Skill Mismatch and Returns to Education in Manufacturing: A case of India's Textile and Clothing Industry

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Abstract

Today, as India treads the path of becoming a knowledge economy, we face a paradox of intensifying skill shortages coupled with unemployment or underemployment among highly educated workers. While a shortage of skills (or under-education) is definitely a cause of concern, surplus education (or over-education) can also lead to underutilization of skills and further lower demand for low skill workers. Given this scenario, the paper attempts to measure the incidence and extent of skill/education mismatch and analyse the economic returns/cost to over/under education in one of India's largest labour intensive industries: Textiles and Clothing. The study is based on the 68th round of NSS Employment and Unemployment Survey estimates. Using the over-education/required education/under-education (ORU) models on a cross section dataset of individuals employed (as a regular salaried/ wage employee or as casual wage labour) in India's T&C industry, we find that the overall educational mismatch ratio during 2011-12 was to the tune of 67.61%. Further, results indicate that while returns to surplus education is positive, it is less in magnitude as compared to returns to required education, suggesting underutilization of excess education. There's also a significant wage penalty associated with each deficit year of education.

Keywords: Skill mismatch; textiles, clothing; over-education; required education; under-education

JEL : J20, J24, P36, M53

1. Introduction

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Over the past few years, most developing countries, including India, have been experiencing three major developments, viz. globalisation, technological advancement and competition. In India, globalisation, which was largely a result of economic reforms that took place in the early 1990s, has raised concerns about its impact on factors of production, particularly labour. Being a young nation, with around 62 per cent of its population in the working age group (15-59 years) and more than 54 per cent of the total population below 25 years of age, India has a great potential to climb up the growth ladder. As it stands today at the threshold of becoming one of the world's fastest growing economies, a large and young labour pool, in fact, serves as a double-edged sword. While the demographic dividend that the nation possesses, is definitely an opportunity, it also reflects the inability of the government to employ the upcoming generation of young workers. Lack of adequate skills and education levels combined with a huge dearth of jobs act as an impediment in India's growth path.

According to a World Bank study, more than 12 million youths between 15 and 29 years of age are expected to enter the labour force every year for the next two decades. The key to reaping this demographic dividend lies in using the working age population to its full potential and thereby enhancing production to the maximum possible. However, there are serious concerns over their employability due to inadequate education/training and market-ready skills. This skill gap in the labour market creates huge unemployment while at the same time employers do not get workers with requisite skill.

Following the economic reforms of 1990s, it was expected that a greater openness would increase the pace of job creation and improve employment conditions. Since India's comparative advantage has historically lied in unskilled labour intensive industries, it seemed likely that better technology as a result of greater openness would allow these industries to yield higher benefits and create gainful employment. Unfortunately, the country's manufacturing sector has failed to create enough jobs to employ its fast rising labour force. As per the estimates of the various rounds of National Sample Survey, between 1993-94 and 2011-12, employment in India's manufacturing sector grew by merely 2.55 per cent. Further, as Chowdhury (2014) reports, within manufacturing sector, labour intensive industries are found to have lower labour efficiency (calculated as a ratio of total revenue to total number of workers employed) as compared to capital intensive industries. This points towards sector's inability to create gainful employment. She also estimates that the employment elasticities in the manufacturing sector has changed from positive (0.76) to negative (-0.31) between 2000 and 2010, with a more pronounced decline in case of labour intensive industries, which, among other things, indicates ‘absence of skilled manpower’ inducing substitution of labour.

Besides skill shortage, there are growing concerns that higher education is not equipping students with skills and competencies required in the global knowledge economy. As a result we face a paradox of intensifying skill shortages coupled with unemployment or underemployment among highly educated workers. According to the 68th round of National Sample Survey on Employment and Unemployment Situation in India estimates, around 68 per cent of graduates and 53 per cent post graduates from general education background and almost 45 per cent of graduate or post graduates and 51 per cent of graduate or post-graduate diploma holders with technical education were unemployed during 2011-12 (Sengupta, 2017). This clearly indicates that there exists a severe skill mismatch in the Indian labour market today. While a shortage of skills (or under-education) is definitely a cause of concern, surplus education (or over-education) can also lead to underutilization of skills and further lower demand for low skill workers.

While a persistent skill mismatch can have an adverse impact on most industries, it becomes more pronounced in case of a labour-intensive industry like textiles and clothing, which is one of the largest sectors, not only in terms of size, but also in terms of providing employment. Being the second largest employer after agriculture, it provides direct employment to around 45 million people. Various schemes have been implemented in recent times by the Indian government to cater to the skilled manpower needs of various segments of the textiles industry. Apart from the ones introduced under the ‘Skill India’ mission, the Integrated Skill Development Scheme (ISDS) for textiles was initiated, particularly for this sector, for which the government allocated INR 1900 crore, aiming to train over 15 lakh people up to 2017, covering all sub-sectors. The public dashboard for the ISDS, which has recently been introduced by the Ministry of textiles, and which displays live training, assessment and placement status, indicates that till date, about 11.14 Lakh people have been trained, out of which 6.84 Lakh have managed to get placed, which means that more than 30% of people even after completing training remain unplaced. Moreover, the kind of jobs (in terms of quality as well as in terms of level of skills/education required) offered as placement through the scheme remains unknown.

Since there is no guarantee that the right candidate will be matched with the right job, the surplus skilling or education could result in inefficient allocation of resources and wastage of social resource in the form of mis-targeted subsidy or irrational investment in decision making (Mukhejee and Paul, 2012). In fact, skill mismatch can have dire consequences on economic efficiency, growth and competitiveness. While under education can create a significant welfare loss due to misuse of human resources, workers with over education, on the other hand, could incur financial losses, in terms of high opportunity costs. This substantially reduces job satisfaction and efficiency and increases turnover rates for overqualified workers.

Even though there is a vast literature on matching and skill misallocation in case of developed countries, there is a huge dearth of such studies in case of India, particularly at sectoral level. Against this backdrop, the current study attempts to measure the extent of skill/education mismatch in India’s textile and clothing industry and analyse the economic returns/cost to over/under education. In the section that follows, we provide a brief review of literature related to measuring skill mismatch and analysing the effects of educational mismatch on returns to education. In section 3, we describe the data sources, summary statistics and the methodology followed. In section 4, we estimate firstly, the extent of skill mismatch existing in the sector, followed by the calculation of returns/cost to over/under education. The paper ends with some concluding remarks and discussion presented in section 5.

2. Review of Literature

The term “Skills”, as defined by Acemoglu and Autor (2011) is nothing but a worker’s endowment of capabilities for performing various tasks, ‘task’ being understood as a unit of work activity that produces output. Mismatch of skills, then, would occur, when the level of skills possessed by an individual is different from the level of skills required for the job.

OECD (2014) explains two kinds of skill mismatches in the labour market: (a) Qualification mismatch that occurs, when the level of qualification of the worker is different than that required by the job; and (b) Field of study mismatch, when the field of education of individual is different than the economic sector of her job. An alternate approach is proposed by Sloane (2014) who divides mismatches into two groups (a) Horizontal and (b) Vertical. While Horizontal mismatch is explained as being similar to the Field of Study mismatch as per OECD classification, Vertical mismatch is further subdivided into the following three categories by Sloane: (i) Over/under education; (ii) Over/under qualification; (iii) Over/under skilling. While skill mismatch is a more complex phenomenon than education mismatch as highlighted by Quintini (2011), in this paper, we consider the two to be interchangeable[†]

So, the literature broadly classifies problem of job/skill mismatch into two broad categories: Firstly, when the education/skill level possessed by the worker is not up to the requirements of the job, known as under-education; and secondly, where, the education/skill level possessed by the worker exceeds those required by the job, known as over-education.

There is a vast literature analysing the causes and consequences of skill mismatch. Duncan and Hoffman (1981) were among the firsts to examine the effects of educational mismatch on wages. They used Panel Study of Income Dynamics data to find that 40 percent of US workforce and about 50 percent of black males have more education than what their job requires. They also find that the resources spent on education are not really deadweight loss, as the individual return to an year of surplus education is positive and significant. Return to surplus education is however, less than the return to required education. Their finding was reinforced by a number of subsequent studies, including Rumberger (1987), Verdugo and Verdugo (1989), Tsang et al. (1991), Sicherman (1991), Cohn and Khan (1995) and Groot (1996). Hersch (1991), using primary data collected in Oregon, 1986, found that overqualified workers are less satisfied with their jobs and therefore, are more likely to quit. Mukherjee and Paul (2012), using national level employment survey data, analyse the extent of skill misallocation in the Indian labour market. They find that the incidence of over education is significantly high and varies across occupations. While the returns to over-education are found to be positive and significant though lower than the returns to adequate education level, the returns to under-education are found to be negative and significant. Orbay and Aydede (2015) carry out a similar exercise in case of Turkish labour markets. Using household surveys between 2009 and 2012, they firstly estimate the levels of educational mismatch for different occupations in different regions, and then analyse the effects of educational mismatch on wages in Turkish labour market. They find the cost of under-utilization and productivity loss due to educational mismatch to be substantial in Turkey. Among the major occupations, wage effects are found to be highest for office clerks.

A crucial discussion however, in this entire string of literature is on how to determine the required level of education for each occupation. Leuven and Oosterbeek (2011) list three main approaches to measuring education mismatch: 1. *Job titles (JT) method*: where the

[†] This assumption is due to lack of quantifiable data on skills of workers

requirements for a specific occupation are identified by sectoral experts. 2. *Workers self-assessment (WSA) method:* where the job requirements are of the opinion of a worker. 3. *Realised matches (RM) method*: where the match is understood as a difference of the individual's level of education and the mean or mode level of education among the workers in the same occupation (Chlon-Dominczak and Zurawski, 2017). Each of these methods has both merits as well as demerits. As per Quintini (2011), the major disadvantage of using the JT and the RM method is that they are based on the interpretation of the occupation titles and these titles vary significantly among different companies. Having said this, as Storen and Wiers-Jenssen (2010) point out, the WSA method is also not free from deficiencies. Since WSA is a subjective measure, employees may be extremely optimistic about their own assessment of skills as well as about the skills required at their workplace. Consequently, the measure of skill mismatch estimated using this method might suffer from a bias arising due to an inappropriate perception of skill levels and requirements. While the JT approach seems to be the most appropriate, as it is less prone to biasedness arising due to misreporting, it is costly to implement. Measurement of mismatch using RM method, though free from misreporting problem is unable to uncover the technological requirements of a job. Therefore, measurement is partly influenced by actual allocation of skill resulting from hiring and matching process and labour market conditions (Mukherjee and Paul, 2012). Nonetheless, for the scope of our analysis, we follow the RM method. The choice of approach is largely influenced by data availability.

Based on several studies conducted in the past, it seems evident that the findings are independent of the method being used to estimate required level of schooling. Hartog (2000), after comparing the results of a wide range of studies which were conducted using one of these methods, concluded that effects of over/under education on earnings do not depend on the type of measurement of required education being used. Chiswick and Miller (2010) compared RM and WSA methods and showed that general findings are independent from types of measurement. There are other studies that have directly compared these measurement approaches. While Santos (1995) compared the RM and the JT approach using data from Portugal, Rumberger (1987) compared WSA and JT methods for US data and obtained similar findings, irrespective of the method being used.

Verdugo and Verdugo (1989), using the RM method, estimate the mean years of schooling for each occupation and consider workers as over or under educated if their completed years of schooling deviate at least one standard deviation from the mean. Kiker et al. (1997), on the other hand, use mode of the completed schooling years instead of mean and examine deviations of workers' actual years of schooling from mode, rather than from a random choice such as one standard deviation.

Empirical findings in this type of literature on the economic effects of educational mismatch on wages are in general consensus. While returns to under-education are negative and significant, returns to over-education are positive but lower than the returns for required education (See Hartog and Osterbeek, 1988 in case of Netherlands, Groot, 1996 in case of UK, Kiker et al., 1997 in case of Portugal, Di Pietro and Urwin, 2006 in case of Italy, Budria and Moro-Egido, 2008 for the Spanish case, Tsai, 2010 in case of US, Ren and Miller, 2012 in case of China, Orbay and Aydede, 2015 in case of Turkey).

Majority of studies discussed above have measured the extent of overall educational mismatch in the context of developed world. This is the first study of its kind, to the best of our knowledge that measures the extent of educational mismatch and the returns to over/under education at sectoral level in case of India.

3. Data and Methodology

Data on employment has been obtained from the various rounds of Employment and Unemployment Survey conducted by National Sample Survey Organisation. NSSO carries out nation-wide quinquennial household enquiry to collect information on various characteristics pertaining to employment and unemployment across Indian states. It uses the stratified multi-stage sampling method and therefore, all units are assigned with adjusted sampling weights. We report all results in our analysis using appropriate sample weights. Out of the total people surveyed, we consider only the ones who are employed in the textile and clothing industry (NIC: 13 and 14) as per Usual Principal Activity Status. Further, since our focus is to measure the mismatch in skills/education, we drop all self-employed individuals.

Our sample consists of all regular and casual salaried/ wage employees working in the textile and clothing industry of India. NSS does not collect information on years of schooling, rather it collects information about worker's level of education. We match each education level to corresponding years based on Indian education system, as shown in table A-1. Table A-2 presents the descriptive statistics.

Using this information, we estimate distribution of workers across years of schooling for the top five sub-sectors (in terms of employment) within India's textiles and wearing apparel industries respectively, as shown in Table 1. Comparing textile with wearing apparels, we find a clear disparity in the proportion of workers with no formal schooling. While the highest proportion of workers with no formal schooling in Manufacture of Textiles is as high as 36.7% in the sub-sector: *Zari work and other ornamental trimmings,* its counterpart in case of Manufacture of Wearing Apparel is estimated to be merely 18.69% in the subsector: *Manufacture of all types of textile garments and clothing accessories*. On the other hand, while the highest proportion of workers with more than school level education (>14 years) in Manufacture of Textiles is merely 9.29% in the sub-sector *Finishing of cotton and blended cotton textiles*, the proportion was much higher in case of *Manufacture of knitted or crocheted wearing apparel and other made-up articles directly into shape* (which comes under Manufacture of Wearing Apparel) to the tune of 31.5%. Clearly, there is a strong disparity in the educational distribution of workers employed in India's textiles sector vis-à-vis the wearing apparel sector. While the former typically seem to employ a majority of workers with preliminary level of general education, the latter seems to have a relatively higher educated workforce.

Table 1: Sub-sector wise distribution of workers across years of schooling

Sub-sectors and years of schooling	0	3	5	8	11	13	15	17	19
Manufacture of Textiles (NIC:13)									
Weaving, manufacture of cotton and cotton mixture fabrics	21.93	14.26	18.92	19.05	10.92	7.26	0.44	7.05	0.18
Embroidery work and making of laces and fringes	14.57	8.37	18.26	31.24	19.42	7.64	0.00	0.38	0.12
Preparation and spinning of cotton fiber including blended cotton*	6.61	19.80	15.94	23.82	18.25	9.74	2.30	2.92	0.61
Zari work and other ornamental trimmings	36.70	10.87	27.86	22.52	1.06	1.00	0.00	0.00	0.00
Finishing of cotton and blended cotton textiles	17.25	14.25	15.82	26.92	11.67	4.81	0.13	4.32	4.84
Manufacture of Wearing Apparel (NIC:14)									
Custom Tailoring	17.88	12.47	26.07	23.21	10.61	5.13	3.17	1.47	0.00
Manufacture of all types of textile garments and clothing accessories	18.69	14.59	18.14	15.73	18.07	7.08	1.43	5.60	0.67
Manufacture of wearing apparel n.e.c.	3.67	33.93	20.24	14.99	6.10	2.05	0.00	17.58	1.44
Manufacture of other knitted and crocheted apparel including hosiery	10.95	10.98	9.95	8.41	12.53	37.74	0.00	8.29	1.16
Manufacture of knitted or crocheted wearing apparel and other made-up articles directly into shape	0.00	8.56	11.24	20.61	27.28	0.83	0.00	22.18	9.31

Source: Author's computation based on NSS 68th round survey

4. Estimation Results

4.1 Incidence of Educational Mismatch

We use firstly the RM method in order to estimate the level of required education and the extents of over-education (OE) and under-education (UE) for each worker in India's textile and clothing industry. As discussed above, the RM method identifies the required level of education by the average values of years in schooling for each skill group. Despite several shortcomings, as already mentioned, RM method is justified based on the argument that the labour markets can reveal only objective criteria about the "required" level of education by skill levels.

The literature usually identifies skill groups based on occupation categories. NSS follows the National Classification of Occupation (NCO) categorisation to classify workers into different occupations. The 68th round of NSS used for the present study follows the NCO-2004 categorisation to classify workers. While the information on occupation is collected by NSS at 3-digit level, we use a broader level of classification by aggregating the three digit codes to one-digit. As a result, we are left with 9 different levels of NCO-2004, 1 digit occupations. In order to introduce a more detailed classification that identifies the required education for each worker, we created a new set of skill categories by extending 9 NCO-2004 occupation categories for each subsector within India's T&C industry, which is given by 57 (NIC-2008) different product categories. Thus, our industry-occupation classification has 513 different skill categories.

NSS provides information about workers' education under two categories: General and Technical. For the purpose of our study we restrict ourselves to general education level. There are 13 general education categories in total, in increasing order of years of schooling. Since NSS does not collect data on years of schooling, we match each education level to corresponding years based on Indian education system (see table A-1).

The required education in the RM method reflects the "usual" or "reference" education of each skill group (Orbay and Aydede, 2015). In the literature, this "reference" education is estimated based on the modal years of schooling (Kiker et al., 1997) and on average years of schooling (Verdugo and Verdugo, 1989) for each industry-occupation classification. Table 2 reports the incidence of educational mismatch calculated using modal values.

The first notable finding that emerges out of table 2 is that educational mismatch ratio in India's T&C industry is around 67.61%. This value is much above the overall educational mismatch ratio in much of the developed world. The ratio in Europe is estimated by Galasi (2008) to be just 33%, whereas Orbay and Aydede (2015) estimate the same in Turkey to be around 54%. The findings also suggest that around 26% of people are employed in jobs requiring no formal general education, 88% are in jobs requiring up to eight years of education, whereas just around 4% of people are employed in jobs requiring graduate or above education level. Further, among the people employed in jobs requiring no formal education, 68% are over educated, whereas among the people employed in jobs requiring graduate or above education, merely 19% are under educated. This implies that the education mismatch in this industry is mainly prevalent in jobs requiring lower education qualification. This finding does not seem obscure since the jobs requiring higher education level usually demands greater level of skills as well as responsibility, and therefore may not be fulfilled by people with lower skill set.

Table 2: Incidence of educational mismatch by modal values in India's T&C industry

Attained and required years of education	0	3	5	8	11	13	15	17	19	Total
0	4,23,874	11,845	78,989	3,93,412	22,985	698	-	-	-	**9,31,803**
3	2,02,763	54,228	56,778	4,18,865	13,742	2,430	-	3,197	-	**7,52,003**
5	2,34,587	22,727	1,79,073	4,74,180	25,856		-	7,261	-	**9,43,684**
8	2,70,215	11,448	1,16,025	6,06,960	27,374	7,070	-	8,560	-	**1047652**
11	96,140	1,192	68,312	4,12,395	1,19,988	3,477	-	8,290	-	**7,09,794**
13	82,070	-	28,629	1,56,664	21,646	86,038	-	2,554	-	**3,77,601**
15	3,394	2,196	16,577	43,061	2,520	-	50,444	10,548	-	**1,28,740**
17	36,715	2,093	20,076	58,837	3,279	-	-	1,32,370	-	**2,53,370**
19	2,886	2,196	-	3,127	12,170	-	-	6,549	32,591	**59,519**
Total	**1352644**	**1,07,925**	**5,64,459**	**2567501**	**2,49,560**	**99,713**	**50,444**	**1,79,329**	**32,591**	**5204166**
					% Distribution					
0	31.34	10.98	13.99	15.32	9.21	0.70	0.00	0.00	0.00	17.90
3	14.99	50.25	10.06	16.31	5.51	2.44	0.00	1.78	0.00	14.45
5	17.34	21.06	31.72	18.47	10.36	0.00	0.00	4.05	0.00	18.13
8	19.98	10.61	20.56	23.64	10.97	7.09	0.00	4.77	0.00	20.13
11	7.11	1.10	12.10	16.06	48.08	3.49	0.00	4.62	0.00	13.64
13	6.07	0.00	5.07	6.10	8.67	86.29	0.00	1.42	0.00	7.26
15	0.25	2.03	2.94	1.68	1.01	0.00	100.00	5.88	0.00	2.47
17	2.71	1.94	3.56	2.29	1.31	0.00	0.00	73.81	0.00	4.87
19	0.21	2.03	0.00	0.12	4.88	0.00	0.00	3.65	100.00	1.14
Total	25.99	2.07	10.85	49.34	4.80	1.92	0.97	3.45	0.63	100.00

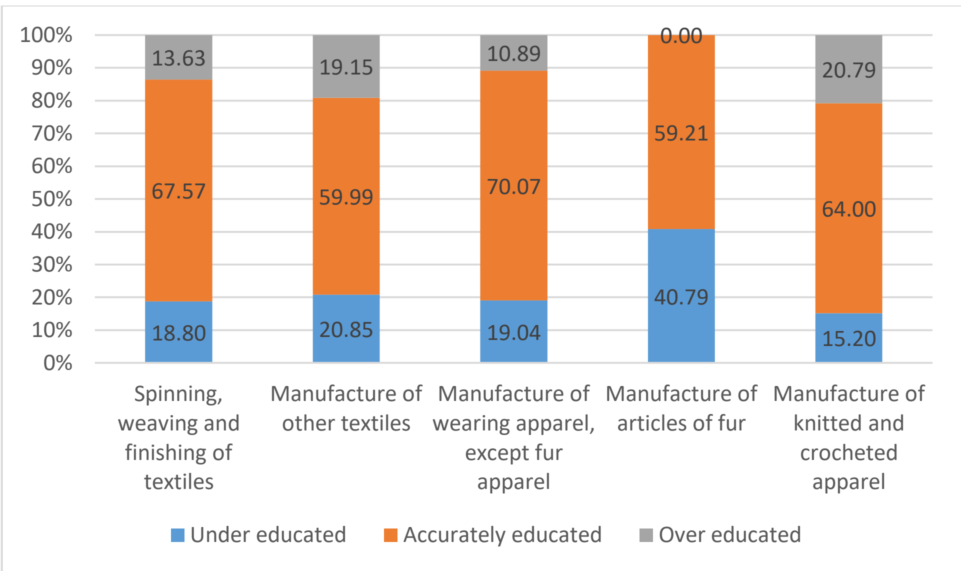
Notes: Underlined numbers reflect educational match

Source: Author's computation based on NSS 68th round survey

Interestingly, we find that close to 82% of people with secondary education, 76.5% people with higher secondary education, 47.8% graduates, whereas 45.2% postgraduates are employed in jobs requiring lower education level. On the other hand, around 54.5% people with no formal education, close to 66% with below primary education and 53.7% with primary education are found to be employed in jobs requiring higher education level.

Alternatively, when the "reference" education level is calculated by mean values, the distribution of educational mismatch across industries and occupations cannot include matched education. Verdugo and Verdugo (1989) classifies an individual as being "adequately educated" if the education level of the individual is within one standard deviation of the mean education levels of all workers in that industry-occupation combination. If the education level of the individual is more than one standard deviation of mean, he/she is classified as being "over-educated", whereas, in case it is less than one standard deviation of mean, he/she is classified as being "under-educated". We classify individuals in these categories for all the 9 one-digit level NCO2004 occupation categories separately. To do so, we firstly estimate means of education levels of all individuals in our sample by their occupation categories. Now, for each of these categories, we estimate 'one-standard deviation of mean' band, which becomes the benchmark level of education. Then, the sample is divided into three groups: over-educated, under-educated and adequately educated using the above definition. Figure 1 shows the incidence of education mismatch across all NIC-2008 three-digit subsectors lying within India's T&C industry, using one standard deviation around mean as the benchmark or "required education" (Verdugo and Verdugo, 1989).

Figure 1: Incidence of educational mismatch by mean values in India's T&C industry



Source: Author's computation based on NSS 68th round survey

As figure 1 shows, highest matched education level appears to be in the subsector: *Manufacture of Wearing Apparel except fur apparel,* where, as high as 70% of people are found to be employed in the job requiring exactly the level of education possessed by them. Further, as the figure shows, the subsector: *Manufacture of articles of fur* consists of the highest proportion of undereducated workers (40.79%), whereas the subsector: *Manufacture of knitted and crocheted apparel* consists of the highest proportion of over educated workers (20.79%).

4.2 Wage effect of Educational Mismatch

In the literature, wage effects of educational mismatch has typically been examined using two models: The first model, pioneered by Duncan and Hoffman (1981), decomposes the actual years of education (AE) into required years of schooling (RE), years of over-education (OE) and years of under-education (UE). Therefore, we can define AE as:

$$AE = RE + OE - UE \tag{1}$$

Where, OE = AE-RE, if AE>RE and 0, otherwise

UE = RE-AE, if AE<RE and 0, otherwise

Therefore, at any time, at least one of OE or UE must be 0. Given this, we employ the usual human capital earning function (or the Mincer equation), where the returns to education depend on the productivity of an individual that is fully embodied.

According to the Mincerian wage equation, wage is determined by:

$$lnW_i = \alpha AE_i + X_i\beta + \varepsilon \tag{2}$$

Where, W_i denotes the hourly wage of worker i, AE_i denotes the actual education attained by individual i and X_i is a vector of all other covariates capturing individual and demographic characteristics, such as gender, age, age square, marital status, regional and year fixed effects and so on. However, this wage determination does not capture the possibility of matching. If productivity is also determined by matching of workers and the jobs, we get a modified version of (2), given by:

$$lnW_i = \alpha_0 + \alpha_1 RE_i + \alpha_2 OE_i + \alpha_3 UE_i + X_i\beta + \varepsilon \quad (3)$$

Where RE_i, OE_i and UE_i denote respectively the years of required education, over education and under education by individual i. Years of required education is defined as the mean education level of workers within 36 skill categories (each of the 9 different one-digit NCO-2004 occupation categories under all the 4 three-digit NIC-2008 product classifications). Using the estimated values of the variable RE as well as of the actual number of years of schooling of workers, values for OE and UE can easily be calculated using (1). The coefficient of RE (α_1) reveals the percentage change in daily wage as a result of an additional year of education required by the sub-sector/occupation. If we assume that productivity is fully embodied and standard human capital theory applies, $\alpha_1 = \alpha_2 = \alpha_3$, which means that the returns to over-education or under-education would be equal to returns to required education. On the other hand, in case productivity is uniquely determined by the job profile, and years of over/under-education do not influence wages, then, $\alpha_2 = \alpha_3 = 0$. In both these cases, we can say that skill-mismatch plays no role in influencing workers' wage. This is clearly a special case. In reality, we do expect workers' wage to depend on the years of over- and under-education, and therefore, we would expect $\alpha_1 \neq \alpha_2 \neq \alpha_3$.

Intuitively, a person working in a job requiring 5 years of schooling shall be earning more than a person working in a job requiring 3 years of schooling. Therefore, we would expect α_1 to be positive. Since α_2 indicates the returns to surplus education, it is also expected to bear a positive sign but less in magnitude, compared to α_1, in order to account for under-utilization of excess education, where the difference between the two coefficients indicate the degree of this under-utilization. α_3, on the other hand, measures the magnitude of wage penalty owing to deficit in education and therefore, is expected to bear a negative sign.

Another model, which is put forward by Verdugo and Verdugo (1989) is used. As discussed above, an individual is classified as "adequately educated" in their model, if his/her education level lies within one standard deviation of the mean education levels of all workers in that industry-occupation combination. They use two binary variables (OED and UED) to identify whether a worker is over-educated or under-educated. The variables OED and UED take value 1 if the worker is over-educated or under-educated respectively and 0, if the individual is correctly matched. Based on this specification, our earning equation can be modified as follows:

$$lnW_i = \beta_0 + \beta_1 AE_i + \beta_2 OED_i + \beta_3 UED_i + X_i\beta + \varepsilon \quad (4)$$

While specification (4) also reveals the wage effects of educational mismatch, unlike the DH model, it is conditional on the level of actual education, rather than required education. Therefore, while we continue to expect β_1 to bear a positive sign (since each additional year of education is expected to increase the daily wage of worker), β_2 should be negative, and $\beta_3$should now be positive, in order to account for underutilization of excess education. For example, suppose there are two workers with exactly same level of education, but are employed in two different jobs requiring different levels of education, such that person A works in a job, that correctly matches his education, whereas person B works in a job requiring a lower level of education. Given this scenario, one would clearly expect person B to earn less than person A, and reverse shall be true if person B is working in a job requiring a higher level of education, that is, person B should be earning more than person A, whose education correctly matches the job requirement. It is important to note here that while the coefficients α_2 and α_3 are expected to bear different signs than β_2 and β_3, the findings in both the models are consistent with each other. A positive α_2 in the DH model suggests that an individual with a higher education attainment than what is required by the job, while earns a lower return on surplus schooling, it is positive. Since, in the VV model, this positive return, is captured by the absolute value of β_2 itself, it also reflects the magnitude of underutilization of over-education. A corresponding argument holds for α_3 and β_3.

Table 3 presents the estimation results of (2), (3) and (4). In the first column, we present the estimation results of a standard earning equation. All variables bear the expected signs and are statistically significant with robust standard errors corrected for heteroskedasticity. While most variables are significant at 1% level, the variable: *Marital Status* is significant at 10% level. The coefficient corresponding to *Actual years of schooling* indicates that every additional year of schooling increases daily wage of workers employed in the T&C industry by 2.5%.

The second column provides estimation results based on the Duncan-Hoffman (1981) model, where the required education is calculated using the mean values. So the required education variable for each individual, estimated using this method would be the mean of actual years of education of all individuals within that subsector-occupation category. The coefficient corresponding to this variable indicates that every additional year of schooling that is required for a specific occupation in a specific subsector of the industry is associated with 8.9

per cent increase in daily wage of the workers. Further, we can clearly infer from the value of coefficient corresponding to OE that every additional year of surplus education increases daily wage by merely 3.3% beyond the usual level, which is of course, much lower for each education year as compared to 8.9%, thus accounting for the underutilization of excess education. Also, there is a penalty associated with deficit education, as indicated by the value of coefficient corresponding to UE. Every year of education less than the usual level reduces the workers' wage by 1.6%.

Table 3: Estimates on Wage Effects of Educational Mismatch

Variables	**Standard**	**DH-Mean**	**DH-Mode**	**VV**
Age	0.0575*** (8.58)	0.0567*** (8.46)	0.0559*** (8.04)	0.0566*** (8.34)
Age square	-0.00067*** (-7.69)	-0.00065*** (-7.54)	-0.00064*** (-6.97)	-0.00065*** (-7.32)
Sector (Rural-1, Urban-2)	0.0735*** (2.56)	0.0764*** (2.68)	0.0870*** (2.93)	0.0850*** (2.94)
Sex (Male-1, Female-2)	-0.496*** (-12.86)	-0.506*** (-13.28)	-0.497*** (-12.49)	-0.515*** (-13.4)
Marital Status (Married-1, Unmarried-2)	0.054* (1.65)	0.06* (1.9)	0.059* (1.82)	0.056* (1.74)
Actual years of education (AE)	0.0252*** (8.26)			0.052*** (11.79)
Required years of education (by mean) (RE)		0.089*** (13.01)		
Years of Over-education (based on RE) (OE)		0.033*** (5.42)		
Years of Under-education (based on RE) (UE)		-0.016** (-2.53)		
Required years of education (by mode) (REM)			0.044*** (9.31)	
Years of Over-education (based on REM) (OEM)			0.041*** (7.25)	
Years of Under-education (based on REM) (UEM)			-0.025*** (-4.84)	
Over-educated (based on one standard deviation band) (OED) (Yes-1 No-0)				-0.176*** (-4.1)
Under-educated (based on one standard deviation band) (UED) (Yes-1 No-0)				0.185*** (4.15)
Fixed Effects				
Sub-sector	Yes	No	No	No
Occupation	Yes	No	No	No
State	Yes	Yes	Yes	Yes
Constant	3.88	3.82	4.1	4.07
No. of Observations	1,951	1,951	1,876	1,951
R square	0.45	0.44	0.41	0.42

Notes: 1. Standard errors are robust, corrected for heteroscedasticity. 2. Figures in parentheses represent t-statistics. 3. (*) significant at10% level; (**) significant at 5% level; (***) significant at 1% level. 4. Models DH-Mean, DH-Mode and VV denote respectively, the Duncan-Hoffman (1981) model with RE calculated with

mean values, the Duncan-Hoffman model with RE calculated with modal values, and the Verdugo & Verdugo (1989) model calculated with a 1-standard deviation band
Source: Author's computation based on NSS 68th round survey

These coefficients somewhat differ when we estimate RE using using modal values, instead of mean values, as depicted in the third column of table 3, named DH-Mode. Every additional year of REM (Required education estimated using mode) increases daily wage of workers by 4.4%, whereas every additional year of surplus education (OEM) increases daily wage by 4.1% beyond the usual level. Wage penalty owing to deficit education as per this model is estimated to be high at 2.5%. The last column of table 3 presents the estimation results based on the Verdugo & Verdugo (1989) model. The VV model is conditional on actual years of education, rather than required years of education. The coefficient corresponding to AE suggests that each additional year of schooling increases daily wage by 5.2%. However, being overeducated results in a 17.6% loss in daily wage. In other words, a person employed in a job requiring a lower education than what is possessed by him would on an average, earn a daily wage which is 17.6% lower than the person with the same level of education, but employed in a correctly matced job. On the other hand, an undereducated worker, on average, earns a daily wage, which is 18.5% higher than the worker with equivalent education working in a matched job. In case of the standard earning equation, we also take fixed effects in order to capture the heterogeneity with respect to subsector, occupation and state. However, in case of the rest of the specifications, we take only the state fixed effects, since required education (irrespective of how it is calculated), is unique to each subsector/occupation cell, it also controls industry and occupation fixed effects.

5. Conclusion

This study aims at analysing the potential outcomes of skill mismatch in case of India's textile and clothing industry. We began by analysing the incidence and extent of educational mismatch existing in this industry using the 68th round of NSS Employment and Unemployment Survey estimates. Using this data, the study further examines the effect of educational mismatch on the daily wage of workers employed in the industry using the ORU models. The overall educational mismatch ratio in India's T&C industry during 2011-12 is found to be to the tune of 67.61%, which is much above the ratio for overall manufacturing in the developed world. The findings also suggest that around 26% of people in the industry are employed in jobs requiring no formal general education and close to 68% of them are over educated. Further, just about 4% of people are employed in jobs requiring graduate or above graduate education level, of which merely 19% are under-educated. The estimates using the Duncan Hoffman (1981) model suggest that every additional year of surplus education increases daily wage of workers employed in this industry by 3.3% beyond the usual level, whereas, every year of education less than the usual level reduces the workers' wage by 1.6%. On the other hand, estimates using Verdugo and Verdugo (1989) model indicate that being overeducated results in a 17.6% loss in daily wage, whereas an undereducated worker's wage is 18.5% higher than the worker with equivalent education employed in a matched job. The findings of the study are in line with the available literature and estimates are found to be consistent across different models.

Clearly, there is a substantial educational mismatch prevailing in India's T&C industry, and as a result, right candidate fails to get matched with the right job. Therefore, it's not only the lack of adequate skills, which is hampering the industry's employment growth but more importantly, the fact that there is an incongruity in terms of education attainment and the job requirement, and significant costs tied to it. While under-education can create a significant welfare loss due to misuse of human resources, workers with over education, on the other hand, could incur financial losses. This substantially reduces job satisfaction and efficiency and increases turnover rates for overqualified workers. Therefore, on the demand side, the government should take appropriate steps towards determining specific labour force needs of the entrepreneurs operating in various segments of the industry. On the supply side, well-planned education policies are required in order to mitigate productivity losses arising due to mismatch.

Appendix

Table A-1: Education level and Years of schooling

Years of schooling	Education Level
0	Illiterate
0	Literate without formal schooling
3	Below Primary
5	Primary
8	Middle
11	Secondary
13	Higher Secondary
15	Diploma/Certificate course
17	Graduate
19	Post Graduate and above

Source: Based on Author's judgement

Table A-2: Descriptive Statistics

Spinning, weaving and finishing of textiles					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Wage per day (Rs.)	2205112.00	193.09	155.43	0.00	3214.29
Age	2205112.00	34.46	12.15	11.00	75.00
Age square	2205112.00	1335.52	953.27	121.00	5625.00
Sector	2205112.00	1.70	0.46	1.00	2.00
Sex	2205112.00	1.23	0.42	1.00	2.00
Marital Status	2205112.00	1.76	0.53	1.00	4.00
Actual years of education (AE)	2205112.00	6.91	4.76	0.00	19.00
Required years of education (by mean) (RE)	2205112.00	7.25	2.05	6.24	15.17
Years of Over-education (based on RE) (OE)	2205112.00	1.62	2.45	0.00	12.62
Years of Under-education (based on RE) (UE)	2205112.00	1.96	2.42	0.00	12.17
Required years of education (by mode) (REM)	2165889.00	8.36	2.26	0.00	17.00
Years of Over-education (based on REM) (OEM)	2165889.00	1.10	2.32	0.00	19.00
Years of Under-education (based on REM) (UEM)	2165889.00	2.62	2.98	0.00	14.00
Over-educated (based on one standard deviation band) (OED)	2205112.00	0.17	0.38	0.00	1.00
Under-educated (based on one standard deviation band) (UED)	2205112.00	0.15	0.36	0.00	1.00
Manufacture of other textiles					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Wage per day (Rs.)	1551646.00	175.26	148.74	0.00	1607.14
Age	1551646.00	30.22	12.04	10.00	72.00
Age square	1551646.00	1058.39	908.15	100.00	5184.00
Sector	1551646.00	1.63	0.48	1.00	2.00
Sex	1551646.00	1.16	0.37	1.00	2.00

Marital Status	1551646.00	1.71	0.53	1.00	4.00
Actual years of education (AE)	1551646.00	6.45	4.77	0.00	19.00
Required years of education (by mean) (RE)	1551646.00	6.27	1.37	0.00	16.50
Years of Over-education (based on RE) (OE)	1551646.00	1.95	2.82	0.00	13.31
Years of Under-education (based on RE) (UE)	1551646.00	1.78	2.32	0.00	13.83
Required years of education (by mode) (REM)	1537596.00	3.25	3.98	0.00	11.00
Years of Over-education (based on REM) (OEM)	1537596.00	3.97	4.79	0.00	19.00
Years of Under-education (based on REM) (UEM)	1537596.00	0.88	2.04	0.00	11.00
Over-educated (based on one standard deviation band) (OED)	1551646.00	0.18	0.38	0.00	1.00
Under-educated (based on one standard deviation band) (UED)	1551646.00	0.21	0.40	0.00	1.00
Manufacture of wearing apparel, except fur apparel					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Wage per day (Rs.)	2201606.00	172.19	175.81	0.00	2142.86
Age	2201606.00	28.99	11.08	11.00	75.00
Age square	2201606.00	963.35	737.86	121.00	5625.00
Sector	2201606.00	1.69	0.46	1.00	2.00
Sex	2201606.00	1.23	0.42	1.00	2.00
Marital Status	2201606.00	1.61	0.57	1.00	4.00
Actual years of education (AE)	2201606.00	6.58	4.75	0.00	19.00
Required years of education (by mean) (RE)	2201606.00	7.26	1.45	6.44	17.67
Years of Over-education (based on RE) (OE)	2201606.00	1.56	2.43	0.00	12.02
Years of Under-education (based on RE) (UE)	2201606.00	2.24	2.57	0.00	7.79
Required years of education (by mode) (REM)	1996372.00	8.23	1.37	8.00	17.00
Years of Over-education (based on REM) (OEM)	1996372.00	1.12	2.23	0.00	11.00
Years of Under-education (based on REM) (UEM)	1996372.00	2.88	3.04	0.00	12.00
Over-educated (based on one standard deviation band) (OED)	2201606.00	0.12	0.33	0.00	1.00
Under-educated (based on one standard deviation band) (UED)	2201606.00	0.19	0.39	0.00	1.00
Manufacture of articles of fur					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Wage per day (Rs.)	37326.00	199.43	42.92	114.29	228.57
Age	37326.00	33.82	6.22	29.00	44.00
Age square	37326.00	1182.32	446.77	841.00	1936.00
Sector	37326.00	2.00	0.00	2.00	2.00
Sex	37326.00	1.78	0.42	1.00	2.00
Marital Status	37326.00	1.78	1.13	1.00	4.00
Actual years of education (AE)	37326.00	9.47	2.03	5.00	11.00
Required years of education (by mean) (RE)	37326.00	8.76	1.40	5.00	9.50
Years of Over-education (based on RE) (OE)	37326.00	0.89	0.74	0.00	1.50
Years of Under-education (based on RE) (UE)	37326.00	0.18	0.49	0.00	1.50
Required years of education (by mode) (REM)	10779.00	6.93	1.44	5.00	8.00
Years of Over-education (based on REM) (OEM)	10779.00	0.00	0.00	0.00	0.00
Years of Under-education (based on REM) (UEM)	10779.00	0.00	0.00	0.00	0.00
Over-educated (based on one standard deviation band) (OED)	37326.00	0.00	0.00	0.00	0.00
Under-educated (based on one standard deviation band) (UED)	37326.00	0.29	0.45	0.00	1.00
Manufacture of knitted and crocheted apparel					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Wage per day (Rs.)	301853.00	246.97	131.73	100.00	714.29
Age	301853.00	30.64	7.99	15.00	60.00
Age square	301853.00	1002.62	583.57	225.00	3600.00
Sector	301853.00	1.68	0.47	1.00	2.00
Sex	301853.00	1.18	0.39	1.00	2.00
Marital Status	301853.00	1.64	0.48	1.00	2.00
Actual years of education (AE)	301853.00	10.19	5.21	0.00	19.00
Required years of education (by mean) (RE)	301853.00	9.37	2.97	7.29	19.00
Years of Over-education (based on RE) (OE)	301853.00	2.14	2.42	0.00	9.71

Years of Under-education (based on RE) (UE)	301853.00	1.32	2.32	0.00	10.28
Required years of education (by mode) (REM)	301853.00	9.42	4.14	5.00	17.00
Years of Over-education (based on REM) (OEM)	301853.00	1.86	2.69	0.00	12.00
Years of Under-education (based on REM) (UEM)	301853.00	1.09	2.40	0.00	13.00
Over-educated (based on one standard deviation band) (OED)	301853.00	0.14	0.34	0.00	1.00
Under-educated (based on one standard deviation band) (UED)	301853.00	0.13	0.34	0.00	1.00

Source: Author's calculation based on NSS 68th round survey

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