Community identity and skill mismatch: A study on Indian labour market*

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and

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September, 2012

Abstract

The current paper characterizes skill mismatch in Indian labor market and finds the role of community identity in explaining the existence of skill mismatch measured by the difference between a laborer's education level and the educational requirement of a job (s)he is in. Such mismatch leads to inefficient allocation of resources asking for policy reorientation in both the education and labor sectors. This research agenda is inspired by the fact that network plays an important role in getting a job or being discriminated in the job market. Therefore if a community identity acts as an adverse (favorable) signal, people from that community should acquire more (less) education than the educational requirement for a job to compensate for the signal coming out of their community identities. This may lead to over or under education depending whether the community identity transmits an adverse or favorable signal. We find that both Muslim and SC/ST identity have positive significant impact on the probability of over education. We also find that in case of under education

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Muslim identity is positive significant while SC/ST is not. We calculate the extent of over and under education for different industries and the wage effect of over education which is found to be positive.

1 Introduction

Skill mismatch as reflected in over or under education implies inefficient allocation of resources as the resources spent on training the worker was not required in the first place for performing her duty in the first place. This amounts to wastage of social resource either in form of mistargeted subsidy in a highly subsidized education system or irrational investment decision in a privately funded one. The current paper looks at the wage effect of skill mismatch in India and tries to identify the possible reasons behind it. Specifically, it enquires the role of community network in explaining skill mismatch in India.

The current paper is related to the literature of return to education in general and mismatch between education and occupation in particular. There is already a large literature documenting existence of over education in different labor markets (Rumberger, 1987; Sicherman, 1991; Groot, 1996; Verdugo and Verdugo, 1989). Duncan and Hoffman (1981) found using Panel Study of Income Dynamics data that nearly 40 percent of US workforce and about 50 percent of black male have more education than their job requires. However, the resources spent on acquiring education are not deadweight loss as the individual return to a year of surplus education is positive and significant. However, return to surplus education is less than the return to required education. Similar result was found by Rumberger (1987), Tsang et al. (1991), Cohn and Khan (1995). Hersch (1991) sheds light on the problem of skill mismatch from a different angle. Using primary data collected in Oregon, 1986 the author found that overqualified workers are less satisfied with their jobs and therefore more likely to quit. There are number of studies that focus on the effect of skill mismatch for different occupations.

The decision to acquire more education than what is required for a current job is explained in the current literature by other human capital components such as experience or by the mobility pattern of the workers (Sicherman and Galor, 1990). In the first case more years spent in schools acts as a substitute for work experience. According to the second explanation acquiring more education is a forward looking decision by the employee to move up the skill ladder in the job market and her current employment in a low skilled profession is just a transitory phase. Sicherman (1991) found that in the context of American labor market both these factors work. The decision to acquire more education than required by the job profile can also be explained by *signaling model* in a labor market where the employers use educational qualification as a screening device (Spence, 1973). Emphasizing the role of mobility Buchel and van Ham (2003) explained over education using regional restrictions on labour mobility.

Though there is vast literature on matching and skill misallocation in developed countries, there is no study on India to the best of our knowledge. Our study provides an important insight for designing labour and education policies geared towards avieving efficient allocation of skills. The question of skill mismatch in the Indian labor market becomes even more important after the economic reforms in 1991 which led India to the path of skill-biased growth. Changes in the Indian labour market over recent decades has raised concern over misallocation of skill. Since opening up of the economy in 1991 new job opportunities have led to supply side response as well. Like all other developing countries Indias share of industrial and service sector output in GDP grew over time. The share of services in GDP (at factor cost, current price) increased rapidly from around 31 percent in 1950-51 to 55 percent in 2009-10. However, employment share is still disproportionally high in traditional sector. Between 1993-94 and 2004-05 the share of employment in traditional sector decreased sharply and the consequent rise in share of employment in secondary and tertiary sector was almost equally divided. The share of employment in services was 21.2 percent in 1993-94 and that increased to 24.8 percent in 2004-05. It is evident that service sectors output growth rate is mainly driven by some selected skill intensive sectors. Employment share in formal services is again dwarfed by stubbornly high employment share in informal sector. Overall, informal sector absorbs around 86 percent of total 457 million workers (2004-05). Between 1999-00 and 2004-05, employment in informal sector grew at almost equal rate of 2.9 percent with formal sector. Skill based technological change is evident in 1990s (Berman et al. (2010)). However, the timing of the skill based technological change arrived late in India compared to other emerging economies. While most high and middle income countries experienced skill-based technological change in the 1980s, India did show this symptom only after opening up of the economy in 1990s. Berman et al. (2010) confirm that while 1980s were a period of falling skill demand, skill demand increased in 1990s.

On the supply side, the proportion of high skilled workers increased substantially between 1983 and 2004-05. In 1983 the proportion of illiterate workers in working age population (not enrolled in any educational institution) was around 50.6 percent and proportion of graduate workers was around 3.75 percent. The corresponding figures are 29.6 and 8.4 in 2004-05. There is remarkable growth in the share of secondary educated workers (from 9 percent in 1983 to 19 percent in 2004-05). The moderate growth of secondary and above workers and workers with technical education in recent decades has increased the pool of skilled workers. According to World Bank (cite), India has the third largest higher education system after China and the United States. Since independence, the number of universities has increased by 18 times, the number of colleges by 35 times and gross enrollment ratio more than 10 times. At the early stage of Indian higher education system, the enrollment drew mostly from elite class. Over time, the system became more mass-based and democratic. However, as expected, there is a big gap in rural-urban divide in higher education.

In this context this paper performs three tasks: characterize sector wise skill mismatch in India, finds the factors behind the decisions to acquire more or less skill in India and finds the wage effect of under and over education. More importantly, we invoke the network perspective in the question which has its unique place in India's perspective. The role of network in the both the education decision and labor market participation is well researched (Montgomery, 1991; Munshi and Rosenzweig, 2006; Munshi, 2003; Simon and Warner, 1992) which implies that over education/under education decision may also be linked with community identity. However, there is no study to the best of our knowledge which directly addresses this question. There are a few channels through which community identity may affect skill mismatch. One possible way is that community network gives required training which cannot be obtained through formal schooling. Then what we capture as under education is not necessarily a skill mismatch as the under educated person is investing his/her time in getting training through community level apprenticeship. On the other had there can be wide spread social discrimination against a community which makes them attaining higher education than their non-discriminated counterpart. Over education can also exist if one's occupation is completely determined by her network (as in the caste system) but education decision is driven by low cost of education (e.g reservation policy) or education being a status symbol leading to over education. In this paper we see if skill mismatch has any community dimension and find that both SC/ST and Muslim dummy is positive and significant for over education while only Muslim dummy is positive and significant for under education.

In this paper, using the National Sample Survey data since 1983 to 2004-05 we will examine the evidence of skill mismatch and their possible links with different socio-demographic covariates with a particular emphasis on community identities. We also look into the time trend of returns to over-education and under-education during 1983 to 2004-05. We also estimate the return to over education to see if it pays to acquire more education. If over-education has a premium, then we will see decline in this premium in long run due to greater mobility in education ladder. One of the important questions in this context is whether we see any declining trend in returns to over education. The longer time span of our samples will shed light on issues like this.

The remaining part of the paper is organized as follows. The data source and summary statistics are described in next section. The third section contains methodology of measuring skill mismatch. The results are presented in the fourth section followed by a section on general equilibrium effects of skill misallocation. The last section concludes.

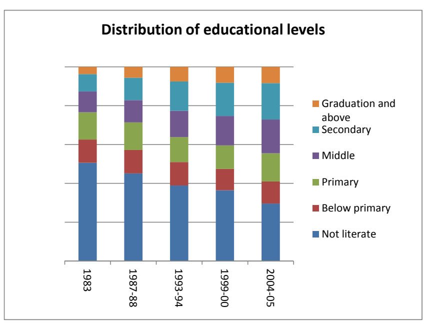
2 Data

National Sample Survey Organisation conducts large surveys on employment and unemployment situation in India. Though these surveys are frequent in recent times (almost every year), empirical analysis is usually drawn from quinquennial 'thick rounds. We use round 38th (1983), 43rd (1987-88), 50th (1993-94), 55th (1999-00), and 61st (2004-04). Therefore, our sample consists of multiple cross sections spanning a period of 20 years. Since our sample period starts in the early 1980s, we will be able to capture the trend in our results before and after the liberalisation process initiated in 1991. The surveys collect socio-economic and demographic information of households and individual members across all states except some remote and inaccessible pockets. This is a stratified multi-stage sample and therefore, all units are assigned with adjusted sampling weights. In our analysis, all results are reported using proper sample weights. It should be noted that sampling strategy and questionnaire is very similar across rounds therefore, the complications regarding the comparability issues do not arise. The surveys collect information on individual occupation, education (disaggregated categories), industry of employment, age, sex, marital status, status of employment, etc. It also collects household level characteristics like monthly consumption spending, social group, religion, household size, etc. On an average, there are 200 thousands individuals in working age population (16-65), not enrolled in any educational institution, and with education and occupation information. There are fewer samples with complete information on wages. A larger portion of working age population report self-employed therefore, no wage information is available. It should be noted that wage or regular salaried employment is much lower in India. We use both regular or salaried wage earners and other types of wage earners in our analysis. We conduct our analysis based on two different samples: overall sample and wage sample. Wage sample is a subset of overall sample. Wage sample is about 35 percent of overall sample except the round 1987-88. This is due huge missing wage data for this particular sample. It is reported in the literature that 1987-88 wage sample is problematic therefore; we take special caution while explaining any time trend in our result. All wage analysis is based on wage sample, whereas all other results are based on overall sample. We will specify sample size and sample selection whenever necessary.

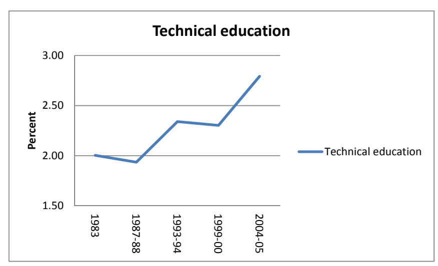
Table A1 reports sample summary statistics. Our sample consists of entire working age population, not enrolled in any educational institution, having information on their educational qualification and occupation. Since National Sample Surveys (NSS) do not collect data on years of schooling, we match each education level to corresponding years based on Indian education system. We also classify education levels in six uniform education categories: edu 1 (illiterate), edu 2 (below primary), edu 3 (primary), edu 4 (middle school), edu 5 (secondary), and edu 6 (graduation and above). On average, our sample is around 36 years old and around 78 percent of them are married. About 16 percent of our sample is working at a regular or salaried job. The sample consists of more than 70 percent male. It is also clear than rural population has greater representation (around 78 percent). The lower castes groups are around 29 percent of the sample. It should be noted that according to population census, scheduled castes and scheduled tribes consist of around 24 percent of total population. Therefore, our sample has higher representation of backward castes groups (OBC excluded from our definition of SCST). Muslims consist of around nine percent of our sample whereas the corresponding figure for entire population is 13.4 percent according to 2001 census. The trends of these numbers are flat over the sample period. Most important trend we observe from the table is educational attainment. The average years of education was 2.8 in 1983 and that increased to 4.6 in 2004-05 registering around 65 percent growth. The average household size also decreased over the sample period. All nominal figures in our sample is deflated using poverty line of rural Maharashtra.

2.1 The supply side

We now briefly discuss the supply side of the skills. Figure 1(a) shows the distribution of education categories over the sample period. The proportion of illiterate people has been falling significantly. Two important facts are seen from the figure. First, the mobility in education ladder is prominent in higher education level. The drop in the proportion of illiterate people is mainly matched by the rise in proportion of people with middle school or above education level. Second, there is no change in the proportion of people with primary or below primary but literate. Within the semi and high skills workers, there is substantial rise in proportion of workers with secondary and above (13 percent in 1983 to 27 percent in 2004-05). We also find that the proportion of working age population with technical education has increased from 2 percent in 1983 to 2.8 percent in 2004-05 (Figure **??**). These figures include both post-secondary technical degree as well as diploma.



(a) Education distribution



(b) Technical education

Note: Technical education includes any technical degrees or diplomas.

Figure 1: Distribution of education across NSS rounds

The pool of skilled labour influences the labour force participation rates. While proportion of lower skilled workers has been falling over time, the rate of participation in labour force is showing increasing trend for these skill levels (Figure 2). More precisely, the rate of labour force participation of illiterate working age population has increased from 58.2 percent in 1983 to 63.4 percent in 2004-05. Semi-skilled workforce (below primary, primary and middle school) has stable rate of labour force participation at around 70 percent during the same period. On the other hand, the skilled population (secondary and above) has declining trend in labour force participation rate. Graduate and above working age population had 82 percent participation rate in 1983 which declined to 76 percent in 2003-04. We see similar declining trend for secondary educated population. In a nutshell, there is significantly greater number of people with higher skill level left out of active labour force in 2003-04 compared to twenty years back. What may cause this declining supply (not in absolute sense) of talent pool? One reason could be higher educational attainment of women but less participation due to several social constraints, especially after marriage exit from labour force. To understand the dynamics, we also calculate the labour force participation rates by sex (not reported). It is found that labour force participation rate by skill level remained constant over time for male population. Therefore, our conjecture is partly true. Our focus of this study is not to delve deeper into gender issues of the labour market. However, the evidence of gender gap encourages us to control several important demographic variables in formal analysis.

2.2 The demand side

What do the increasing trend in educational attainment and falling labour force participation mean for the actual skill premium? To understand this we have to see the trends in demand side of the labour market. The employment rate of skilled workers is lower than their skilled counterpart (Figure 3(a)). While the skilled and the semi-skilled cohorts have increasing employment rates, the two extreme cohorts -unskilled and extremely skilled (graduate and above) workforces show relatively flat trend in employment rates. In summary, there is an increasing trend in demand for skills. However, all these employment may not be full time or regular salaried jobs. NSS do not uniformly define full time and part time workers. We define full time workers using weekly employment status. If someone is employed in gainful economic activity for at least 2.5 days in a week,

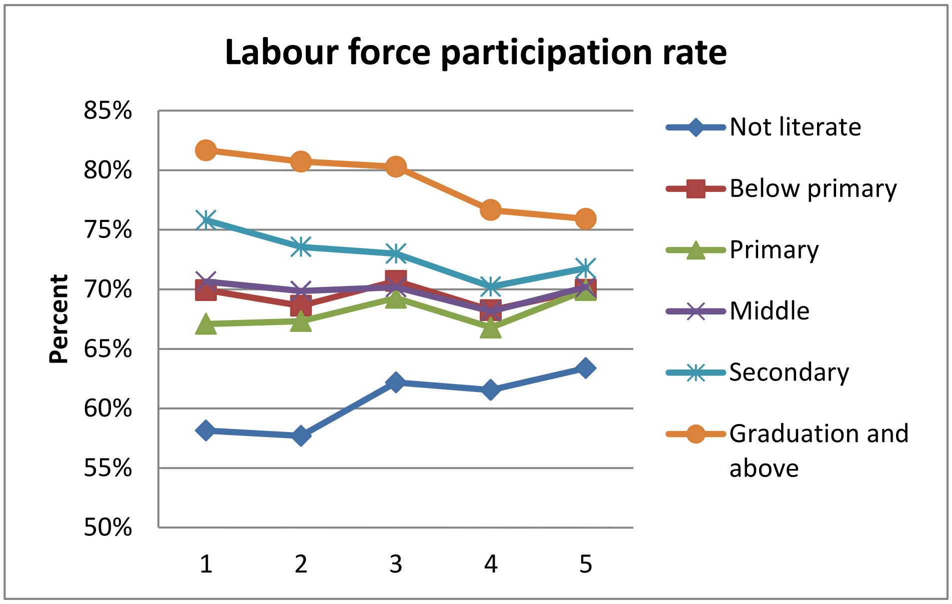
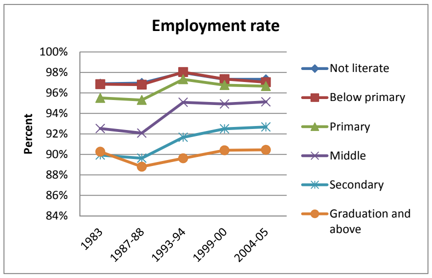


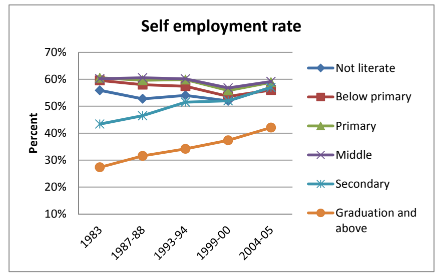
Figure 2: Labour force participation rates across skills

we define her as full time employed. Using this standard, the proportion of full time employment is higher for skilled workers. The self-employment rate is quite high in India. Figure 3(b) shows the trend in self-employment rates over time. Two important results are evident from the figure. First, the self-employment rate is highest for semi-skilled workers (middle school). Second, though the self-employment rate for secondary and graduate workers are consistently lower than all skill levels, the rate is increasing steadily over time. In fact, in 2003-04, the self-employment rate of secondary workers converged to that of all lower skill levels.

While the summary statistics of demand and supply side of the labour market gives an overall picture, we need a proper methodology to identify the presence



(a) Employment rate



(b) Self employment rate

Figure 3: Employment rates and self-employment rates

of skill mismatch and possible effect thereof. In general skill mismatch means someone is stuck in a job with more(less) than the required education level for that job profile. The measurement of over-education or under-education, which is very subjective sometimes, is challenging. The literature, however, defines several methodologies to measure the extent of skill mismatch. The next section describes the methods of defining and measuring the skill misallocation. We also explain the hypothesis to be tested in the following section.

3 SKILL ALLOCATION AND EARNINGS

In the standard human capital theory, wage is completely determined by skill and other characteristics of an individual where the productivity of the individual is fully embodies. Thus, productivity is not influenced by the matching of skill and job characteristics. If mismatching is present in an economy and it influences productivity, the wage determination will be partly affected by over-education and under-education. This section provides evidence of over-education and under-education and further evidence on the returns to over-education and under-education. The methodology described below also enable us to test empirically whether Indian labour market is characterised by standard human capital theory or matching theory (presence of mismatch between job characteristics and skill level and impact on productivity thereof). We also examine the extent of wage gain and loss due to skill misallocation. The results are important for setting up labour and education policy towards allocation of skill. If the skill misallocation is not transient, rather permanent, we have to devise proper policy incentive so that there is no gap is demand for skill and supply of skill and also improved search process so that productivity of individual workers are fully utilised. The possibility of slower mobility should be addressed as well to this end.

3.1 Measurement issues

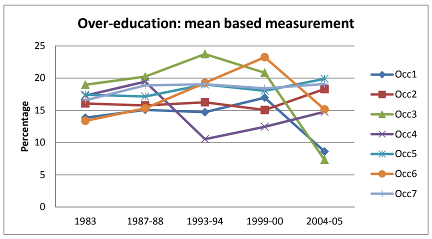
There is substantial work in the area of over-education and under-education. Two different approaches have been used in literature to measure the over-education and under-education. First, in subjective approach the skill mismatch is defined as the gap between actual skill of as individual and skill required for the job as assessed subjectively by the employee or some independent job analyst. In second approach, the skill mismatch is defined by the gap between actual skill and some objective benchmark of skill level for the job. The objective benchmark is often set at one standard deviation band around the mean education level. Therefore, the objective classification of workers in over-education and under-educated groups is influenced by the sample. Both the methodologies have some drawbacks. For example, the subjective approach is often biased because the self-assessment is partly influenced by job satisfaction of the employee and dissatisfied workers may misreport themselves as over-educated. The main advantage of this approach is that the measurement is job specific and does not depend on sample characteristics. Some studies have utilised expert opinion to determine job specific skill requirements where bias due to misreporting will be less. However, this approach, although superior, is costly to implement. Whereas, in the objective approach, the chances of misreporting are low, however the measurement of over-qualification or under-qualification is unable to uncover the technological requirements of a job. This measurement is partly influenced by actual allocation of skill resulting from hiring and matching process and labour market conditions.

We follow the objective approach in the following analysis. The choice is largely dictated by data availability. Though there is a disaggregated occupation classification in India, dictionary of occupation titles (or any such information) is not readily available. We classify an individual as "over-educated if the education level of the individual is more than one standard deviation of the mean education levels of all workers in that occupation. Similarly, "under-education is defined as education level below one standard deviation of mean. If the education level is within the one standard deviation band, we define it as "adequately educated. This objective definition of skill mismatch is widely used in literature (cite). We find means of education levels of all individuals in our sample by their occupation groups. We use three digit levels National Occupation Classification code of 1968 (NCO 1968). We calculate the means for each round separately. Then, the sample is divided into three groups: over-educated, under-educated and adequately educated using the above definition. The incidence of skill mismatch and their effect on wage earning is reported in the following sub-sections.

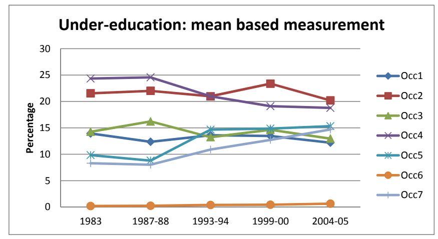
3.2 Results

3.3 Incidence of skill mismatch

The estimated proportions of over-educated and under educated workers are given in Figure 4(a) and 4(b) respectively. We groups three digit levels into seven broad occupation categories. The detail of the groups is given in table A2. Occupation 1 is a collection of all professional, technical and related workers. Administrative, executive and managerial workers are grouped in Occupation 2. Occupation group 3 collects all clerical and related workers. Sales workers and service workers are included in occupation 4 and 5 respectively. All traditional occupations like farming, fishing, hunting, logging and related works are grouped in occupation 6. Occupation six is a very broad group consisting mainly production and related workers, transport equipment operators and labourers. This groupification follows the international standard of occupation classification into three broad classes: white color, blue color and traditional jobs. The first three occupation groups are white color jobs whereas the sixth occupation group is the traditional occupation category. All other jobs are mainly blue color jobs like sales and production workers and other labourers.



(a) Over-education



(b) Under-education

Figure 4: Incidence of skill mismatch

The rates of over-education are significantly high for all occupation groups ranging from 13 percent to 19 percent. During 1983, the rate was very similar across all occupations. Over time, the rates diversified. For example, the range of over-education rates in 1983 was 5.6 which increased to 12.6 in 2004-05. Some occupations show steady trend in over-education rates during the period whereas, some occupations have fluctuating rates. There is a clear trend of decline in over-education rates in recent years for professional and technical workers, clerical and related workers, and traditional workers like farmers. However, the over-education rates for the sales workers, service workers, production workers and other related workers have increased since 1999-00. Administrative executive and managerial workers, service workers and production workers are more likely to be over-educated now compared to 1983. On the other hand, professionals and technical workers, workers in clerical and related jobs are less likely to be overeducated in 2004-05 compared to twenty years back. We also plot the rates of under-education by occupation groups. The under-educations rates are quite high was very diverse across occupations. In 1983, the under-education rate for production and related workers, transport equipment operators and labourers were 8.3 percent and that for sales worker was 24.3 percent. Over the time the rates converged. White color job workers (Occ 1, 2, and 3) have stable under-education rates over the sample period. However, under-education rates have increased for some blue color jobs (Occ 7 and 5) except sales workers (Occ 4). There is a clear trend in convergence of under-education rates across occupation groups over time. The range was 12.5 in 1983 and that decreased to 8 in 2004-05. Overall, we observe three important aspects of skill mismatch in India. First, the rate of mismatch is quite significant. Second, there is divergence in under-education and over-education rates across occupations. Third, the blue color workers are more likely to be over-educated now.

It is import to note that over-education and under-education rates not only varied across occupation groups, it is also diverse across social groups, between sexes, sector of residence (rural-urban), etc. Next, we formally analyse the probability of over-education and under-education. A Probit model is estimated to find the possible association between different socio-economic and demographic characteristics of an individual and the likelihood of skill-mismatch. The probability is assumed to be a function of the following form:

$$\begin{aligned} P(y_i = 1) &= \beta_0 + \beta_1 Age + \beta_2 Age^2 + \beta_3 SCST + \beta_4 Rural \\ &+ \beta_5 Muslim + \mathbf{EDU}\boldsymbol{\delta} + \mathbf{OCC}\boldsymbol{\gamma} + \epsilon \end{aligned} \quad (1)$$

where $y_i = 1$ if the i^{th} individual is over(under)-educated. $SCST$ is a dummy for lower castes group, $Rural$ is a dummy for sector of residence, $Mulsim$ is Muslim dummy. We control for age and age squared as well. OCC is the vector for six occupation dummies and EDU is the vector for five education dummies described earlier. ϵ is the disturbance term with all standard assumptions. Our main interest is to see whether probability of skill mismatch varies across occupation groups after controlling for other covariates. Table A3 and A4 show the regression results for over-education and under-education respectively. As we see from the table, the occupation dummies are all significant for both over-education and under-education. It is also tested that the marginal effects are significantly different across occupations [1]. The other important results are: 1) lower caste association leads to higher probability of over-education and lower probability of under-education, 2) Rural people are more likely to be over-educated and less likely to be under-educated in their occupation [2], 3) the effect of being Muslim on probability of under-education and over-education is positive except for the year 1993-94[3], 4) the older the person is, the more they may be probable to become over-educated, and 5) as expected, the probability of becoming over-educated increases with education level and the probability of becoming under-educated decreases with education level.

3.3.1 Wage effect of skill mismatch

In the following section we report the wage effect of over-education and under-education. In the standard Mincerian wage equation, the returns to education depend on the productivity of an individual that is fully embodied. That is, wage is determined by

$$lnW_i = \alpha S_i + \mathbf{X_i}\boldsymbol{\beta} + \epsilon \tag{2}$$

where S_i is the actual educational attainment of individual i and X_i is a vector of all other covariates capturing individual and demographic characteristics. However, this wage determination does not capture the possibility of matching. If productivity is partly determined by matching of workers and the jobs, the wage equation should be given by

$$lnW_i = \alpha_1 S_i^a + \alpha_2 S_i^o + \alpha_3 S_i^u + \mathbf{X_i}\boldsymbol{\beta} + \epsilon \tag{3}$$

where S^a, S^o, and S^u are years of adequate education, over-education and under-education respectively. Here, adequate education is defined as mean edu-

[1]Not reported in this draft. We are working on the marginal effects and change in marginal effects of important covariates

[2]This could be due to several reasons most likely reason to be mobility. We will delve deeper in future draft to understand the reasons behind each of these important findings. More formal analysis is required to draw any conclusion.

[3]We will also include several other important covariates in future draft of this paper gender and caste gaps would be important aspects.

cation level of the occupation of the individual i. If productivity is fully embodied and standard human capital theory applies, all the α coefficients would be same. In other words, the returns to over-education or under-education would be equal to returns to adequate education. On the other hand, if productivity is solely determined by the job profile, $\alpha_2 = \alpha_3 = 0$. That means wage should not depend on over-education or under-education level of the individual. Rather, it will solely depend on required skill level for the job. If skill mismatching exists, $\alpha_1 \neq \alpha_2 \neq \alpha_3$ would be expected. We estimate equation 3 and test whether returns to under-education and over-education are same as returns to adequate education. In general, returns to one year of extra over-education are positive but lower than the returns to adequate education whereas, return to under-education is negative.

Figure 5 shows the coefficients of over-education, under-education and adequate education in the regression of equation 3. Table A5 reports the complete estimation result of equation 3. Three main results confirm the presence of skill mismatch in India. First, $\alpha_1 \neq \alpha_2 \neq \alpha_3 \neq 0$. Second, the returns to over-education are positive and significant. However, it is lower than returns to adequate education in absolute value. Third, returns to under-education are significantly negative. As we see from the table, we control for some important covariates: lower caste dummy, Muslim dummy, quadratic of age, and rural dummy [4]. We also test the hypothesis $\alpha_1 \neq \alpha_2 \neq \alpha_3 \neq 0$. The null hypothesis is rejected (results not shown) for all rounds.

3.4 Wage gains and general equilibrium effect

In this section we intend to estimate the potential wage gains if misallocation problem is fixed. The existence of over-education and under-education indicates that misallocation of skill exists in Indian labour market. As proposed by Groot (1996), improvement in skill allocation could be achieved by either an adjustment in job skill requirement or an adjustment of skill supply. The supply of skill is

[4] We will incorporate a much richer model allowing interactions and other important covariates in next version.

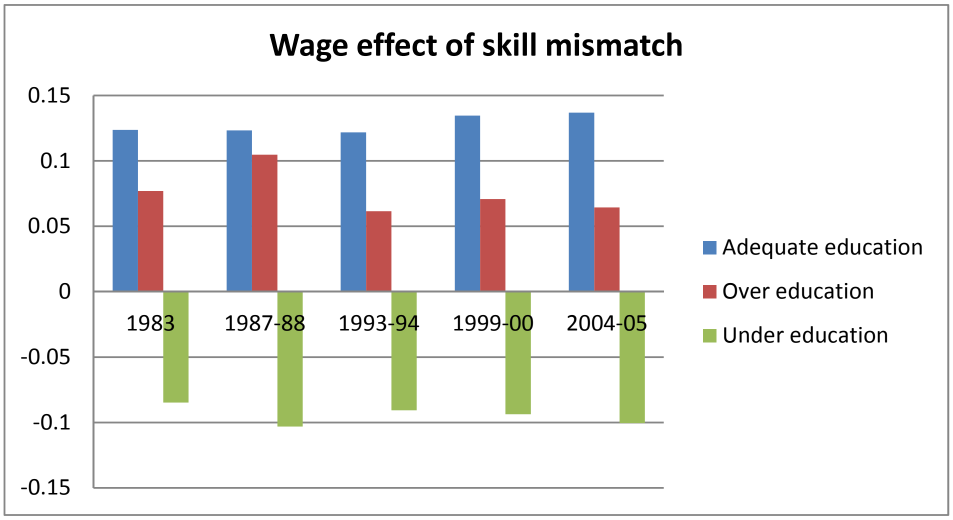


Figure 5: Distribution of education across NSS rounds

very much linked to education system, whereas adjustment is skill requirement is in the domain of labour policy. We will follow Ng (2003) and Groot (1996) to estimate the wage gains and losses associated with skill mismatch. With an adjustment in skill requirements holding supply of skills fixed, the returns to education would be $\alpha_1 S = \alpha_1 S^a = \alpha_1(S^a + S^o - S^u)$ since $S = S^a$ after adjusting the skill requirement. The existing allocation, however, yields different returns: $\alpha_1 S^a + \alpha_2 S^o + \alpha_3 S^u$. The difference between these two expressions will give us the extent of wage gains due to adjustment is hiring policy (skill requirement adjustment). On the other hand, if policies are addressed towards adjusting the supply of over-educated skills, the wage loss will be calculated by $-\alpha_2 S^0$. Similarly, if supply of under-educated workers are reduced to zero, i.e. years of education has been increased to the adequate level, the wage gains would be expressed as $-\alpha_3 S^u$. It should be noted that the expected sign of α_2 is positive whereas expected sign of α_3 is negative.

We also intend to estimate overall general equilibrium effect of skill misallocation following Dougherty and SelowskyReviewed (1973).

4 Conclusion

We examine the extent of skill misallocation in Indian labour market using national level employment survey data. The incidence of over-education is significantly high and varies across occupations. In general, over-education rates are high for blue colour and traditional jobs mainly in informal sectors. The under-education rates are also significantly high among sales, managerial and administrative workers. The returns to over-education are positive and significant though lower than the returns to adequate education level. On the other hand, returns to under-education are negative and significant.

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TABLE A1: Summary statistics

	age	edu years	male	married	rural	hh size	muslim	scst	salaried /regular wage
1983	35.06	2.80	0.72	0.78	0.79	6.02	0.09	0.29	0.16
se	0.04	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00
1987-88	35.27	3.03	0.73	0.79	0.80	5.86	0.09	0.29	0.16
se	0.03	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00
1993-94	35.67	3.66	0.74	0.78	0.78	5.56	0.09	0.29	0.15
se	0.04	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00
1999-00	35.82	4.08	0.69	0.79	0.78	5.73	0.10	0.31	0.15
se	0.04	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00
2004-05	36.26	4.63	0.72	0.78	0.76	5.53	0.10	0.30	0.16
se	0.04	0.02	0.00	0.00	0.00	0.01	0.00	0.00	0.00

TABLE A2: Occupation classification

Occupation code	Occupation description	Group
0-1	Professional, technical and related workers	Occ1
2	Administrative, executive and managerial workers	Occ2
3	Clerical and related workers	Occ3
4	Sales workers	Occ4
5	Service workers	Occ5
6	Farmers, Fishermen, hunters, loggers and related workers	Occ6
7-8-9	Production and related workers, transport equipment operators and labourers	Occ7

TABLE A3: Probit model of over-education

	(1)	(2)	(3)	(4)	(5)
	1983	1987-88	1993-94	1999-00	2004-05
Age	-0.0146***	-0.0176***	-0.0115***	-0.0111***	-0.0147***
	(0.0039)	(0.0036)	(0.0038)	(0.0042)	(0.0041)
Age squared	0.0000	0.0001	-0.0000	-0.0000	0.0001
	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)
SCST	0.3980***	0.4281***	0.3667***	0.3894***	0.3740***
	(0.0235)	(0.0201)	(0.0214)	(0.0207)	(0.0202)
Rural	0.1510***	0.1712***	0.1400***	0.1517***	0.1671***
	(0.0241)	(0.0191)	(0.0203)	(0.0216)	(0.0223)
Muslim	0.0695***	0.0553**	-0.0033	0.0753***	0.0797**
	(0.0260)	(0.0236)	(0.0279)	(0.0285)	(0.0320)
edu_one2	1.1613***	0.9935***	3.1246	2.8180***	2.2284
	(0.2720)	(0.1996)	.	(0.2863)	.
edu_one3	4.0459***	4.0126***	6.2788***	6.2565***	4.4556***
	(0.2338)	(0.1716)	(0.1607)	(0.1305)	(0.2305)
edu_one4	5.7284***	5.4385***	8.1840***	8.2587***	6.4488***
	(0.2343)	(0.1718)	(0.1620)	(0.1284)	(0.2282)
edu_one5	6.3874***	6.1228***	8.5004***	8.6111***	7.5823***
	(0.2364)	(0.1731)	(0.1637)	(0.1255)	(0.2285)
edu_one6	8.0337***	7.7347***	10.3962***	11.0077***	9.5183***
	(0.2418)	(0.1768)	(0.1717)	(0.0811)	(0.2381)
occ_one2	0.7196***	0.6295***	0.7665***	0.8772***	1.3888***
	(0.0581)	(0.0447)	(0.0488)	(0.0629)	(0.0558)
occ_one3	0.5836***	0.6003***	0.8696***	0.7163***	0.1732***
	(0.0420)	(0.0350)	(0.0414)	(0.0552)	(0.0570)
occ_one4	1.9097***	1.9798***	1.2404***	1.5500***	2.0478***
	(0.0611)	(0.0443)	(0.0440)	(0.0790)	(0.0636)
occ_one5	2.8951***	2.7378***	2.6769***	2.8707***	3.3888***
	(0.0852)	(0.0532)	(0.0650)	(0.0990)	(0.0811)
occ_one6	3.7428***	3.6136***	4.0601***	4.6408***	3.6793***
	(0.0590)	(0.0433)	(0.0486)	(0.0982)	(0.0742)
occ_one7	2.7034***	2.7800***	2.6299***	2.7647***	3.3239***
	(0.0577)	(0.0451)	(0.0468)	(0.1019)	(0.0779)
Constant	-7.9187***	-7.5889***	-10.5012***	-11.1000	-10.1345***
	(0.2503)	(0.1876)	(0.1872)	(0.0000)	(0.2494)
N	198552	212998	187544	209648	208989
Pseudo R2	0.6741	0.6631	0.6857	0.6999	0.5922

Standard errors in parentheses
="* p<0.10 ** p<0.05 *** p<0.01"

TABLE A4: Probit model of under-education

	(1)	(2)	(3)	(4)	(5)
	1983	1987-88	1993-94	1999-00	2004-05
Age	0.0132***	0.0022	-0.0003	-0.0049	0.0020
	(0.0039)	(0.0047)	(0.0038)	(0.0043)	(0.0042)
Age squared	-0.0001	0.0000	0.0001	0.0001**	0.0000
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0001)
SCST	-0.2306***	-0.1930***	-0.2320***	-0.2477***	-0.2529***
	(0.0227)	(0.0234)	(0.0199)	(0.0202)	(0.0213)
Rural	-0.1958***	-0.1907***	-0.1737***	-0.1897***	-0.1094***
	(0.0183)	(0.0177)	(0.0179)	(0.0201)	(0.0201)
Muslim	0.1350***	0.1606***	0.1248***	0.1235***	0.1422***
	(0.0216)	(0.0216)	(0.0222)	(0.0263)	(0.0235)
edu_one2	-0.5563***	-0.5104***	-0.4792***	-0.4241***	-0.1694***
	(0.0258)	(0.0264)	(0.0240)	(0.0293)	(0.0222)
edu_one3	-1.8181***	-2.1311***	-1.9537***	-1.9931***	-2.1080***
	(0.0448)	(0.0737)	(0.0412)	(0.0458)	(0.0467)
edu_one4	-2.3570***	-2.2539***	-2.2579***	-2.5215***	-2.6019***
	(0.0444)	(0.0470)	(0.0411)	(0.0437)	(0.0475)
edu_one5	-3.2106***	-3.1561***	-2.7853***	-3.0018***	-2.9469***
	(0.0565)	(0.0616)	(0.0553)	(0.0499)	(0.0500)
edu_one6	-4.3864***	-4.4446***	-4.3902***	-4.9013***	-5.2536***
	(0.1361)	(0.1365)	(0.1098)	(0.2204)	(0.2208)
occ_one2	-0.7765***	-0.7335***	-0.8270***	-0.9291***	-0.7902***
	(0.0790)	(0.0609)	(0.0649)	(0.0530)	(0.0525)
occ_one3	-0.3864***	-0.1825***	-0.4044***	-0.3166***	-0.2938***
	(0.0458)	(0.0404)	(0.0452)	(0.0483)	(0.0487)
occ_one4	-1.3717***	-1.3713***	-1.4458***	-1.6982***	-1.4908***
	(0.0545)	(0.0532)	(0.0536)	(0.0519)	(0.0547)
occ_one5	-2.4326***	-2.5742***	-2.1436***	-2.4047***	-2.2715***
	(0.0636)	(0.0640)	(0.0634)	(0.0606)	(0.0655)
occ_one6	-4.2313***	-4.2210***	-4.0529***	-4.2944***	-4.1486***
	(0.0619)	(0.0713)	(0.0604)	(0.0578)	(0.0598)
occ_one7	-2.5033***	-2.5819***	-2.3017***	-2.4107***	-2.2490***
	(0.0575)	(0.0586)	(0.0569)	(0.0547)	(0.0573)
Constant	1.3485***	1.6396***	1.6935***	2.1111***	1.8908***
	(0.0942)	(0.0913)	(0.0947)	(0.0973)	(0.1026)
N	198552	212998	187544	209648	208989
Pseudo R2	0.4783	0.4743	0.458	0.4836	0.4872

Standard errors in parentheses

="* p<0.10 ** p<0.05 *** p<0.01"

TABLE A5: Effect of education mismatch on returns to education

	(1)	(2)	(3)	(4)	(5)
	1983	1987-88	1993-94	1999-00	2004-05
Adequate edu (yrs)	0.1237***	0.1234***	0.1218***	0.1347***	0.1369***
	(0.0010)	(0.0011)	(0.0011)	(0.0014)	(0.0012)
Over-edu (yrs)	0.0770***	0.1047***	0.0616***	0.0709***	0.0644***
	(0.0027)	(0.0040)	(0.0030)	(0.0027)	(0.0034)
Under-edu (yrs)	-0.0848***	-0.1031***	-0.0907***	-0.0937***	-0.1005***
	(0.0066)	(0.0090)	(0.0064)	(0.0083)	(0.0076)
Age	0.0421***	0.0644***	0.0451***	0.0431***	0.0454***
	(0.0017)	(0.0024)	(0.0018)	(0.0015)	(0.0017)
Age squared	-0.0005***	-0.0007***	-0.0005***	-0.0004***	-0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
SCST	-0.0238***	-0.0113	-0.0355***	-0.0231***	-0.0365***
	(0.0072)	(0.0103)	(0.0077)	(0.0066)	(0.0069)
Rural	-0.0367***	-0.0502***	0.0983***	0.1292***	0.2076***
	(0.0074)	(0.0108)	(0.0082)	(0.0092)	(0.0087)
Muslim	0.0183*	-0.0140	-0.0213*	-0.0124	-0.0252**
	(0.0095)	(0.0134)	(0.0125)	(0.0098)	(0.0107)
Constant	0.8773***	0.4578***	0.8869***	0.9646***	0.8799***
	(0.0286)	(0.0421)	(0.0326)	(0.0274)	(0.0313)
N	69300	43683	69144	73526	71451
R-sq	0.423	0.447	0.301	0.446	0.435

Standard errors in parentheses
="* p<0.10 ** p<0.05 *** p<0.01"

Test for existence of skill mismatch in wage regression equation

1983

(1) - over_ed_yr + under_ed_yr = 0
(2) - mean_ed2 + under_ed_yr = 0
F(2, 69291) = 554.44
Prob > F = 0.0000

1987-88

(1) - over_ed_yr + under_ed_yr = 0
(2) - mean_ed2 + under_ed_yr = 0
F(2, 43674) = 307.13
Prob > F = 0.0000

1993-94

(1) - over_ed_yr + under_ed_yr = 0
(2) - mean_ed2 + under_ed_yr = 0
F(2, 69135) = 647.13
Prob > F = 0.0000

1999-2000

(1) - over_ed_yr + under_ed_yr = 0
(2) - mean_ed2 + under_ed_yr = 0
F(2, 73517) = 478.56
Prob > F = 0.0000

2004-05

(1) - over_ed_yr + under_ed_yr = 0
(2) - mean_ed2 + under_ed_yr = 0
F(2, 71442) = 618.93
Prob > F = 0.0000