WORKING PAPER NO: 642

Exploring the impact of policy mediated technological change on female workforce representation in occupations across industries in India

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Year of Publication – May 2021

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Abstract

Technology evolution historically had implications on the demand for workforce in different occupations, but its effects on such occupations are often mediated by industrial policies of a country which shape the way technologies diffuse across different industrial sectors. In this study we explore the indirect relationship between technological upgradation triggered by liberalization reforms of the 1990s and the representation of workforce in occupations across different industrial sectors, with a particular focus on female workforce representation. Relying on NSSO surveys on employment and unemployment, we illustrate this relationship by showcasing patterns of workforce representation before and after the reform period at an aggregate and a disaggregated level. At an aggregate level we follow extant literature to group occupations into four major categories - 1) routine manual, 2) non-routine manual, 3) routine cognitive, and 4) non-routine cognitive. We observe a routine-biased effect of technological upgradation owing to the 1990 reforms, which shows an increased representation in non-routine cognitive occupations. Such occupations at the aggregate were also found to accommodate women workforce at least proportionately relative to their representation at higher education levels. Adopting a network-based method we conduct a disaggregate-level analysis within these non-routine cognitive occupations across industries and observe that occupations that better accommodated female workforce were largely assorted into one industrial sector and such a pattern did not significantly alter post the reform period. Our findings broadly pointed us to the need for tackling gender representation at sectoral level through selective industry-specific female-friendly policies.

Key Words: Technology, Industrial Policy, Occupations, Gender

1. INTRODUCTION

Technology evolution is known to have profound implications on demand for jobs/occupations in society. Technologies of the nineteenth and twentieth century increased demand for low-skilled manual work and a subsequent increase in the managerial and clerical workforce to handle the growing complexity of tasks (Frey & Osborne, 2017). Computer technologies of recent times and emerging technologies such as Artificial Intelligence, Cloud, Big Data, BlockChain and others driving the fourth industrial revolution of the future, are touted to automate not just manual jobs but even routine cognitive jobs (Berger & Frey, 2016; Frey & Osborne, 2017; Waschull et al., 2020). While technologies affect demand for different kind of jobs, their effect is mediated by institutions which formulate industrial policies shaping the way technologies diffuse across different sectors in a country (Hayami et al., 2005). According to UNCTAD (2016), industrial policies can be categorized into being functional, horizontal, or selective in nature. Those policies which aim to improve the business environment common to all sectors, e.g., competition or trade policies, are termed as functional. Those which aim to promote specific activities across sectors are termed as horizontal, and those which alter economic activity in favor of specific sectors are termed as selective/vertical (UNCTAD, 2016).

Change in industrial policies of India following the liberalization reforms of the 1990s leapfrogged the country from an agriculture-oriented economy directly into a services-led economy. This break is important in terms of the technological up-gradation of different sectors as indicated by changes in total factor productivity (TFP) before and after this period. While there is a significant technological up-gradation within the Indian industry after the reform period, it is starkly evident in the services sector, which registered consistent annual growth in TFP post the 1990s (Basu & Maertens, 2007; Sarkar, 2019). As industrial policies affect technology up-gradation differently in different sectors, the changes in demand for various occupations may also differ across industrial sectors. In this study, we explore the indirect relationship between technological up-gradation (proxied by the liberalization reforms) and the representation of women in occupations across different industrial sectors. We conduct this exploratory analysis utilizing employment and unemployment surveys conducted by the National Sample Survey Organization (NSSO) to map the changing representation of educated women workforce across different occupations and industrial sectors before and after the reforms. First, we provide a summary picture at an aggregate level where we group disaggregated occupational classes into four categories a) routine manual, b) non-routine manual, c) routine cognitive, and d) non-routine cognitive, that is consistent with classification followed in Cirillo (2018) and Sarkar (2019). Since recent and emerging technologies are poised to increase demand for non-routine cognitive occupations, we restrict to the workforce in these occupations having a minimum education level and perform a disaggregated occupation level analysis. To allow for parsimonious comparisons at a disaggregated occupation level, we formulate an occupation network, with the strength of the connection between two occupations determined by the similarity of their workforce across different industrial sectors. We further define a custom index to capture the extent to which occupation is accommodative of the women workforce. Superimposing this index over occupations in a network, we then end our exploratory analysis by measuring gender assortativity over occupational networks observed for population cohorts in workforce before and after the year 1990.

Our findings broadly point to the need for industrial policies to adopt a more sectoral approach tackling gender representation across occupations within each industrial sector, in addition to existing functional policies that aim to tackle this problem generically across industrial sectors.

2. BACKGROUND OF THE STUDY

2.1. Impact of technology and automation on jobs

The evolution of technology is known to have profound implications for the nature of work in terms of the kind of education and skills expected for different kinds of jobs across various industrial sectors. Technologies in the nineteenth century, for example, led to the process of de-skilling several jobs in the manufacturing sector, where the factory system was successful in dividing work into several simpler tasks and substituted few artisanal skill-based workers with more workers having less specialized skills. Subsequently, with the advent of electrification, establishments increased in size, expanded their operations across the globe, and the number and complexity of tasks grew significantly, resulting in an increase in the share of the managerial and clerical workforce in addition to blue-collar production workers (Frey & Osborne, 2017). A growing body of literature suggests that computer technologies of the recent past have increased demand for jobs requiring greater cognitive skills and less manual labor. These technologies have increased the demand for a high-skilled workforce and had a negative effect on the demand for a low-skilled workforce, indicating skill-biased effects of technological change (Acemoglu, 2002). As computerization is expected to reduce the wages of low-skilled manual jobs, it is also expected that the workforce could relocate from low-skilled manual jobs to routine cognitive jobs or low-skilled service occupations (David & Dorn, 2013). Emerging technologies such as AI, Big Data, and others that are fuelling the fourth industrial revolution – or industry 4.0 – are further expected to increase the demand for non-routine and cognitive jobs and substitute even the routine cognitive jobs (Berger & Frey, 2016). This argument is captured as routine-biased effects of technological change, as IT and emerging technologies can easily codify and program even cognitive tasks so far as they are conducted in a routine manner (Autor et al., 2003; Fernández-Macías & Hurley, 2017).

2.2. Role of policies on industrial sectors – case of structural reforms in India

While technologies affect the demand for different kinds of jobs or occupations, their effect is mediated by other structural factors within any nation. Institutions and Industrial policies in a country can shape the way technologies diffuse across different industrial sectors (Hayami et al., 2005) and consequently affect the demand for different kinds of occupations (Berger & Frey, 2016). Industrial policies, for example, can be functional (less-interventionist targeting improvement in business environment common to all sectors), horizontal (specific activities promoted across sectors), and selective/vertical (structuring economic activity towards specific sectors), acting differently across different sectors (UNCTAD, 2016). Sectors showing higher potential for economic growth are commonly favored through sectoral policies facilitating rapid technological dissemination in such sectors. IT sector in India is one such example (Balakrishnan, 2006). In addition to facilitating the growth of industries themselves, policies can also target potential workforce through skill-development policies, and can also alter the social composition of workforce through reservation or affirmative action policies in education and occupations in different forms.

In the context of India, industrial policies have come in varied forms. For example, policies surrounding 'import-substitution industrialization' shielded Indian industries (especially in the capital-intensive manufacturing sector) while they scale the learning curve so as to compete with industries across the globe. These policies roughly continued until the 1980s and 90s, after which liberalization reforms have contributed towards a shift to pro-business or pro-market policies across sectors (Basu, 1993; Kohli, 2006). While there were targeted industrial policies in specific sectors such as the 'Green Revolution' for agriculture in the 1960s, policies favoring IT sector growth after the 1990s, and others, a majority of the policies were either functional or horizontal in nature. Although liberalization reforms were primarily functional in nature, technological up-gradation, growth, and employment consequences followed very different trajectories in the three major sectors of the country - agriculture, manufacturing, and services (Basu & Maertens, 2007). For agriculture, a major structural break happened in the 1960s in the form of the Green revolution. Nevertheless, there was little change before and after the 1990 reforms in this sector as the total factor productivity (TFP), which represents the change in efficiency or changes in production technology, has been increasing but very slowly during this period. For manufacturing, although there was a positive structural break in terms of improvement in total factor productivity in the 1980s, it surprisingly went into negative post the liberalization reforms in the 1990s. For the service sector, there is a consistent annual growth since the 1990s (Basu & Maertens, 2007).

2.3. Occupations and Gender in India

Rapid economic growth over the past few decades, along with an overall increase in the level of education among its workforce together, has not been able to improve the employment scenario in India, in particular for women. Post liberalization reforms, India has seen a shift in the workforce from agriculture to the service sector without much expansion of employment in the manufacturing sector. While the contribution to growth by the service sector is over 50% over the past few decades, the share of employment it contributed was less than 25% during this period (Basu & Maertens, 2007; Tandem Research, 2018). Indian industry is also highly unorganized and employs a majority of the workforce informally (Basole, 2018; NCEUS, 2007). According to Labour Bureau (2016), two-thirds of the workforce do not have any form of a written work contract, and even less of the remaining are engaged in a regular or salaried position. Women are highly concentrated in low-paying and insecure informal jobs (NCEUS, 2009), and even within the formal workforce, they are largely accommodated in traditionally female-dominated occupations indicating a persistent trend of gender segregation in the country (Agrawal, 2016). Even in non-routine cognitive occupations that are expected to be in demand owing to technological changes, Agrawal (2016) shows that women are better represented only in traditionally female-dominated occupations like teaching and nursing.

In this study, we take the structural break of 1990 as a point of comparison to look at whether or not the situation has changed for women across occupations and industrial sectors. We look at the workforce within occupations distributed across different industrial sectors – at an aggregate and disaggregated level – to understand if there is any improvement in the employment scenario for women, and if so, in which occupations and industrial sectors.

3. DATA AND METHOD

3.1. Data – NSSO surveys

Employment and unemployment surveys conducted periodically by National Sample Survey Organization (NSSO) are representative sources of data about the labor force in India. To observe changes in the participation of women across occupations before and after the year 1990, we rely on NSSO surveys that are conducted before and after this reform period. We construct datasets separately for the workforce of the pre-reform period from pre-90 surveys and the workforce of the post-reform period from the post-90 surveys. Among the post-90 NSSO surveys, we have two survey rounds that match the occupational coding structure at a disaggregated level with the pre-90 surveys and two other rounds that cannot be matched at the disaggregated level but can be grouped consistently into aggregate occupational categories as we shall discuss subsequently. These surveys adopt the National classification of occupations (NCO) which follows the International Standard Classification of Occupations (ISCO), for defining the occupational codes up to the level of 3-digits. Survey rounds 60 (Year 2004) and 61(Year 2004-05) are the NSSO rounds conducted after the reform period with NCO-

1968 occupational classification that was also followed in the pre-90 survey rounds. However, the most recent rounds, 66 (Year 2009-10) and 68 (2011-12) follow the NCO-2004 classification that is different from NCO-1968. Although the concordance table published by the Ministry of Labour and Employment (MoLE), Government of India, can be used to match the occupations at the finer level (MoLE, 2004a), we believe that the results would be reliable only for comparison at more aggregate level. As a result, we pool rounds (60 and 61: post-90A) for carrying out disaggregate occupational level comparisons of the workforce before and after the reform period and most recent rounds (66 and 68: post-90B) for analysis at an aggregate level. To ensure the robustness of aggregate analysis, we also repeat it using post-90A in place of post-90B rounds.

For disaggregate level analysis of changes in the female workforce across occupations and industries, we formulate an occupational network to allow for parsimonious comparison before and after 1990. We rely on pooled pre-90 rounds and post-90A rounds for this analysis. Following Table-1 gives the details of these datasets and the kind of analysis for which we employ them.

Table 1: Details of datasets constructed from various NSSO Employment and Unemployment Surveys

Dataset	Surveys Pooled	NCO schema	Analysis
Pre90	Surveys placed in the pre-reform period constituted by round-38 (1983) and round-43 (1987-88).	NCO-1968	Both aggregate analysis and disaggregate analysis.
Post90A	Surveys placed in the post-reform period constituted by round-60 (2004) and round-61 (2004-05).	NCO-1968	Disaggregate analysis.
Post90B	Surveys placed in the post-reform period constituted by round-66 (2009-10) and round-68 (2011-12).	NCO-2004	Aggregate analysis.

In each of these surveys, the variables of our interest are individual age, gender, occupation, and industry, where individuals are engaged for a major part of their time (which the surveys indicate under the label usual activity status), education level, and sampling weights. To avoid inconsistency in comparing disaggregated education levels captured in different surveys, we group education into four major categories that were consistently found across surveys. These categories are numerically indicated as – Below primary education (1), Above primary and below secondary education (2), Above secondary and below graduate (3), and above graduate (4).

3.2. Aggregate Analysis

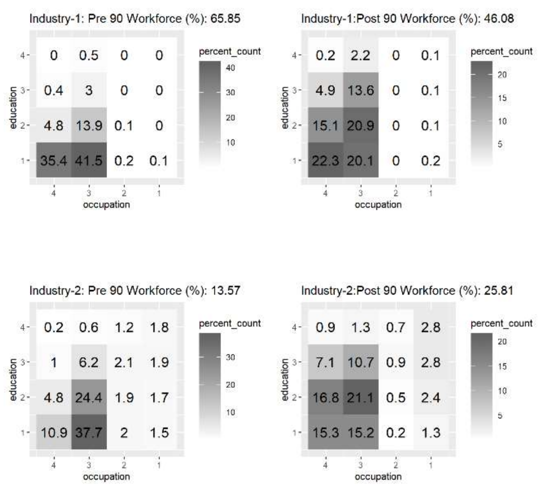
We categorize occupation codes into four major categories following Cirillo (2018), who rely on ISCO-88 skill-based classification. The first category is 'managers,' which include legislators, senior officials, managers, professionals, technicians, and associate professionals. The second category is 'clerks,' which include clerks, service workers, and shop and market sales workers. The third category is 'craft workers,' which include skilled agriculture and fishery workers, craft and related workers. The fourth category is 'manual workers,' which include plant and machine operators and assemblers, and elementary occupations. This categorization is neat for the recent NSSO rounds as they follow the NCO-2004 classification, which in turn is based on ICSO-88 skill-based classification (MoLE, 2004b). For the older NSSO rounds, we mapped the NCO-1968 occupation codes into these four major groups on their similarity with NCO-2004 codes following the concordance table published by the Ministry of Labor and Employment (MoLE, 2004a). We note that these four broad categories also coincide with the categorizations of 'non-routine cognitive,' 'routine cognitive,' 'non-routine manual' and 'routine manual' respectively, following Sarkar (2019). To maintain consistency with regard to industrial groups, we follow Basu & Maertens (2007), who describe the structural break of the 1990 reform period through the changes in the workforce, contribution to GDP, and changes in total factor productivity, across five major industrial sectors. Following Table-2 gives details of the aggregate occupation and industry categories, made consistent across various rounds.

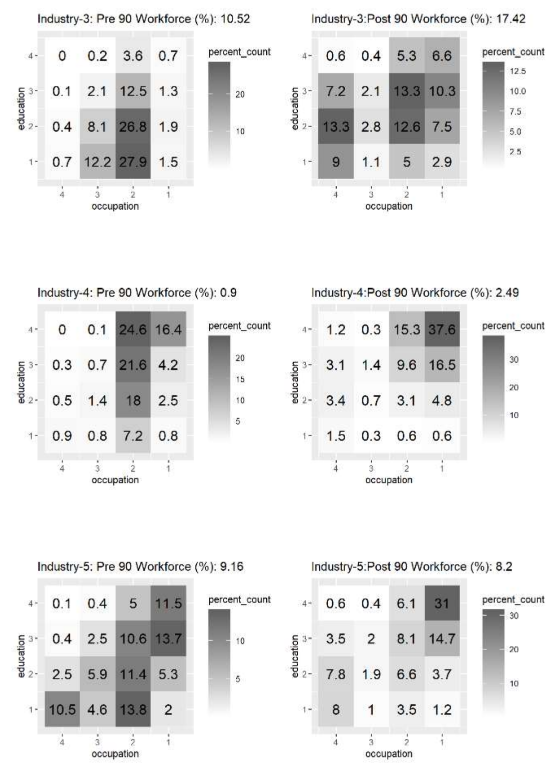
Table 2: Aggregate categorization of occupations and industries

	Round (Year)	**38 (1983)**	**43 (1988)**	**66 (2010)**	**68 (2011)**
Broad Industry Category	**NIC** *(Surveys capture by 3-Digit codes in older rounds, and 5-digit codes in recent ones)*	**1970**	**1970**	**2004**	**2008**
1	Agriculture, forestry, fishing, mining, and quarrying	000 - 199	000 - 199	01111 - 14299	01111 - 09900
2	Manufacturing, construction, and electricity, gas, and water supply	200 - 519	200 - 519	15111 - 45500	10101 - 43900
3	Trade, hotel, transport, and communication	600 - 759	600 - 759	50101 - 64204	45101 - 63999
4	Financing, insurance, real estate, and business services	800 - 830	800 - 830	65110 - 74999	64110 - 82990
5	Public administration, education, health and other services (which include sanitary services, community services, arts and entertainment and others)	900 - 990	900 - 990	75111 - 99000	84111 - 99000
Broad Occupation Category	**NCO** *(Surveys capture by 3-Digit Codes)*	**1968**	**1968**	**2004**	**2004**
1	Managers, senior officials, legislators, professionals, technicians and associate professionals (non-routine, cognitive)	000 - 299	000 - 299	111 - 348	111 - 348
2	Clerks, service workers and shop and market sales workers (routine cognitive)	300 - 490; 500 - 529; 550 - 599	300 - 490; 500 - 529; 550 - 599	411 - 523	411 - 523
3	Skilled agriculture and fishery workers, craft and related workers (non-routine manual)	600 - 629; 660 - 669; 670 - 689; 750 - 949; 960 - 989	600 - 629; 660 - 669; 670 - 689; 750 - 949; 960 - 989	611 - 744	611 - 744
4	Plant and machine operators and assemblers, and elementary occupations (routine manual)	630 - 659; 530 - 549; 710 - 749; 950 - 959	630 - 659; 530 - 549; 710 - 749; 950 - 959	811 - 933	811 - 933

3.2.1. Changes in the workforce across sectors

We consider individuals whose year of birth is before 1970 to be entering the workforce before the reform period and others to be entering after it. To make a comparison between the workforce working before and after the reform period, we look at only the workforce born before 1970 in the Pre90 surveys and born after 1970 in the Post90 surveys. Within each industrial sector, we observe the distribution of workforce along combinations of aggregate occupation and education categories - See Figure-1. Percentage of the workforce within each sector separately for the Pre90 workforce and Post90 workforce is also indicated above the corresponding sub-figures within Figure-1. We see that the percentage of the workforce increased in manufacturing and services related sectors (except sector 5) while the percentage of the workforce declined in the case of the agriculture sector. Focusing on the workforce within each sector, we observe that there is a movement of workforce towards highest occupation – education combination across all the sectors but to a very less extent in the agriculture sector. A significant shift is conspicuous towards managers, professionals, technicians, and related occupations (1), at the higher education levels – above secondary and below graduate (3) and above graduate (4). There is also a shift observed in terms of movement from clerks and related occupations (2) towards managers, professionals, technicians, and related occupations (1), indicating routine-biased effects.





Index for industry sectors: (1) Agriculture, forestry, fishing, mining, and quarrying, (2) Manufacturing, construction, and electricity, gas, and water supply, (3) Trade, hotel, transport, and communication services, (4) Financing, insurance, real estate, and business services, (5) Public administration, education, health, and other services
Index for aggregate occupation categories: (1) Managers, senior officials, legislators, professionals, technicians, and associate professionals (non-routine, cognitive), (2) Clerks, service workers, and shop and market sales workers (routine cognitive), (3) Skilled agriculture and fishery workers, craft and related workers (non-routine manual), (4) Plant and machine operators and assemblers, and elementary occupations (routine manual)
Index for aggregate education levels: (1) Below primary education, (2) Above primary and below secondary education, (3) Above secondary and below graduate, and (4) Above graduate

Note: Distributions across occupations and education levels (for a particular time-period - pre/post-reform - and industry) are showcased as heat maps, where for each heat map, cells capture the percentage of the workforce that add up to 100%. The percentage of the workforce in a given industry for each time period is shown at the top of each of the heat maps.

Figure 1: Workforce changes before and after the 1990s

Looking at the representation by gender (See Figure-2), overall, there is a significant movement of both male and female workforce towards non-routine cognitive occupations – managers, professionals, technicians, and others (1). There is a significant gap in the overall representation of men (~77%) over women (~23%) in the workforce, which has remained more or less stagnant post the reform period. Within the respective workforce, we observe that the percentage of men who are graduates or completed secondary education is higher in comparison to women, and such a gap continued even post-reforms. In the pre-reform period, 3.8% of the male workforce are graduates, and 9.9% completed their secondary education. These percentages were 1.7% and 2.6% respectively for women workforce before this period. Post-1990s, we observe that there has been an increase in these percentages among both men and women. It can be seen that 9.8% of the male workforce are graduates, and 26% completed secondary education, and these percentages are 8% and 13% respectively for women. This indicates that women are still at a disadvantage relative to men in terms of their representation in higher levels of education. However, we see that in the aggregate, non-routine cognitive occupations are representing women more or less equitable relative to men. The percentages indicate that 9.8% of the male workforce are educated above secondary education and are in such occupations, and this percentage is a close 9.2% for women. Prima-facie, it seems that non-routine cognitive occupations accommodate female workforce educated above secondary better despite the low proportion of such educated ones among females (21%) relative to that among males (35.8%).

In summary, the movement of the workforce to non-routine cognitive occupations indicates that India seems to have gone through routine-biased effects of technological change widely discussed in the literature (Acemoglu, 2002; Acemoglu & Autor, 2011; Autor et al., 2003; Fernández-Macías & Hurley, 2017). It also looks as if non-routine cognitive occupations better accommodate educated (above secondary) women workforce at an aggregate level. However, we explore further and conduct a disaggregated analysis by paying attention to these non-routine cognitive occupations at a more disaggregated level.

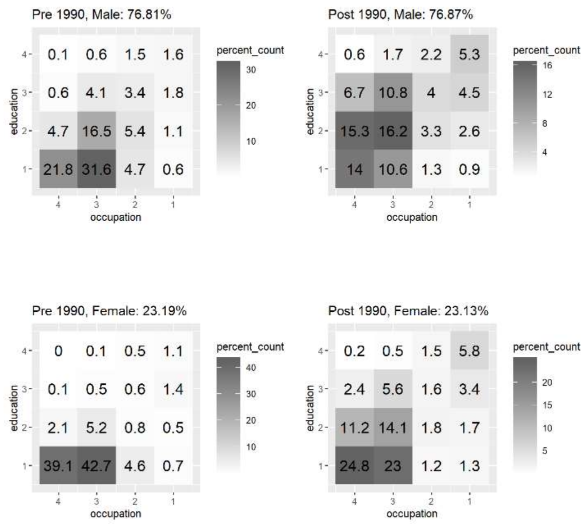


Figure 2: Changes in the workforce before and after the 1990s by gender

In order to ensure the robustness of these arguments and to justify the use of the Post90B dataset (comprising the most recent survey rounds) for disaggregated analysis, we conduct a similar aggregate analysis carried out here using the Post90B dataset. These results are shown in Appendix (Figures A1 and A2) indicate very similar trends.

3.3. Disaggregate Analysis

3.3.1. Gender accommodativeness of an occupation

At a disaggregated level, in order to understand in which occupations are women workforce better accommodated, rather than relying directly on the proportion of women in a particular occupation, we instead compare this with their proportion in a particular education level. Since we are interested in non-routine cognitive occupations (Broad occupation code: 1) with education level above secondary (Codes: 3 and 4), for every disaggregate occupation i within this broad occupational class where workforce have education level e (which here is above secondary), following is the index we use for analysis.

$$A_{i|e}^{w} = \frac{\pi_{ie}^{w}}{\pi_{e}^{w}}$$

Here $A_{i|e}^{w}$ is the accommodative index for women in occupation i given workforce has education level e, π_{e}^{w} is the proportion of women in the workforce with education level e, relative to men, and π_{ie}^{w} is the proportion of women in occupation i with education level e, relative to men. For the purpose of our study, we choose an occupation to be accommodative if $A_{i|e}^{w} \geq 1$ and less-accommodative otherwise.

Accommodative occupations are, therefore, only those occupations that represent women at least in proportion to their representation in the corresponding education level e within the overall workforce.

In the previous section, we stated that non-routine cognitive occupations seemed to accommodate women better. To indicate this below, we compute the accommodative index for non-routine cognitive occupations.

$$\pi_e^w = \frac{0.21\,W}{0.21\,W+0.358\,M} = \frac{1}{1+\frac{0.358}{0.21}(\frac{M}{W})};\ \pi_{ie}^w = \frac{0.092\,W}{0.092\,W+0.098\,M} = \frac{1}{1+\frac{0.098}{0.092}(\frac{M}{W})};$$

$A_{i|e}^w > 1$ because $\pi_{ie}^w > \pi_e^w$. Therefore occupation i, which here is the non-routine cognitive category, is indeed accommodative for women overall.

3.3.2. Occupational network and gender assortativity

The above index allows us to identify which of the non-routine cognitive occupations at a disaggregated level better accommodate the female workforce having a certain education level (here it is above secondary). Since different industrial sectors went through different technology up-gradation trajectories owing to the reforms (Basu & Maertens, 2007), demand for accommodative occupations may likewise be affected depending on which sector or sectors they were predominantly concentrated in before the reforms. Formulating a space of disaggregate occupations distributed across industries and indicating their accommodativeness will allow us to visualize where the accommodative occupations were concentrated before reforms and where they are now. From a gender perspective, such visualization could be insightful to identify and highlight the extent to which accommodative occupations are assorted across industries. We believe adopting a network-based methodology can both facilitate such visualization and help us to measure the intended assortativity before and after the reform period.

Therefore, we define an occupational network that captures the space of occupations as they are distributed across major industrial sectors. Occupations form the nodes in this space, and the distance between two occupations is defined by the similarity of their workforce distribution across the five major industrial sectors we defined before. We use total variation distance to compute the distance between any two distributions, and the closer the distributions are, the stronger is the connection between the corresponding occupations. The following definition clarifies what we mean by strength of the connection between any two occupations.

> **Definition**: Consider occupation i in which proportion of the workforce in an industry k is given by π_i^k and in occupation j it is π_j^k. The proportions sum to one. $\sum_{k=1}^{I} \pi_i^k = 1$. Total variation distance between these two occupations is given by the expression
>
> $$D_{ij} = 0.5\left|\sum_{k=1}^{I}(\pi_i^k - \pi_j^k)\right|$$
>
> I is the total number of industrial sectors (5 in our case). The strength of the connection between the two occupations is given by, $1 - D_{ij}$. That means, when the two occupations are distributed similarly across different industries since the distance between their distributions is close to zero, their strength of the connection is close to one. The strength lies in the interval [0,1].

For visualizing changes in the female workforce across disaggregated occupations and industries, we consider an unweighted network, where the strength of connections is either zero or one. In order to do this, we choose a threshold value for determining an edge/connection in this network. If the strength of the connection between any two occupations is greater than 0.6, only then do we treat this as a connection between the two occupations, otherwise not. Within an occupational network, two occupations are closer implies that the workforce in each of these occupations is distributed similarly across industries. The networks we construct in this study only look at workforce belonging to non-routine cognitive occupations (Aggregate occupation code: 1) and having education level above secondary (Education codes: 3 and 4). Labeling occupations or nodes in such networks with their respective gender accommodativeness allows us to get an understanding of where women are concentrated within the occupational space.

Further, over an occupational network, nominal or categorical assortativity measure proposed by Newman (2003) allows us to measure the extent to which women accommodative occupations are concentrated within this occupational space. According to Newman (2003), assortativity defines the property of a network or graph where nodes with similar attributes have a tendency to be strongly connected than those with dissimilar attributes, or vice versa.

4. FINDINGS

In the following Figure-3, the two columns represent occupational networks before and after the reform period. In the first row of this figure, the node attributes represent the proportion of the women workforce, and in the second row, node attributes represent which of the occupations were accommodative of the female workforce and which were less-accommodative.

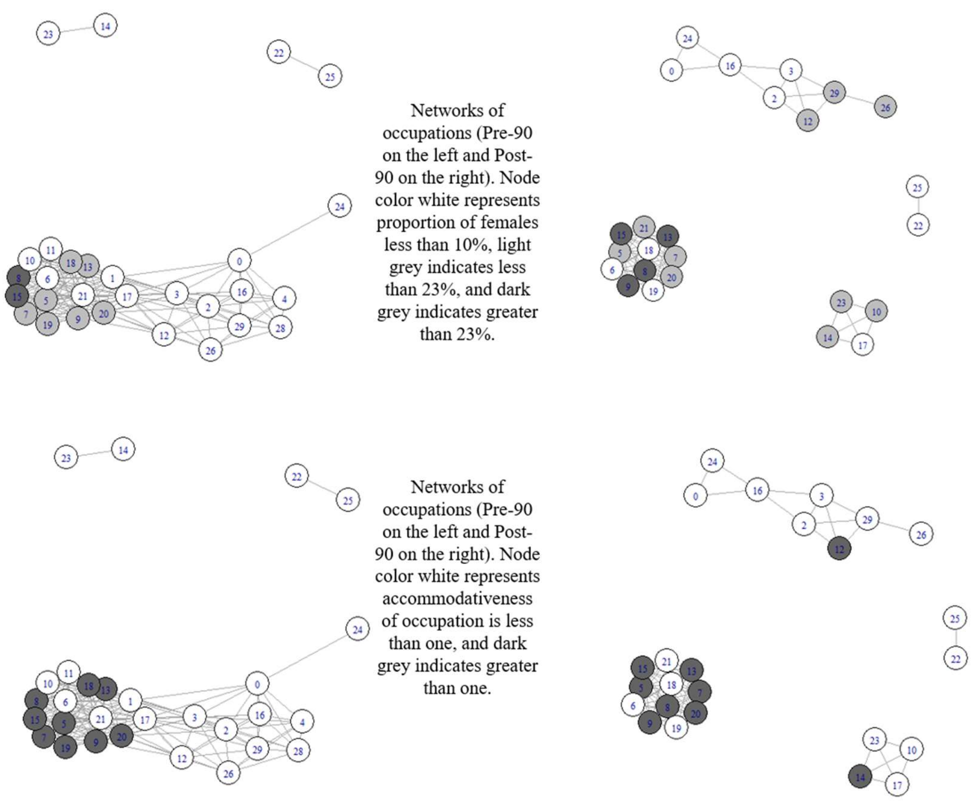


Figure 3: Network Plots

4.1. Moving towards locally clustered occupational space

The above network diagrams (Figure-3) clearly indicate that while a lot of occupations were clustered before the reform period, they have moved into silos/clusters in the post-reform period. On close observation, looking at table-3 below, we find that industry sector 5 (constituted by public services, education, health, arts, entertainment, and social services) is what contributed to the higher strength of the connection between occupations and characterized the dominant clusters both before and after. Within the services sector, this particular sector seemed to have constituted a relatively greater diversity of occupations in the pre-reform period. Post-reform, we see that some occupations have diversified significantly out of sector five into other sectors (occupation code 12, for example).

Following table-3 provides the distribution of each occupation across industries before (columns to the left) and after (columns to the right) the reform period. For a detailed disaggregated list of non-routine cognitive occupation codes see Table-A1 in Appendix. We observe that occupations that are accommodative for women (their index greater than one) both before and after the reform period were concentrated mostly within the cluster determined predominantly by the industrial sector: public services, education, health, arts, entertainment, and social services (Code: 5). The traditionally female accommodative occupations such as Life scientists (5), Physicians and surgeons (7), Nursing and other Medical and Health Technicians (8), Scientific, Medical and Technical Persons, other (9), Social Scientists and Related Workers (13), Teachers (15) remained accommodative post-reform period. Accommodativeness improved post-reform period in occupations 12 (Accountants, Auditors and Related workers) and 14 (Jurists) concentrated in sectors other than five. This observation is also evident from the dispersed clusters within the networks shown in the right-hand side column of Figure-3. However, the professional workers constituted by Architects, Engineers, Technologists and Surveyors (2), Engineering Technicians (3), and managerial workers constituted by Working Proprietors, Directors, Managers and so on (22-26) which are spread across other industrial sectors like manufacturing, trade, logistics and communication, finance, real estate, and so on are still not very accommodative for women.

Table 3: Industry distribution and accommodative Index of Occupations

	1	2	3	4	5	n	Index (Pre)	1	2	3	4	5	n	Index (Post)
0	0.08	0.56	0.04	0.00	0.32	110	0.16	0.00	0.64	0.36	0.00	0.00	15	0.17
1	0.17	0.23	0.00	0.00	0.60	50	0.37	-	-	-	-	-		-
2	**0.02**	**0.50**	**0.04**	**0.04**	**0.41**	**921**	**0.20**	**0.01**	**0.53**	**0.05**	**0.29**	**0.12**	**283**	**0.59**
3	**0.02**	**0.38**	**0.08**	**0.02**	**0.50**	**820**	**0.42**	**0.00**	**0.47**	**0.08**	**0.33**	**0.12**	**218**	**0.56**
4	0.00	0.45	0.29	0.00	0.26	71	0.35	-	-	-	-	-		-
5	**0.05**	**0.04**	**0.00**	**0.04**	**0.88**	**91**	**1.32**	**0.00**	**0.18**	**0.00**	**0.00**	**0.82**	**17**	**1.14**
6	0.17	0.01	0.00	0.00	0.82	43	0.93	0.00	0.00	0.00	0.01	0.99	11	0.61
7	**0.01**	**0.02**	**0.01**	**0.00**	**0.97**	**1101**	**1.28**	**0.00**	**0.00**	**0.01**	**0.00**	**0.98**	**477**	**1.34**
8	**0.01**	**0.02**	**0.00**	**0.00**	**0.96**	**827**	**4.78**	**0.01**	**0.05**	**0.02**	**0.00**	**0.92**	**548**	**3.14**
9	**0.01**	**0.11**	**0.06**	**0.00**	**0.81**	**66**	**1.31**	**0.02**	**0.17**	**0.11**	**0.06**	**0.64**	**27**	**2.53**
10	0.03	0.03	0.00	0.09	0.84	109	0.92	0.01	0.05	0.03	0.85	0.06	115	0.99
11	0.02	0.00	0.00	0.08	0.90	23	0.95	-	-	-	-	-		-
12	**0.01**	**0.19**	**0.12**	**0.23**	**0.46**	**835**	**0.46**	**0.01**	**0.41**	**0.13**	**0.40**	**0.05**	**172**	**1.04**
13	**0.00**	**0.10**	**0.02**	**0.02**	**0.86**	**175**	**1.86**	**0.01**	**0.02**	**0.00**	**0.14**	**0.83**	**77**	**2.32**
14	**0.00**	**0.00**	**0.01**	**0.78**	**0.21**	**522**	**0.41**	**0.00**	**0.02**	**0.00**	**0.86**	**0.11**	**179**	**1.42**
15	**0.00**	**0.00**	**0.00**	**0.00**	**0.99**	**7978**	**3.43**	**0.00**	**0.00**	**0.00**	**0.00**	**1.00**	**5018**	**3.05**
16	0.00	0.40	0.03	0.25	0.32	85	0.91	0.00	0.68	0.00	0.07	0.25	35	0.48
17	0.01	0.30	0.02	0.03	0.64	121	0.34	0.01	0.07	0.01	0.74	0.17	136	0.44
18	0.00	0.03	0.05	0.03	0.88	50	2.49	0.00	0.03	0.00	0.02	0.96	43	0.53
19	0.00	0.02	0.00	0.01	0.97	228	1.60	0.00	0.02	0.00	0.06	0.92	176	0.45
20	0.00	0.14	0.05	0.02	0.78	35	1.64	0.00	0.00	0.05	0.00	0.95	20	1.17
21	0.01	0.05	0.05	0.05	0.83	737	0.52	0.00	0.10	0.14	0.11	0.65	63	0.69
22	**0.00**	**0.15**	**0.79**	**0.01**	**0.05**	**641**	**0.31**	**0.01**	**0.02**	**0.95**	**0.02**	**0.00**	**751**	**0.39**
23	**0.00**	**0.01**	**0.00**	**0.95**	**0.05**	**358**	**0.34**	**0.00**	**0.00**	**0.04**	**0.96**	**0.00**	**58**	**0.77**
24	**0.01**	**0.92**	**0.03**	**0.01**	**0.04**	**1727**	**0.35**	**0.01**	**0.96**	**0.02**	**0.01**	**0.00**	**1011**	**0.51**
25	**0.00**	**0.07**	**0.83**	**0.03**	**0.07**	**321**	**0.12**	**0.00**	**0.01**	**0.94**	**0.04**	**0.00**	**493**	**0.14**

26	**0.03**	**0.14**	**0.32**	**0.10**	**0.41**	**407**	**0.74**	**0.00**	**0.05**	**0.38**	**0.30**	**0.27**	**679**	**0.69**
28	0.00	0.41	0.32	0.00	0.27	20	0.22	-	-	-	-	-		-
29	0.00	0.43	0.12	0.15	0.29	228	0.73	0.01	0.27	0.23	0.38	0.10	138	0.97

4.2. Assortativity trends

For workforce before reform period in Pre90 survey rounds and workforce after reform period in Post90A survey rounds, we plot assortativity trends by considering 15-year population cohorts. In Figure-4 shown below, each 'year' value within X-axis is read as a population cohort born in the range (year-15, year). For example, if the year equals 1970, then it indicates that the cohort for which occupational network assortativity/density has been measured is born between (1955,1970). In both the plots, we can see a break between 1970 to 1985. This is because, workforce before the reform period needs to have born before 1970, and therefore we consider cohorts between (1945,1960) and (1955,1970) from the Pre90 surveys. Similarly, the workforce after the reform period needs to have born after 1970; we consider cohorts between (1970,1985) and (1980, 1995) from Post90A surveys. From the left plot in Figure-4, it is evident that assortativity seems to have decreased for the recent population cohorts who entered the workforce after the reform period. This is a promising trend. Since the occupational space is determined by industries, this approximately indicates that female-accommodative occupations are getting less concentrated in particular industries and are being found in several industries. This trend is also evident from Figure-3. However, from the right plot in Figure-4, we also see a downward slope for graph density, indicating that the occupational space is getting more locally clustered. This is also observable from the increase in the number of isolated occupational clusters post-reform period within the occupational space from Figure-3. Looking at the distribution of occupations across industries in Table-3, we observe that several occupations (e.g., 2,3,12,14,22,23,24,25,26) have moved out of the one dominant cluster of the pre-reform period determined by sector five. Gender-accommodativeness in several occupations has increased post-reform period, but the dominance of sector five in holding a significant number of female-accommodative occupations still continues.

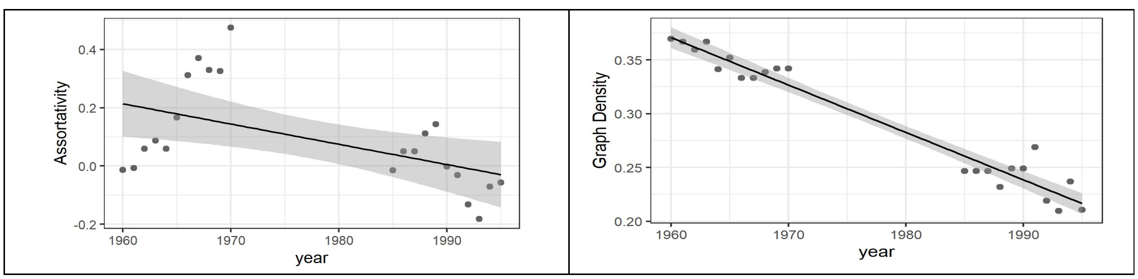


Figure 4: Gender Assortativity

5. CONCLUSION

Our findings reflect that there is a conspicuous movement of the workforce after the 1990s in India towards higher education levels and non-routine cognitive occupations across all the sectors, but to a very less extent in the agriculture sector. While the gap in the overall representation of men and women in the workforce has remained more or less stagnant post-reform period, there is a significant movement of both male and female workforce towards non-routine cognitive occupations – managers, professionals, technicians, and others. The female workforce is still at a relative disadvantage compared to men in terms of their representation in higher levels of education. Nevertheless, in the aggregate, non-routine cognitive occupations are seen to represent women almost equitably relative to men. At a disaggregated level, we observe that a lot of non-routine cognitive occupations are slowly moving out of an occupational cluster dominantly defined by one industrial sector (made up of public services, education, health, arts, entertainment, and social services). Accommodativeness of occupations seems to have increased in some occupations situated even in other industrial sectors. But, the dominance of this one industrial sector in holding a majority of female-accommodative occupations continues even post-reform period. This empirical observation indicates that, although liberalization reforms increased the demand for non-routine cognitive occupations across industrial sectors, they were less successful in bridging the gender gap in these occupations within most of these sectors. Therefore we believe that it is necessary to tackle gender representation in occupations not just through functional policies that apply in general to the workforce across industries but also tackle gender representation at the sectoral level through selective industry-specific female-friendly policies.

Acknowledgement

We would like to thank the audience of public policy brown bag series at IIMB, for their valuable inputs during our presentation in one such talk. All these inputs helped us better contextualize our findings emergent from this exploratory secondary-data-based study.

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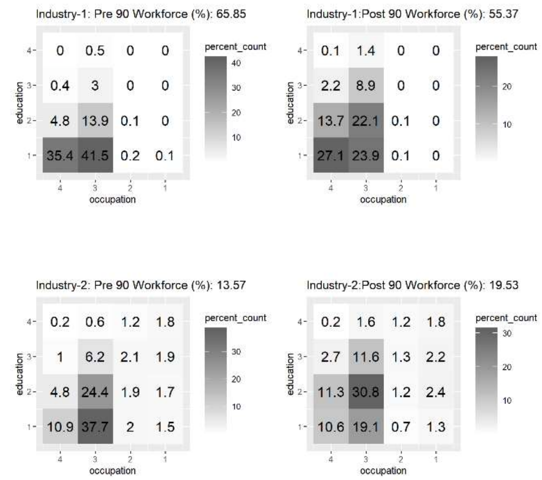
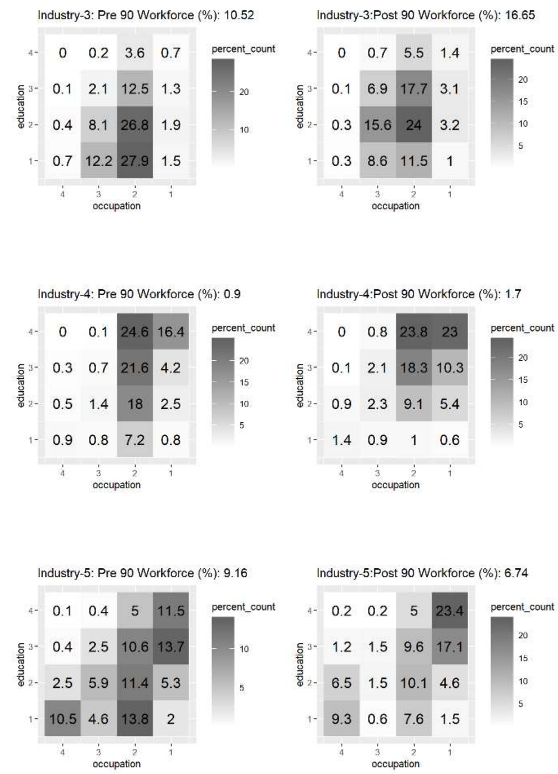
APPENDIX

Table A1: Disaggregate occupations within broad category-1

Occupation Name	NCO-1968 2 Digit Codes
Physical Scientists	0
Physical Science Technicians	1
Architects, Engineers, Technologists and Surveyors	2
Engineering Technicians	3
Aircraft and Ships Officers	4
Life Scientists	5
Life Science Technicians	6
Physicians and Surgeons (Allopathic Dental and Veterinary Surgeons)	7
Nursing and other Medical and Health Technicians	8
Scientific, Medical and Technical Persons, Other	9
Mathematicians, Statisticians and Related Workers	10
Economists and Related Workers	11
Accountants, Auditors and Related Workers	12
Social Scientists and Related Workers	13
Jurists	14
Teachers	15
Poets, Authors, Journalists and Related Workers	16
Sculptors, Painters, Photographers and Related Creative Artists	17
Composers and Performing Artists	18
Professional Workers, not elsewhere classified	19
Elected and Legislative Officials	20
Administrative and Executive Officials Government and Local Bodies	21
Working Proprietors, Directors and Managers, Wholesale and Retail Trade	22
Directors and Managers, Financial Institutions	23
Working Proprietors, Directors and Managers Mining, Construction, Manufacturing and Related Concerns	24
Working Proprietors, Directors, Managers and Related Executives, Transport, Storage and Communication	25
Working Proprietors, Directors and Managers, Other Service	26
Administrative, Executive and Managerial Workers, not elsewhere classified	29





Index for industry sectors: (1) Agriculture, forestry, fishing, mining, and quarrying, (2) Manufacturing, construction, and electricity, gas, and water supply, (3) Trade, hotel, transport, and communication services, (4) Financing, insurance, real estate, and business services, (5) Public administration, education, health and other services
Index for aggregate occupation categories: (1) Managers, senior officials, legislators, professionals, technicians and associate professionals (non-routine, cognitive), (2) Clerks, service workers and shop and market sales workers (routine cognitive), (3) Skilled agriculture and fishery workers, craft and related workers (non-routine manual), (4) Plant and machine operators and assemblers, and elementary occupations (routine manual)
Index for aggregate education levels: (1) Below primary education, (2) Above primary and below secondary education, (3) Above secondary and below graduate, and (4) Above graduate

Figure A1: Workforce changes before and after the 1990s (using Post90A dataset)

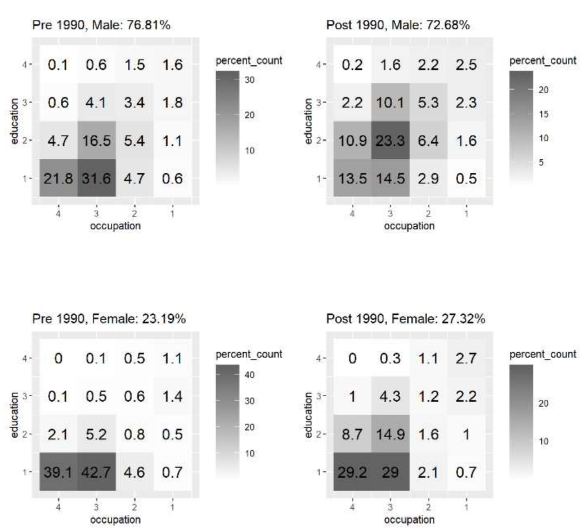


Figure A2: Changes in workforce before and after the 1990s by gender (using Post90A dataset)