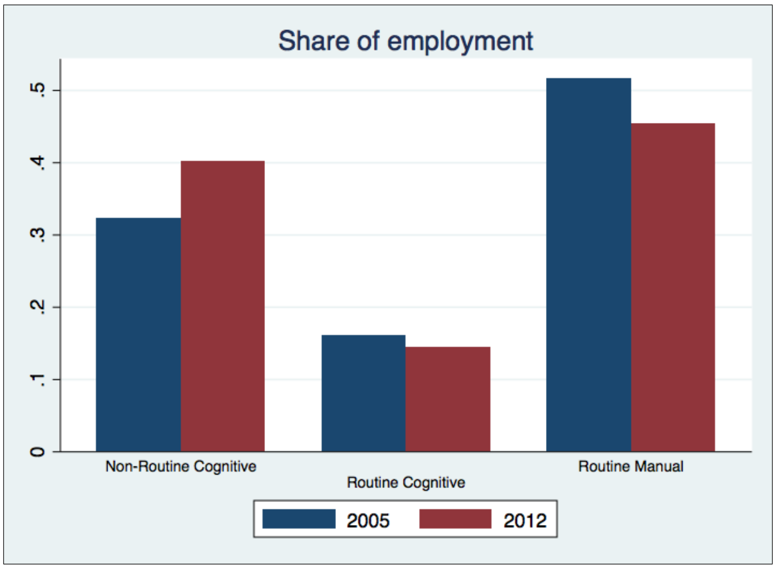


Figure 2: Share of Male Workers in Routine Manual, Routine Cognitive, and Non-routine Cognitive Occupations



Figures 3 and 4 show these trends in the share of employment for male and female workers for all the years from 2005 to 2012.

Figure 3: Year-Wise Employment Shares for Female Workers

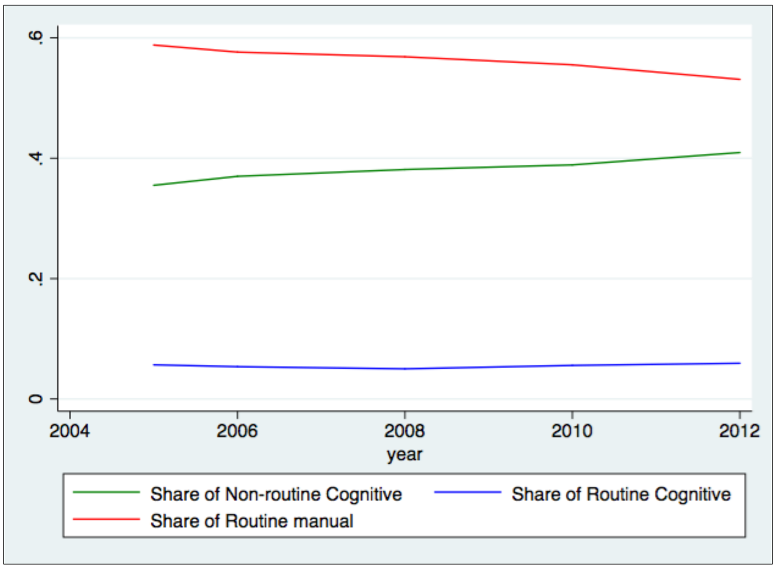
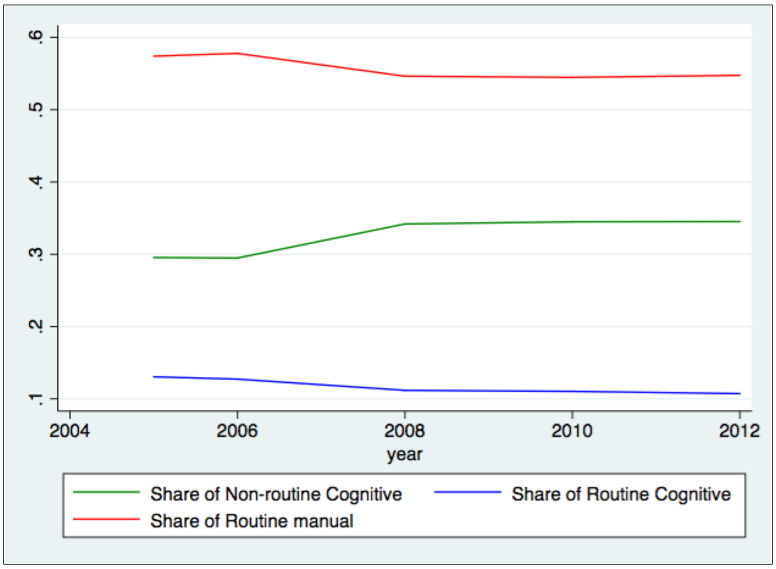
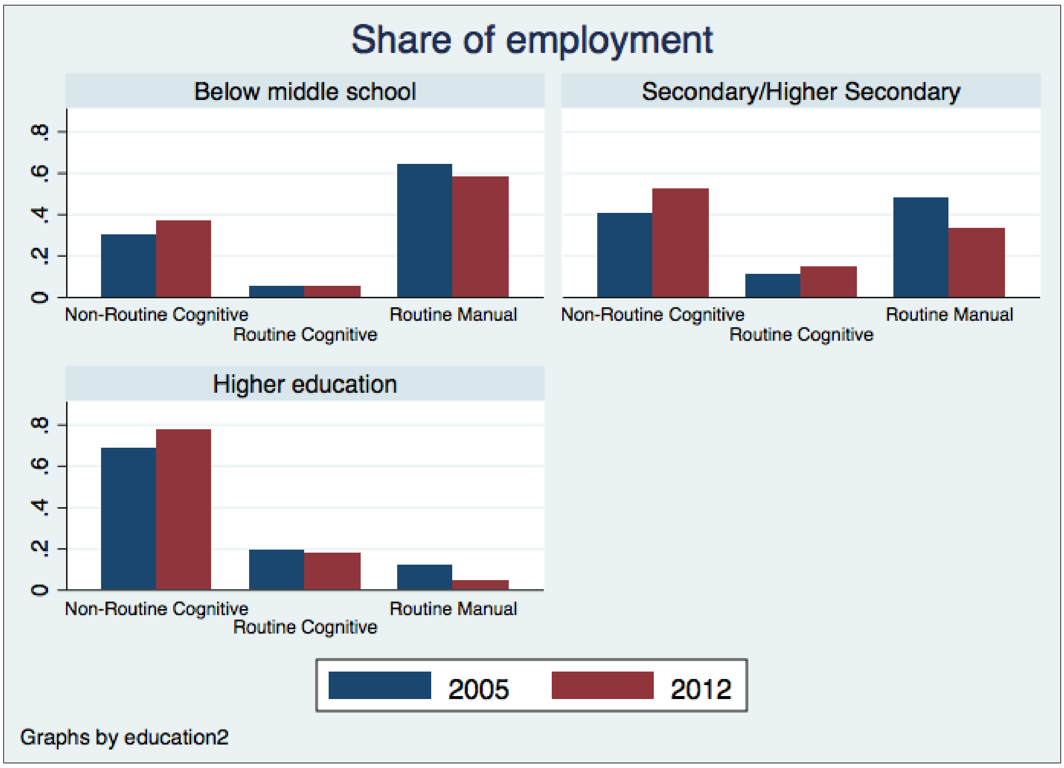


Figure 4: Year-Wise Employment Shares for Male Workers



The next set of figures explores the differences in occupational composition between male and female workers based on educational qualifications. Figures 5 and 6 show this occupational composition across female and male workers based on whether they have a graduate degree or diploma (or higher), have only completed secondary and higher-secondary education, or have attended school for fewer years than the requirement for middle school. For female workers, the share of women with higher education engaged in non-routine cognitive tasks is the largest and grew by 9.2 percentage points from 2005 to 2012, whereas those with education below middle school mostly have routine manual employment, but this share declined by 5.9 percentage points from 2005 to 2012. The share of women engaged in routine cognitive tasks is the smallest across all the education levels, although there was a slight increase of 3.4 percentage points in the share of women with secondary or higher-secondary education in routine cognitive work from 2005 to 2012.

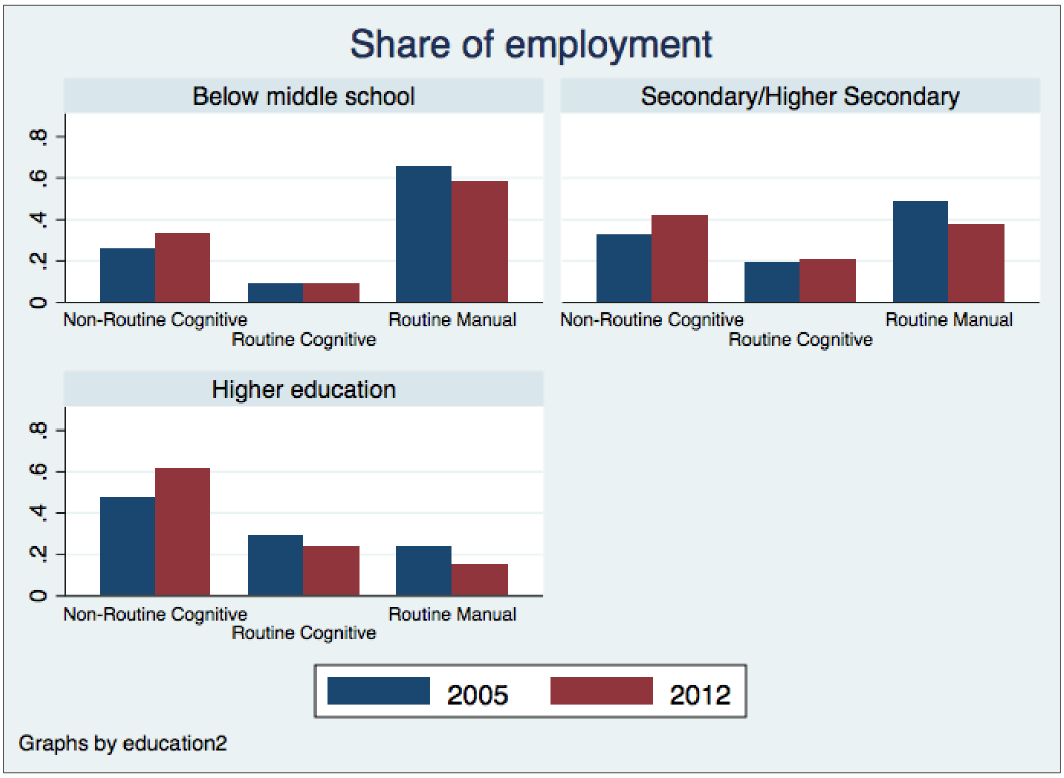
Figure 5: Occupational Composition Based on Education for Female Workers



The main trends are broadly similar for male workers—those with higher education mainly work in occupations intensive in non-routine cognitive tasks, whereas those with education below middle school mainly have occupations consisting of routine manual tasks. Across all the educational categories, the shares of male workers engaged in routine manual tasks declined, whereas the shares of male workers carrying out non-routine cognitive tasks increased.

What is common across both female and male workers is the fact that the share of workers involved in routine cognitive tasks is the smallest. This could be due to the fact that, with the advent of information technology over the past two decades, the automation of routine cognitive tasks has been faster and cheaper than the automation of routine manual tasks. It is possible that much of the displacement of routine cognitive occupations had already occurred prior to the period under investigation. In a developing country like India, the low hourly wages in routine manual jobs make it cheaper to hire workers than to adopt the existing technology, which possibly explains why technology still has not displaced a large amount of routine manual jobs.

Figure 6: Occupational Composition Based on Education for Male Workers



Next, I considered these employment shares across occupation categories for female and male workers based on their industry of occupation. Figures 7 and 8 show these shares. I divided the occupations into three main sectors—agriculture, manufacturing, and services. For female workers, I found that the agricultural sector predominantly employs workers in routine manual occupations. In services, a major share of female workers have non-routine cognitive jobs; however, a fair share of them have routine cognitive jobs. The manufacturing sector employs workers in mainly non-routine cognitive and routine manual occupations.

For male workers, the statistics for the agricultural sector are similar. In the service sector, the share of male workers with routine cognitive occupations is smaller than that for females. In the agricultural sector, the share of male workers with non-routine cognitive occupations is smaller than that for females, and the majority of them have routine manual occupations.

Figure 7: Occupational Composition by Each Sector of Employment for Female Workers

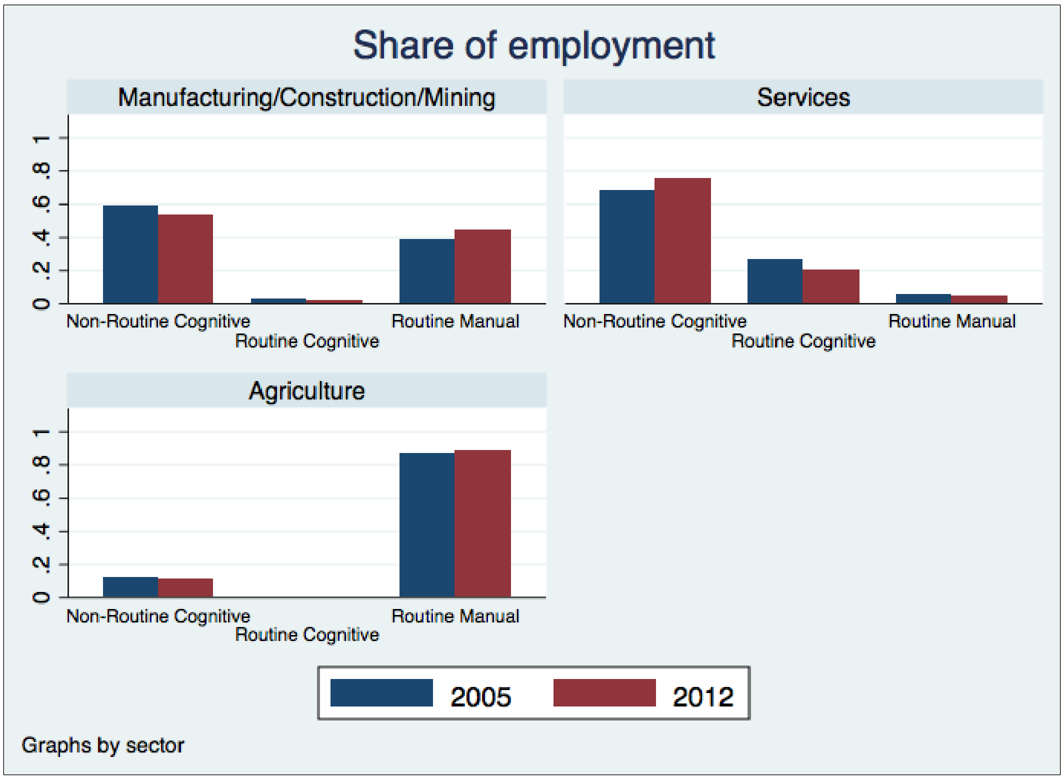
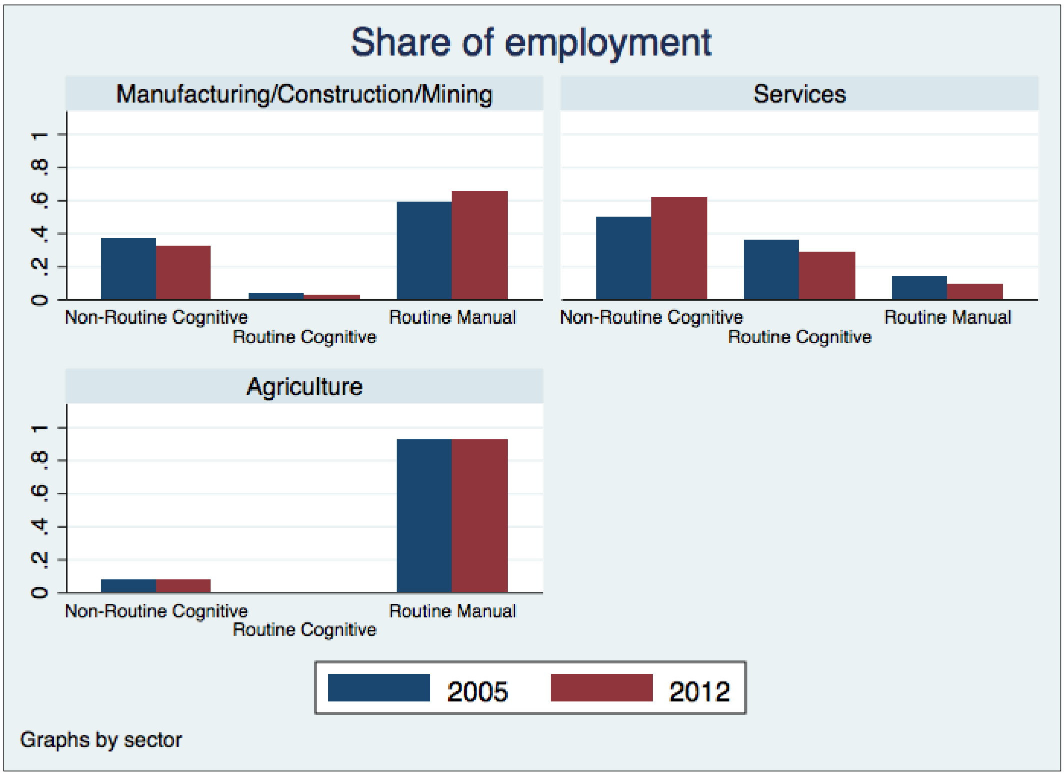


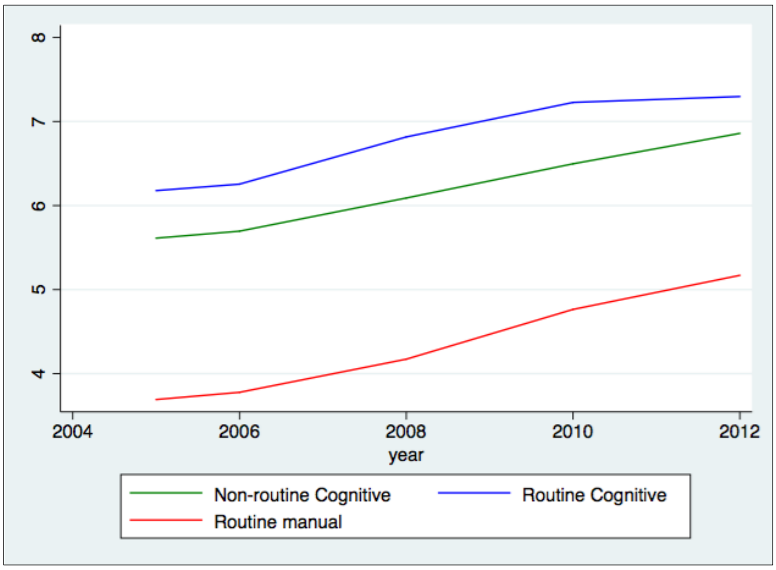
Figure 8: Occupational Composition by Each Sector of Employment for Male Workers



4. TRENDS IN WAGES FOR FEMALE AND MALE WORKERS

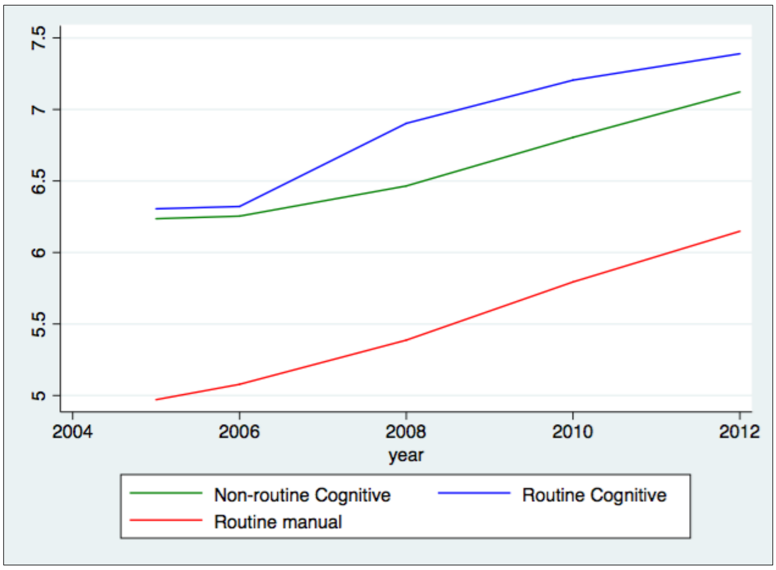
In this section, I examine the trends in wages across each occupational category for male and female workers. Figure 9 shows the trends in the log of average wages for female workers across each occupational category. For females, those employed in routine cognitive occupations earn the highest wages, followed by those in non-routine cognitive occupations and finally those in routine manual occupations. The wages across all these occupations increased from 2005 to 2012. Non-routine cognitive female workers experienced an increase of 248.07% and routine cognitive female workers experienced an increase of 206.32%, while routine manual female workers experienced an increase in wages of 338.5%, during this period.

Figure 9: Log Average Wages for Female Workers in Each Occupational Category



Similarly, for male workers, I found that the wages of those employed in routine cognitive occupations were the highest, followed by the wages in routine cognitive and finally routine manual jobs. This is apparent in Figure 10. Wages across all occupation categories increased from 2005 to 2012—male workers in non-routine cognitive occupations experienced a 142.7% increase, those in routine cognitive occupations experienced a 195.7% increase, and finally those in routine manual occupations experienced a 224.7% increase.

Figure 10: Log Average Wages for Male Workers in Each Occupational Category



Figures 11 and 12 present statistics based on various levels of educational qualification. For female workers who have obtained higher education, the returns to non-routine cognitive occupations are the highest, but the returns to routine cognitive occupations are similar. For those who have attained education levels below high school, the returns to routine cognitive jobs are the highest.

Figure 11: Log Average Wages in Each Occupational Category by Educational Attainment for Female Workers

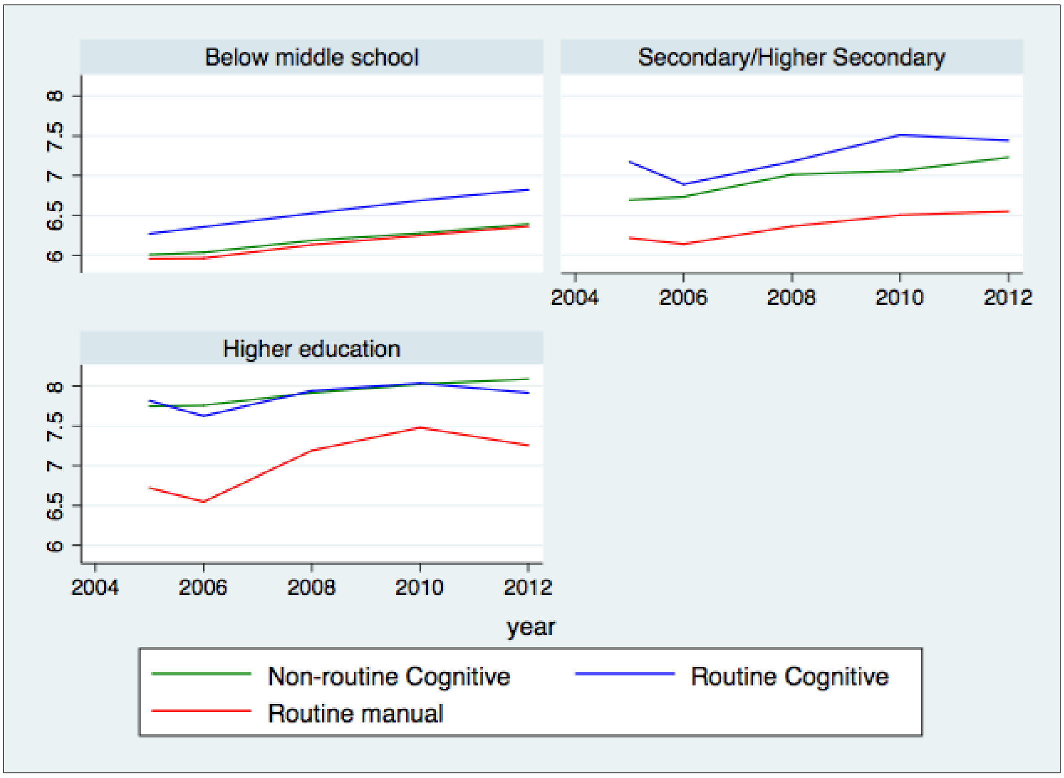
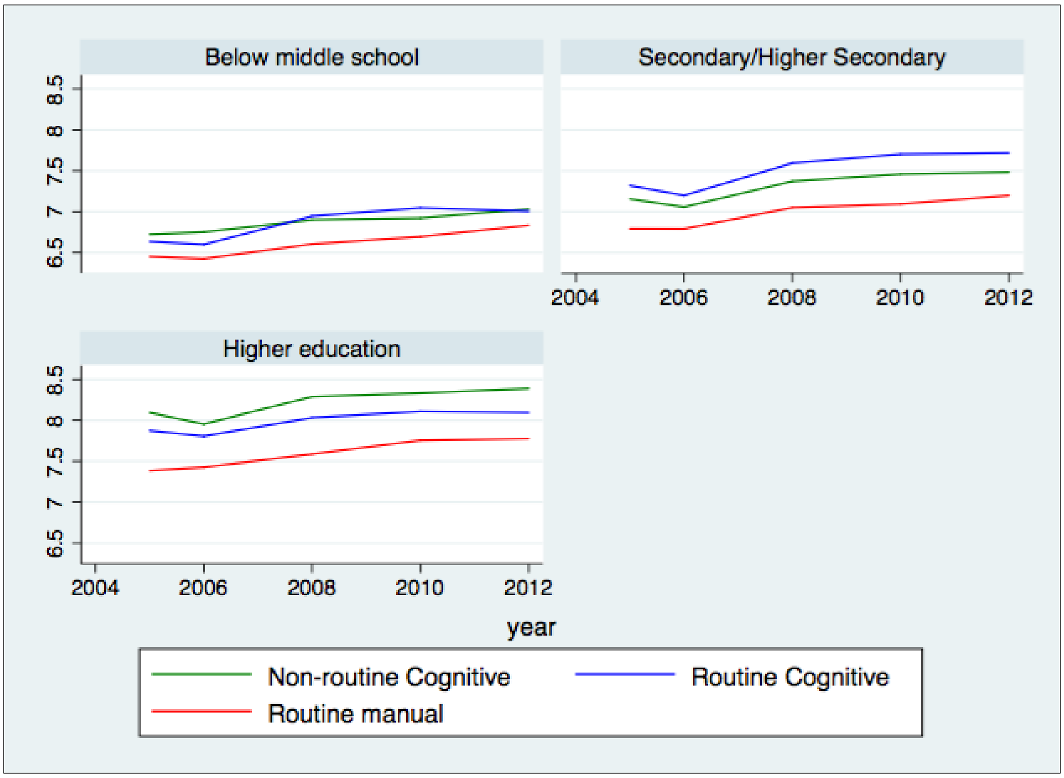


Figure 12: Log Average Wages in Each Occupational Category by Educational Attainment for Male Workers



For male workers who have obtained higher education, the returns to non-routine cognitive jobs are higher than those to routine cognitive occupations. For those in the secondary/higher-secondary category, the wages are highest for those with routine cognitive occupations. For those with just education below middle school, non-routine cognitive and routine cognitive occupations have similar wage returns, whereas routine manual occupations pay the lowest wages.

Figures 13 and 14 show that, for both female and male workers, higher education yields higher returns, as the log of average wages per worker indicates, across all the occupation categories, although the returns to higher education are the greatest in non-routine cognitive occupations.

In these figures, the average wages and the returns to education are higher for male workers than for female workers, pointing to a possible wage gap between the two. An increase in the returns to routine cognitive workers is observable along with a decline in their employment shares. This points to the possibility that those workers in these occupations whom technology cannot replace charge a high premium, either because, despite being routine in nature, they have not been automated yet or because the automated alternative comes at a prohibitively high cost.

Figure 13: Returns to Education for Female Workers across Different Occupational Categories

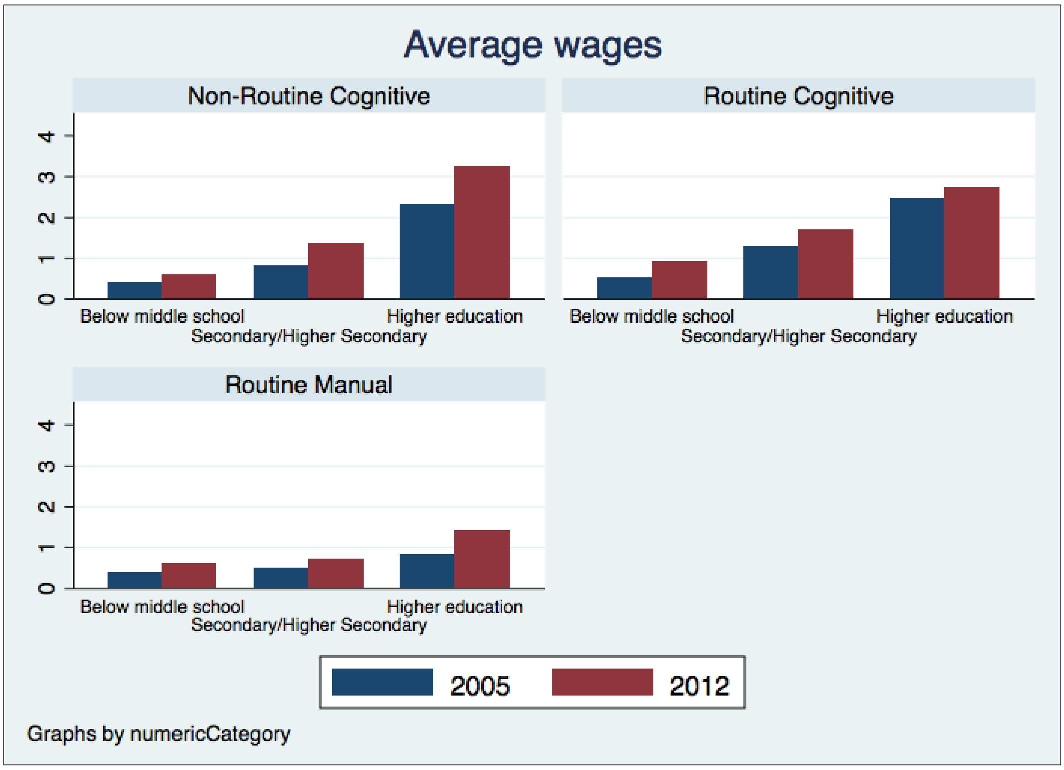
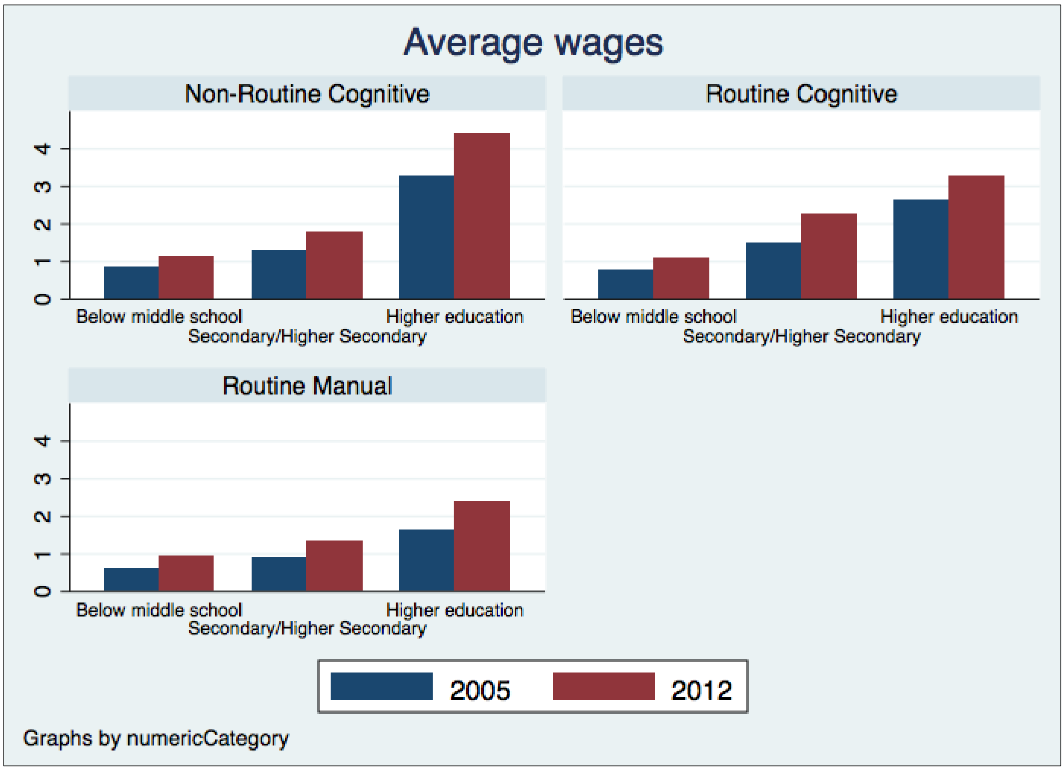


Figure 14: Returns to Education for Male Workers across Different Occupational Categories



5. DECOMPOSITION OF EMPLOYMENT SHARES FOR FEMALE AND MALE WORKERS

In this section, following Acemoglu and Autor (2011), I determine the extent to which the changes in employment shares are within industry and the extent to which changes between industries contributed to them. I use the following:

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

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

$$\Delta E_{jt} = \Sigma_k \Delta E_{kt} \lambda_{jk} + \Sigma_j \Delta \lambda_{jkt} E_k$$

ΔE_{kt} represents the change in industry k's share over the time 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 time period under consideration, whereas λ_{jk} gives the average share.

Tables 1 and 2 show the employment changes and the decomposition for the three main occupation categories for female and male workers, respectively. While the direction of change for non-routine cognitive tasks and routine manual tasks is the same for male and female workers, for routine cognitive jobs, the effects are different. Female workers seem to have gained marginally as far as routine cognitive jobs are concerned, whereas these seem to have declined slightly for men.

For both male and female workers, the changes in employment shares in non-routine cognitive jobs are positive; however, the "between-industry" effects are stronger for female workers than for male workers, whereas the "within-industry" effects are stronger for male workers than for female workers. Both experience a decline in routine manual jobs, and both experience a bigger effect from changes in "between-industry" shares than "within-industry" shares.

Table 1: Decomposing the Changes in Employment Shares for Female Workers

Occupation Type	IndustryΔ	Occupation Δ	Total Δ
Non-routine Cognitive	4.43	0.31	4.74
Routine Cognitive	1.28	–0.96	0.32
Routine Manual	–5.73	0.66	–5.06

Table 2: Decomposing the Changes in Employment Shares for Male Workers

Occupation Type	IndustryΔ	Occupation Δ	Total Δ
Non-routine Cognitive	2.28	2.1	4.46
Routine Cognitive	1.19	–2.15	–0.96
Routine Manual	-3.42	–0.08	–3.5

The next two tables—Tables 3 and 4—show the same decomposition of employment effects for nine broad educational categories by the NCO. Comparing the tables, I found that, for non-routine cognitive positions, such as legislators, senior officials and managers, professionals, and technicians and associated professions, both male and female workers have experienced growth in the employment shares, especially in the "within-industry" employment shares. However, for categories such as service workers, while male workers have experienced a significant decline in "within-industry" employment, this is less severe regarding the shares for female workers. For routine manual occupations, both have experienced a decline in employment, but for categories such as plant operators, while the employment share of female workers has fallen significantly, the employment share of male workers has increased.

Table 3: Decomposition of Employment Shares by NCO Categories for Female Workers

Occupation	Industry*Δ*	Occupation *Δ*	Total *Δ*
Legislators, senior officials, and managers	0.55	1.87	2.42
Professionals	1.57	0.43	2.01
Technicians and associate professionals	1.49	0.07	1.56
Clerks	0.62	–0.05	0.57
Service workers and shop and market sales workers	1.38	–0.68	0.70
Skilled agricultural and fishery workers	–6.84	0.77	–6.07
Craft- and trade-related workers	2.51	–0.18	2.33
Plant and machine operators and assemblers	0.05	–0.30	–0.25
Elementary occupations	–1.27	–1.98	–3.25

Table 4: Decomposition of Employment Shares by NCO Categories for Male Workers

Occupation	Industry*Δ*	Occupation *Δ*	Total *Δ*
Legislators, senior officials, and managers	0.57	3.43	4
Professionals	0.58	0.98	1.56
Technicians and associate professionals	0.39	0.02	0.41
Clerks	0.19	0.11	0.30
Service workers and shop and market sales workers	0.92	–3.14	–2.22
Skilled agricultural and fishery workers	–4.84	0.5	–4.34
Craft- and trade-related workers	1.93	–0.40	1.53
Plant and machine operators and assemblers	0.36	0.65	1.01
Elementary occupations	0	–2.26	–2.26

6. CHANGES IN RETURNS TO OCCUPATIONAL SPECIALIZATION FOR FEMALE AND MALE WORKERS

In this section, I report the study of how the wages of workers, based on their respective occupation categories, changed during the period under consideration. Accordingly, I referred again to Acemoglu and Autor (2011) and divided male and female workers based on their age, level of education, and region of occupation. The occupational categories are the same as the paper discussed earlier—non-routine cognitive, routine cognitive, and routine manual—and I considered the initial occupational categories to be fixed over the period and to serve as a proxy for comparative advantage. The specification that I estimated was the following:

$$log\ w_{sejkt} = \beta_1 * \gamma_{sejk}{}^{NRC} * t_i + \beta_2 * \gamma_{sejk}{}^{RC} * t_i + t_i + \theta_e + \theta_j + \theta_k + e_{sejkt}$$

$\gamma_{sejk}{}^{RM}$ was dropped from the regression because $\gamma_{sejk}{}^{NRC} + \gamma_{sejk}{}^{RC} + \gamma_{sejk}{}^{RM} = 1$. The education, region, and age fixed effects are denoted by $\theta_e, \theta_j\ and\ \theta_k$. As in Sharma (2016), the data are based on the 88 NSS categories that I obtained for region, 12 categories for age, and 5 categories for education. In estimating this regression, I revisited the analysis that Sharma (2016) performed, but, because of the emphasis on the gender differences in employment that this paper explores, I am better able to comment on the gender differences. Table 5 replicates the estimation results from Sharma (2016).

For male workers, I found that those engaged in routine cognitive and non-routine cognitive tasks almost consistently experienced higher returns than those engaged in routine-manual tasks, who constitute the omitted group. The effects for non-routine cognitive tasks are stronger. For female workers, the returns to non-routine cognitive tasks and routine cognitive tasks are higher than those to routine manual tasks only for some years. In addition, in years such as 2005 and 2010, the *log daily average wages* earned for routine cognitive tasks are higher than those earned for non-routine tasks.

Table 5 presents the results of the estimation. I interpreted the coefficients for the specialization category and year dummies relative to the wages of workers in routine manual occupations because this is the omitted group. For all the years under consideration, the wages for workers—both female and male—in non-routine cognitive and routine cognitive tasks increased more than the wages for those engaged in routine manual tasks. When considering male workers, I found that there are higher returns for almost all the years under consideration for those engaged in non-routine cognitive tasks than for those engaged in routine cognitive tasks. For female workers, however, for most of the years under consideration, the wage increases were larger for routine cognitive tasks than for non-routine cognitive tasks. The following section discusses these results.

Table 5: Returns Based on Occupational Specialization for Female and Male Workers

Log Average Daily Wage (Dependent Variable)	Male Workers	Female Workers
2005*Share_non-routine-cognitive_2005	0.412***	0.267**
	(0.0605)	(0.107)
2006*Share_non-routine-cognitive_2005	0.273***	0.220*
	(0.0656)	(0.119)
2008*Share_non-routine-cognitive_2005	0.347***	0.268**
	(0.0624)	(0.111)
2010*Share_non-routine-cognitive_2005	0.394***	0.155
	(0.0629)	(0.129)
2012*Share_non-routine-cognitive_2005	0.313***	0.0797
	(0.0644)	(0.119)
2005*Share_routine-cognitive_2005	0.378***	0.802***
	(0.0721)	(0.195)
2006*Share_routine-cognitive_2005	0.219**	0.315
	(0.0712)	(0.222)
2008*Share_routine-cognitive_2005	0.203**	-0.0348
	(0.0668)	(0.164)
2010*Share_routine-cognitive_2005	0.444***	0.666**
	(0.0772)	(0.286)
2012*Share_routine-cognitive_2005	0.273***	0.270
	(0.0714)	(0.191)
Constant	5.819***	6.221***
	(0.312)	(0.193)
Fixed Effects	Yes	Yes
Observations	9344	3483
R^2	0.7969	0.7105

Note: This table replicates the results from Sharma (2016). The fixed effects include education, region, and age fixed effects. All the models also include time fixed effects. The standard errors are robust and in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$.

7. CONCLUSION

The empirical analyses in this paper reveal many interesting trends and findings regarding the employment and wages of female and male workers based on their occupational specialization. First, for both female and male workers, there is evidence of job polarization. The share of employment in routine cognitive jobs for both male and female workers is the smallest, whereas the share of routine manual jobs decreased while that of non-routine cognitive jobs increased for both groups of workers. The increase in non-routine cognitive jobs is due to both an increase in the share of non-routine cognitive-intensive jobs within industries and an expansion of industries that intensively involve non-routine cognitive tasks. As far as routine manual jobs are concerned, the decline in employment across both male and female workers is mainly a result of the shrinking employment shares in routine manual-intensive industries.

There are many differential effects between male and female workers. Firstly, in terms of changes in employment shares, male workers have experienced a greater decline in routine cognitive occupations than female workers, who might have even experienced a slight increase. Male workers have suffered a significantly bigger decline in "within-industry" employment shares than female workers, while both male and female workers have experienced an expansion in "between-industry" employment shares. The share of non-routine cognitive jobs has been growing for both groups, but it is much larger for male workers than for female workers. Furthermore, the increase in the share of non-routine cognitive employment "within industry" is much greater for male workers than for female workers, while both have experienced an increase in "between-industry" employment shares.

Examining the effects on wages reveals that the returns to both routine cognitive jobs and non-routine cognitive jobs relative to routine manual jobs have been increasing for male workers. Women have experienced significantly higher returns in wages, except for a few instances in routine cognitive occupations and non-routine cognitive occupations. Of these, the relative increase has been the greatest for women engaged in routine cognitive occupations.

Becker's (1957) theory of gender discrimination may provide a possible explanation for these differential effects, and perhaps the advent of technology may have weakened the effects of such discrimination regarding certain positions. The fact that the intensity of non-routine cognitive tasks has risen faster for men than for women may point to the tendency of a bias toward male workers as far as employers' perceptions of capabilities in these jobs are concerned. However, with increasing globalization, a growing economy, and a growing educated female workforce, more opportunities in the skilled service sectors are likely to open up for women. This situation might not be as strong for routine cognitive occupations, in which complementary technology might reduce the perceived skill gap. It is also possible that women are more willing to work in occupations that are intensive in routine cognitive tasks for lower returns as long as they offer other benefits, such as the ability to work from home. These are of course possible explanations; thus, the results of this paper should motivate more research in this area. The analyses in this paper have important implications for labor market policies in developing countries, especially those that aim to provide skills to the labor force, such as the National Skill Development Corporation in India. One of the important lessons is that there needs to be a focus on occupations and a thrust toward providing skills for occupations that will continue to grow with technological change—the "non-routine cognitive" occupations. Additionally, there needs to be an emphasis on providing support for female workers in the "non-routine cognitive" occupational categories, because the research suggests that this share has been growing at a much lower rate "within industry" than for male workers. Support can take the form of outreach and better training for female workers and improved workplace practices in general to work with the aim of eliminating the bias between female and male workers in these occupations.

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