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Article

Return to Skills in India: The Role of Digital Access and Usage

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Abstract

This article analyses the quality of labour force in India using the data from India's Citizen Environment and Consumer Economy (ICE) 360° survey (2016), which provides a view on how Indians earn, spend, save, invest, live, think, access amenities and public goods and consume. The approach adopted here provides an alternative perspective on the quality of labour force, which depends on skill levels, education and technology. The analysis reveals that Indian labour markets depicts a clear dichotomy between higher skill levels being dominated largely by the high-skilled workers and the manual jobs with lower skill levels for the low-skilled workers. Technology and digital usage has further accentuated this earnings differential. Also, higher skill levels in India tend to have both higher average earning and education levels compared to their lower skill counterparts, leading to widening the earning inequality.Further, this analysis provides important insights into the low skill levels of the vast Indian labour force, which would require re-qualification and re-specialisation of the labour force in order to compete in fast-changing globalised India. Thus, it becomes critical for Indian policymakers to relook the skill formation and education system to be able to swiftly and effectively respond to constantly evolving skill demand in the local, national and global market.

Keywords

Skill, earning, digital, education, labour market

Background

Estimates on returns to education and skills learnt while on-the-job are a useful indicator to know the reward for education and skill in the labour market. Studies and estimates on returns to skills—normally

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focus on the ability and skill levels of pre-labour market or skills acquired in the education systems, such as mathematical and language skills. Moreover, skills are acquired through learning-by-doing. Many skills are learnt by on-the-job training, combining production, learning-by-doing and mentoring by more experienced colleagues. Given the difficulty in measuring skills acquired through on-the-job training, often experience has been used as a proxy for skill levels in the returns to education estimates. While experience is usually used as a skill proxy, this article adopts an alternative approach of occupation-based skills. These task-based skill measures are included as one of the arguments in wage regressions, and the resulting coefficients is interpreted as returns to skills (Bacolod & Blum, 2010; Ingram & Neumann, 2006).

Another skill that has come up in a big way is digital skills. Digital technologies have spread rapidly across the world. Digital dividends are the broader development that benefits from using these technologies, including better growth (World Development Report, 2016). In many instances, digital technologies have boosted growth, expanded opportunities and improved service delivery. However, adapting workers' skills to the demands of the new economy is a challenge for the adult unskilled workers. On the other hand, responding to the fast-changing information and communication technology (ICT) and their adoption requires multiplicity of skills, namely higher-order cognitive, socio-emotional and technical skills. The ICT revolution is in its second generation or beyond. However, studies rarely focus on to what extent digital technologies benefit in the earning of workers, in other words, the returns to ICT skills.[1]

This article is an attempt to estimate the return to skills, including ICT skills. In this endeavour, skill levels are classified into four groups adopting the International Standard Classification of Occupations (ISCO).[2] The article uses the data collected by the People Research on India's Consumer Economy (PRICE). The PRICE provides ICE 360° survey (2016) data on occupation by details up to 71 categories, which are regrouped as 4 skill levels following ISCO-08 of the International Labour Organisation (ILO) (2012). Digital technologies include, as noted by the World Development Report (2016), the Internet, mobile phones and all the other tools to collect, store, analyse and share information digitally. In case of ICT skills, PRICE has collected information on various access and frequency of the use of ICT in all spheres of life. This article makes an attempt to use this information as ICT skills are developed further through learning-by-doing. This is facilitated by Internet access and its use. The article adopts the standard Mincerian earnings function in estimating the returns to skills. The log of annual earnings is regressed on skill levels, schooling, experience, ICT access besides a set of control on family and socio-economic factors. To the best of our knowledge, this is the first study that quantifies the effect of market and ICT skills on earning in India.

With this backdrop, the rest of the article is organised as follows: review of the earlier selected studies is given in Section II. Section III explains data, variables and methodology adopted in the article. The subsequent section discusses the descriptive statistics and results of the Mincer equation. The last section concludes with policy implications.

Review of Earlier Studies

Studies and estimates on returns to skills—more often focus on the ability and skill levels of the pre-labour market or skills acquired in the education systems, such as mathematical and language skills. It is because skills are difficult to observe, hence years of schooling have been used as a proxy for skill levels in returns to education estimates. With the availability of better data on national and international achievement surveys, the studies and estimates are available on the returns to skills in the education

sector. Returns to skills in the labour market use occupation-specific task measures as one of the arguments in wage regressions, and the resulting coefficients is interpreted as returns to skills (Ingram & Neumann, 2006).[3] They find that increases in the return to skill as measured by years of education and variance of wage income within skill categories. They estimate the return to various dimensions of skill, including formal education, that mathematical ability or motor skills account for a larger portion of the increased dispersion in income between the college educated and their counterparts.

Extending this, Yamaguchi (2012) makes a distinction of job's tasks into motor and cognitive skills using data from Dictionary of Occupational Titles (DOT).[4] Using this, he finds that returns to skills not only increase but also grow faster in occupations with more complex tasks. This dichotomy between two distinct skill groups was further examined by Acemoglu and Autor (2011). They show that workers with these different skills perform two different and imperfectly substitutable tasks or produce two imperfectly substitutable goods. They examine how these skills with technological change have led to polarisation and earning inequality.

In another stream of research on the extension of human capital theory following Becker (1962), Neal (1995) distinguished between the characteristics of general and firm specific human capital. He suggested that some knowledge acquired by workers while on the job is specific to the industries to which they are employed, differently from general human capital. Hence, workers' skills may have low transferability. Using the displacement survey, Neal (1995) finds that human capital is industry specific, while Kambourov and Manovskii (2009) find it occupation specific. However, Sullivan (2010) finds that human capital can be both industry and occupation specific. He finds that some occupations allow for more accumulation of industry-specific skills, while others for more occupation-specific skills. In few other occupations such as professional employment, occupation- and industry-specific; human capital is found to be the prominent determinant of wages.

Using the recent development in the data available on tasks such as DOT, a proxy for human capital, Poletaev and Robinson (2008) categorise jobs based on tasks and skill requirements and find that human capital is not specific to industry or occupation, but to some basic skills that can be used in various contexts. This article somewhat follows this approach but is different in terms of the skill categorisation, which involve four skill levels following the ISCO-08 by adopting ILO (2012) (details in the next section). It can be noted that studies hardly prevail in India on the occupational skills and their returns in the labour market. This article makes an attempt to estimate the returns to skills in the labour market with a focus on the role of ICT skills.

Digital flows across countries contribute to economic development. These flows have high research and development component and intellectual property and enable exchange of ideas, thoughts and expressions, facilitated by the digital platforms, for instance, the courses offered through digital platforms such as global collaborative design of a 3D printing artefact, tele-medicine by expert doctors and robotics programming done by Artificial Intelligence programmers. It is now a borderless world, and also the online world is becoming a bigger part of everything we do. Hence, these ICT skills are emerging pivotal in the job market. However, empirical evidence on how the labour market rewards ICT skills or what is the influence of these skills on earnings is rare. The main reasons are twofold: unavailability of data that measure ICT skills consistently either within or across countries, and the difficulty in delineating individuals' level of ICT skills from their general ability.

Falck et al. (2016) conducted the first systematic assessment of the wage returns to ICT skills by identifying returns to ICT skills based on differences in ICT skills and wages among age cohorts within countries. Using the unique data on the ICT skills tested in 19 countries, they found that technologically induced variation in broadband Internet availability gives rise to variation in ICT skills across countries and German municipalities. They found that a one-standard-deviation increase in ICT skills raises

earnings by about 25 per cent. Exogenous broadband availability cannot explain numeracy or literacy skills, suggesting that estimated returns are unaffected by the general ability. One mechanism driving positive returns is the selection of occupations with high abstract task content. In terms of magnitude, their estimate implies that if an average worker in the United States increased his/her ICT skills to the level of an average worker in Japan (i.e., the best-performing country in the skill assessment), his/her wages would increase by about 8 per cent; this is close to the well-identified estimates on the returns to one additional year of schooling in developed countries. In Germany, estimated returns to ICT skills are larger at 31 per cent.

Blanco and Florencia (2010) attempted to evaluate the impact of ICT skills on the labour market of two Latin-American cities: Buenos Aires and Bogota. Using cross-sectional data from an experiment that randomly assigned the ICT skills line in the resume, they assess the returns to ICT skills.[5] By fitting a binary choice model to identify differences in callbacks depending on ICT skills, they analyse how gender, place of residence and occupational categories interact with ICT skills. They find that ICT skills could increase the probabilities of inclusion in the labour market for those with some level of disadvantage. Their findings suggest that having ICT skills in the resume can increase the probability of receiving a call back by around 1 per cent or more. This effect is much stronger in Bogota than in Buenos Aires, which suggests that ICT could be acting differently depending on the characteristics of the labour market.

But some other studies find contrasting results. Using data from the 1997 Skills Survey of the Employed British Workforce, Borghans and Weel (2004) compared computer skills with writing and math skills and tested whether wages vary with computer skills, given the specific use that is made of computers. They found that computer skills are not that valuable as the increase in computer use, irrespective of either by higher skilled workers or general adult workers. Their regression results show that the ability to write documents and carry out mathematical analysis yields significant labour-market returns, but not the ability to effectively use a computer. Their estimates suggest that the basic skills of writing and math skills yield higher wages than that of computer skills.

While examining the link between ICT and the demand for high-skilled labour in Spain, Castillo et al. (2008) analysed the determinants of labour productivity of individuals that have taken higher education programmes online to test how occupational skill requirements and the degree of ICT adoption by the industry matches skills of online students. Using a database of the degree students from the Universitat Oberta de Catalunya, their estimates of Mincer equations show that: (a) schooling is not a significant variable to explain wage differentials; (b) experience, expressed in terms productivity, is the proximate determinant of wages and (c) ICT skills have a positive and significant effect on wage levels.

In the Indian context, many studies estimate returns to education at the national level using the National Sample Survey Office data (Dutta, 2006; Duraisamy, 2002), India Human Development Survey (IHDS) of 1993 (Unni, 2001), National Data Survey on Savings Patterns of India (Bhandari & Bordoloi, 2006) and IHDS-I survey data (Agrawal, 2011; Azam, Chin & Prakash, 2011; Rani, 2013). However, hardly studies investigate the labour-market returns to either skills or ICT skills. This article makes an effort to fill this gap. It investigates the labour-market returns to skills where ICT skills have been emerged as one of the prominent factors by controlling different educational levels and age cohorts, besides other socio-economic factors. To the best of our knowledge, this is the first study that quantifies the effect of market and ICT skills in India.

Data, Variables and Methodology

The article uses possibly unique survey data, which provides a view on how Indians earn, spend, save, invest, live, think, access amenities and public goods and consume. It is distinct in its ability to establish

a linkage between economic and other policies and the state of well-being of various strata of people. ICE 360° survey (2016) covers a detailed survey of 60,360 households and 250,720 individuals. Geographically, the sample has been drawn from across 216 districts, 1217 villages and 487 towns spread across 25 major states. The ICE 360° survey (2016) covers multi-dimensional aspects of the economy, society and polity and goes beyond incomes and savings. It also takes a deeper look at the economic and social well-being of Indian households, provides normative measures of social, political and financial inclusion, degree of access to public goods and infrastructure and welfare measures of the government. This article uses data primarily from the four broad areas, namely sources of income, employment, digital use and demographic profile of earners.

The survey covers 250,720 individuals. Individuals who have reported their primary occupation have been considered for defining skills, that is, 94,192, which constitute around 37.6 per cent of the total sample. However, the eligible working-age sample in the age group of 15–65 years excluding the students and people not fit to work constitute 62.4 per cent (N = 156514) of the total sample.

Earnings

ICE 360° survey (2016) collected information on the sources of income from the six broad categories, namely (a) agriculture and allied activities: self-employed people who operate their own farm, (b) self employed (employer) in non-farm activities, (c) regular salary/wage, (d) casual wage labour Agriculture: paid on a daily basis or by piece rate, (e) casual wage labour non-agriculture: paid on a daily basis or by piece rate and (f) other income: not classified elsewhere. The earnings from the first five sources (excluding other income) are taken for analysis. These five categories are reconstituted from 66 subcategories of primary occupation of reported members of the households. Adopting the ISCO-08 classification, these 66 categories have been classified into four skill levels.[6] The ICE 360° survey (2016) reports component wise and total annual household income earned from all sources. However, the challenge lies in attributing the primary occupation of members (i.e., the jobs and skills as defined by the ILO, 2012) with the corresponding component of income so as to arrive at the earnings of individuals. One major difficulty faced here is more than two individuals with the same primary occupation in a household reporting the same income. This is tackled by distributing the income equally across members reporting similar primary occupation. Alternatively, such members reporting the same primary occupation could have been dropped. In order to avoid the information loss, we have followed the method of equal distribution of income across members reporting the similar occupation.

Skill Levels

Skill is defined as the ability to carry out tasks and duties of a given job.[7] It uses skills as derived from jobs and tasks. Tasks or primary occupation/principle activity status is used as proxies for unobserved worker skills. For the purposes of ISCO-08, two dimensions of skills are used to arrange occupation into groups, namely skill level and skill specialisation. Skill level is defined as a function of the complexity and range of tasks and duties to be performed in an occupation. A skill level is measured operationally by considering one or more of: (a) the nature of work performed in an occupation in relation to the characteristic tasks and duties defined for each ISCO-08 of skill level; (b) the level of formal education defined in terms of the International Standard Classification of Education (ISCED-97) referred for competent performance of the tasks and duties involved and (c) the amount of informal on-the-job training and or previous experiences in a related occupation required for competent performance of these tasks and duties.

Tasks and skills are treated the same in this article though there exists close relationship among skills, tasks and occupations. In the task information at the individual level, such as the task-based approach, we use the occupation level data contained in the ICE Survey. Data on tasks performed by workers in each occupation have recently become available, making room for an emerging literature on tasks. As noted earlier, such type of work is rare in India. In this context, we use the Mincerian approach to study the role of tasks performed by workers, classified into four skill levels as a proxy for human capital accumulation.

The sources of earnings have been taken from primary occupation, based on specific skills. Extracting this information, skill levels are classified using the data on primary occupation. The formulation used for the design and construction of ISCO is based on two main concepts, that is, *job* and *skills*. A job is defined as "set of tasks and duties performed or meant to be performed by one person including for an employer or in self-employment". Occupation refers to the kind of work performed in a job. The concept of occupation is defined as "set of jobs whose main tasks and duties are characterised by a degree of similarity". A person may be associated with an occupation through a main job currently held, a second job in the future job or a job previously held.

Within each major group, occupations are arranged into unit groups, minor groups and sub-major groups, primarily on the basis of skill specialisation. The definitions of skill level are as follows: (a) skill level 1 involves the performance of simple and routine physical or manual tasks. They involve tasks that require physical strength/endurance. (b) Skill level 2 involves the performance of tasks such as operating machinery and electronic equipment. It also requires the ability to read information such as safety and instructions. (c) Skill level 3 typically involves the performance of complex technical and practical tasks that require an extensive body of factual, technical and procedural knowledge in a specialised field. It also includes a person to make written records of work completed, make simple calculations and good interpersonal communication skills and (d) skill level 4 involves the performance of tasks that require complex problem-solving, decision-making and creativity based on an extensive body of theoretical and factual knowledge in a specialised field. It requires the ability to understand complex written material and communicate complex ideas in media such as books, images, performances, reports and oral presentations. Task complexity progresses along with higher levels of skills. The same has been adopted in this article. A similar approach was adopted by Shukla (2005) in developing the first India Science Report focussing on the Human Resources in Science and Technology (HRST). This study was an attempt to study the distribution of HRST workforce by the type of occupation (ISCO-88) with different levels of education following the International Standard Classification of Education (ISCED).

Education Levels

For this article, the education levels consist of four broad levels of education such as no education, elementary or basic levels of education, secondary and higher education (details in Table 1).

ICT Skills

Access to the Internet and its usage enable the working population to perform basic functions. The link between ICT and the demand for high-skilled labour is because the introduction of digital technologies alters the skill requirements of occupations in three main ways (Spitz, 2003): (a) it substitutes repetitive manual and repetitive cognitive activities, (b) complementary to analytic and interactive activities and (c) increases the requirement for computing skills. However, currently, there is no commonly adopted definition of ICT skills, but efforts are ongoing to characterise the various types of ICT skills, for

example, through the European e-Skills Forum (2004). The three categories of ICT competencies are distinguished: (a) ICT specialists: who have the ability to develop, operate and maintain ICT systems. In this case, ICTs constitute the main part of their job; they develop and put in place the ICT tools for others. (b) Advanced users: Competent users of advanced, and often sector-specific, software tools. Here, ICTs are not the main job but a tool and (c) basic users: competent users of generic tools (e.g., MS Office tools) needed for the information society, e-government and working life. Here too, ICTs are a tool and not the main job (OECD, 2016). In this article, ICT personnel are defined as those who have access to the Internet and also use the Internet for either of the following purposes, for example, email, social networking, Internet banking, shopping, accessing information related to work, entertainment, tours and travels and others.

Labour Market Participation

Based on the principal activity status, we created a dummy variable based on the information on working category such as self-employed, salaried and casual labour, unpaid family workers and not working because of unemployment. The categories such as students and unfit for work are classified as not working, and hence they are not covered in the analysis. This classification is similar to the framework suggested in the *Manual on the Measurement of Human Resources* devoted to Science and Technology or "Canberra Manual" (OECD, 1995, p.49). Further, this working population covers the age group of 15–65 years.

Demographic Profile

This article uses the information on demographic characteristics such as age, gender, socio-religious groups, location, household size and house type. The variables selected for the present analysis is presented with description in Table 1.

Table 1. Determinants of Earnings: Variables and Notations

Broad Group	Type of Variables	Explanation
Education	Categorical variable	No education; Elementary: if attained between 1 to 8 years of education; Secondary: if having 9 to 12 years of education; Higher: if having above 12 years of education
Age groups	Categorical variable	15–25, 26–35, 36–45, 46–55, 56–65
Experience	Continuous variable	*Difference between current age and years of education.*
Skill levels	Categorical variable	Skill levels **1**, 2, 3 & 4
ICT skills access and use	Categorical variable	User, **Non-user**
Internet use frequency	Categorical variable	**None**, Regular, Occasional, Rare
Location	Categorical variable	**Rural**; Urban
Gender	Categorical variable	Male; **Female**
House type	Categorical variable	**Kutcha**, Semi-Pucca, Pucca, Others
Number of living rooms	Continuous variable	——
Household size	Discrete variable	——
Socio-religious group	Categorical variable	**Hindu (SC/ST)**, Hindu (OBC), Hindu (Upper Caste), Muslim (SC/ST/OBC), Muslim (Upper Caste), Other Minorities

Source: The authors.
Note: Reference category in bold letters.

Methodology: Mincer Earnings Function

In the human capital model, wages reflect the worker productivity, which depends on the human capital stock. Within this framework, the Mincerian equation presents log wages as a function of skill, schooling and experience. This involves fitting a log-earning function using skill levels, years of schooling, years of labour market experience and its square as independent variables (see Mincer, 1974). Besides these basic arguments, the article attempts to find the influence of access to ICT and the frequency of its use. Also, a set of socio-economic factors have been used as control variables. Hence, the semi-log wage equation takes the form of

$$\ln W_i = \beta_0 + \beta_1 S_i + \beta_2 Y_i + \beta_3 E_i + \beta_4 E^2{}_i + \beta_5 ICT_i + \beta_6 ICTF_i + \delta x_i + \varepsilon_i \quad (1)$$

where S_i is skill levels, Y_i is years of schooling and E_i is experience. $E^2{}_i$ is the experience squared, ICT_i refers to the Internet access, a dummy variable, $ICTF_i$ is the frequency of ICT use, x_i is a vector of socio-economic variables, family controls, all of which are exogenous in the population. ε is a disturbance term capturing unobserved characteristics, $\varepsilon_i \sim N(0, \sigma^2\varepsilon)$. The explanatory variables and their descriptions are explained in Table 1. In this function, the β_1 and β_2 coefficients on skill levels and years of schooling can be interpreted as the average rate of return (or the percentage change in wages) to the subsequent skill levels and an additional level of schooling. The experience variable is incorporated in the equation since an individual with higher experience in a job is likely to earn more. The experience squared term captures the possibility of a non-linear relationship between earnings and experience.

A well-known difficulty in estimating this function is the selection bias and endogenity and are ignored. We apply simple Ordinary Least Squares (OLS) in estimating the earning equations.

Descriptive Statistics

Table 2 reports the share of sample population by its demographic profile and key determinants of earnings equation, namely skill levels, education and age cohorts. The distribution of these three key determinants across location and socio-religious groups is further examined. Two-thirds of the population reside in rural India. Almost 89 per cent of the population belong to Hindus. With regard to skill levels, an alarming share of 56 per cent of the sample population owes skill level 2, followed by a 31 per cent share at the basic or rudimentary skill level 1. Skill levels 1 and 2 together add up to 87 per cent of the working population and are indeed distressing share of the working population possessing only rudimentary skills. On the contrary, only 3 per cent of the sample population possess higher levels of skills, that is, Skill level 4. The pattern across locations indicates an edge over urban areas towards higher skill levels of 3 and 4, as in the case of educational attainment. Such an advantage can be further noticed among the Hindu upper-caste population at the same skill levels (Table 2).

Overall, 30 per cent of the eligible to work population has remained illiterate with no levels of education. Another 22 per cent of the population attained schooling between 1 and 5 years. 15 per cent of the working population had 6–8 years of schooling, followed by one-fourth of the population having higher secondary education. Mere 9 per cent of the population has graduation and above levels of education. However, these national scenarios do not hold across locations and socio-religious groups.

Across locations, the educational attainment of the population depicts a quite different pattern except at the middle level of education. After the middle levels of education, the variations in educational

Table 2. Demographic Profile of Eligible to Work Age Group* Population (in %)

	Location		Hindu			Muslim			
	Rural	Urban	SC/ST	OBC	Upper Caste	SC/ST/ OBC	Upper Caste	Other Minorities	All
				Skill Level					
Skill level 1	30.9	29.8	39.4	26.9	19.1	38.5	34.3	26.8	30.6
Skill level 2	60.6	45.0	52.0	59.4	58.7	45.6	49.4	56.2	55.6
Skill level 3	6.7	20.5	6.7	11.0	17.8	12.9	14.0	13.6	11.2
Skill level 4	1.8	4.7	1.8	2.6	4.4	2.9	2.4	3.4	2.7
				Education					
No education	35.2	19.4	38.0	28.3	14.2	46.6	34.2	23.9	29.9
Up to primary	22.9	19.7	23.3	22.0	18.8	21.4	26.3	18.3	21.8
Middle	15.5	14.0	15.2	14.8	15.5	14.8	14.0	14.3	15.0
Higher secondary	20.6	32.6	17.9	26.1	36.6	12.2	18.6	34.4	24.6
Graduate and above	5.8	14.4	5.6	8.8	14.9	5.0	7.0	9.2	8.6
				Age Cohort					
15–35	50.5	49.9	53.0	49.1	45.5	58.5	52.9	47.4	50.3
36–45	22.2	25.6	21.8	24.1	24.8	20.4	24.4	25.1	23.4
46–55	15.5	16.0	15.1	16.2	17.3	11.8	13.3	17.1	15.7
56-65	11.7	8.5	10.1	10.6	12.4	9.4	9.5	10.5	10.6
All	67.9	32.1	31.8	36.8	17.2	5.6	4.7	3.9	100

Source: India's Citizen Environment and Consumer Economy 360° Survey (2016).
Note: * Age group corresponds to the age group of 15–65 years; eligible to work population as it excludes students not fit to work, children below the age of 15 years and old population above the age of 65 years.

attainment between urban and rural areas are widening with an urban edge over higher secondary and graduate and above levels of education. Across the socio-religious categories, the share of graduates and above among the Hindus (upper caste) is the highest and shows an upward trend as they move up the higher levels of education. On the contrary, SC/ST population, irrespective of the religion, constitutes the vulnerable group in terms of educational attainment. ICE data also confirms the young India; with 50 per cent of the population belonging to the young age group of 15–35 years, followed by another 23 per cent of the middle-age group of 36–45 years. Yet another 25 per cent of the population is in above 45 years age group. The pattern more or less holds well across location and socio-religious groups.

Socio-Religious Factors

The article looks at a number of socio-economic factors that determine the earnings of individuals. The variables such as house type and number of living rooms are included so as to capture the economic wealth of the population. The household type and the household size can indicate the social and demographical aspects of the population. Yet another important variable that is included here is the socio-religious groups. Figure 1A exhibits the disparity in earnings across four skill levels by socio-religious categories. Other minorities and Hindu upper-caste groups have an edge over the socially and religiously deprived Muslim population in terms of skill levels. The inter skill level disparity is also higher between these two groups. Muslims are evidently at a disadvantaged position in earnings compared to even Hindu SC/ST across the four skill levels.

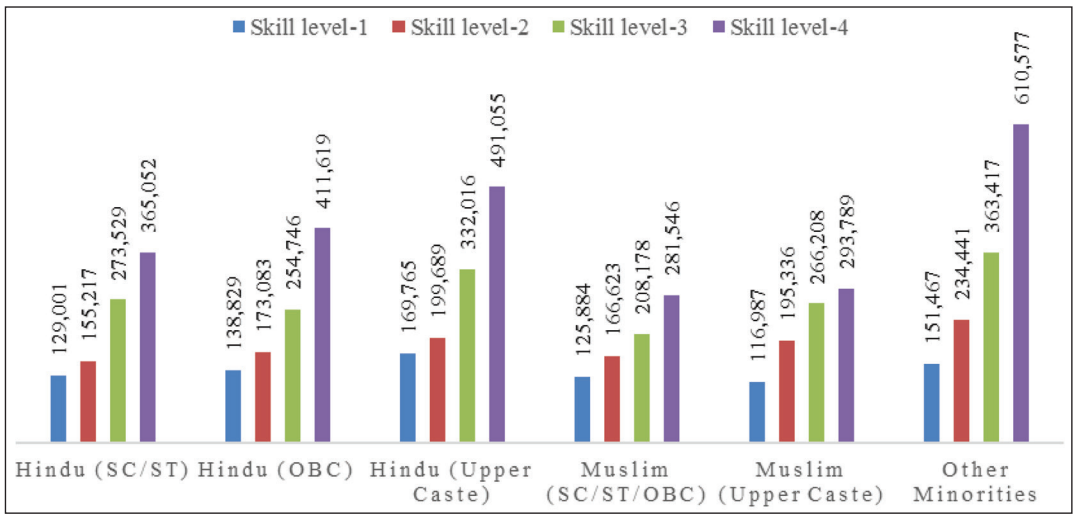

Figure 1A. Mean Earning by Skill Levels across Socio-religious Groups of the Eligible Working Population*

Source: India's Citizen Environment and Consumer Economy 360° Survey (2016).
Note: *Of the age group of 15–65 years

The pattern of distribution of earnings by educational attainments resembles in some cases like earnings of other minorities and Hindu upper caste with higher education at an edge over others. But the variation between the two groups is quite substantial, unlike earnings across skill distribution. Interestingly, Muslim upper caste and Hindu SC/ST workforce fare at almost the same level of earnings. But, in terms of the deprivation, Muslims are socially deprived groups and Hindu OBCs earn the lowest across levels of education (Figure 1B).

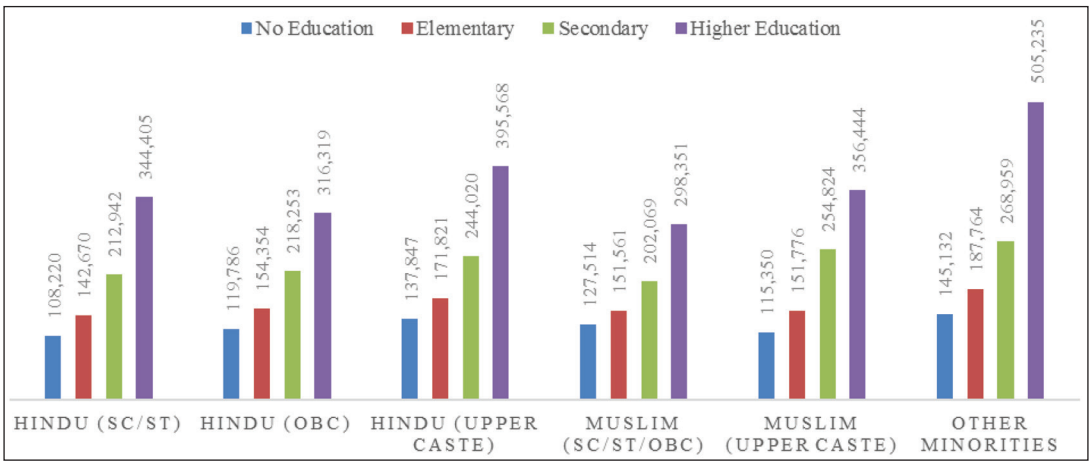

Figure 1B. Mean Earning by Education Levels across Socio-religious Groups of the Eligible Working Population*

Source: India's Citizen Environment and Consumer Economy 360° Survey (2016).
Note: *of the age group of 15–65 years

Figures 1A and 1B clearly indicate the socio-religious advantages of other minorities in terms of both skill and education levels. Hence, we make an attempt to estimate wage equations by these socio-religious groups.

Age-Skills-Earnings Profile

Skill, education and employment are the key mechanisms which influence earnings (Figure 2).

Age indicates the experience of individuals and hence it plays a vital role in explaining the earnings of individuals. However, at the basic skill levels, that is, at skill levels 1 and 2, earnings across different age groups increase, but the rate of increase is found to be marginal. It is important to note that earning at skill levels 3 and 4 starts at the age group of 21–25 years, implying the minimum education required to accomplish the skill requirements at these skill levels, which are of a higher order. Hence, resulting in higher earnings is indicated by the wider gaps between skill levels 1 and 2 versus skill levels 3 and 4. This in combination with Table 2 would indicate a major share (86% of population) owe to skill levels 1 and 2 and hence earn very less compared to higher skill levels of skill levels 3 and 4. This is a serious concern for the young India, which is aspiring to become a Skill India, Stand India in the very near future. It, thus, becomes critical for India to reinvent their education systems (including Technical and Vocational Education and [Training TVET]) to be able to swiftly and effectively respond to the constantly evolving skills demand. Further, this dichotomy between the two broad distinct skill groups was noted by Acemoglu and Autor (2011). The earning distribution by skill levels also indicates the polarisation and earning inequality and is a serious concern for the young India. A similar concern is raised in a recent article by Vashisht and Dubey (2019) that technology could be a major factor behind the evolution of non-routine cognitive task intensities.

Age-Education-Earnings Profile

Conventionally, education has been used as a proxy to measure skill, as skill is harder to quantify. Earnings by levels of education are illustrated with the age-earnings profiles of the population in the age group of

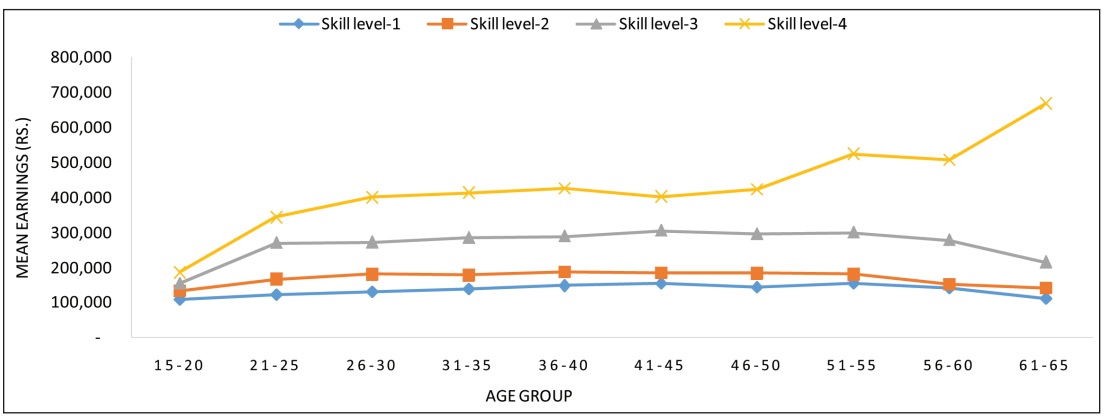

Figure 2. Mean Annual Earnings of Eligible Working Population by Skill Levels across Age Groups

Source: India's Citizen Environment and Consumer Economy 360° Survey (2016).

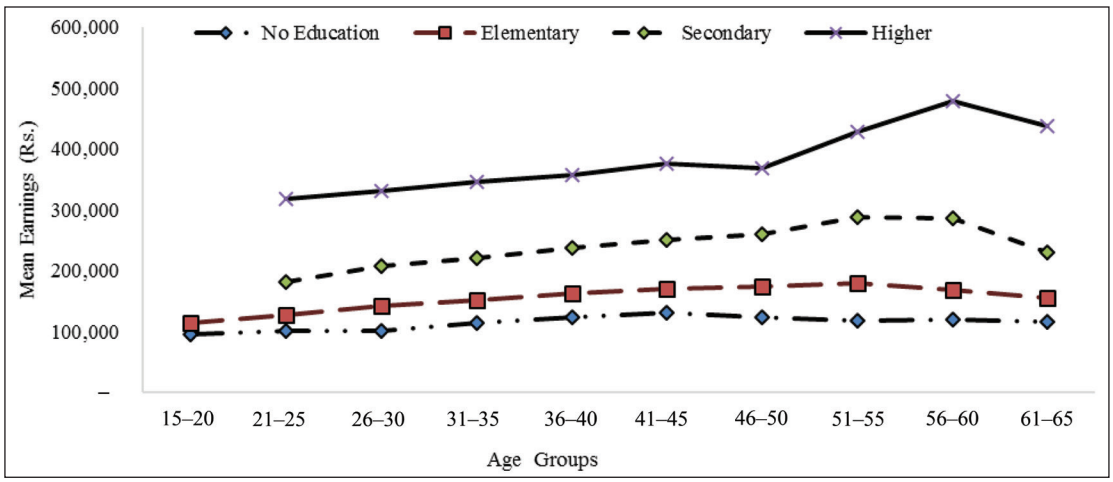

Figure 3. Mean Annual Earnings of Eligible Working Population by Education Levels across Age Groups

Source: India's Citizen Environment and Consumer Economy 360° Survey (2016).

15–65 years. As expected, there is a clear positive relationship between levels of education and earning as experience, that is, on-the-job training, increases over years. This relationship is being strengthened while moving along in the educational ladder (see Figure 3). The general shape in both Figure 2 and Figure 3 is in accordance with the human capital theory. The slope of the education-earnings relationship provides a measure of the private rate of return to education. The slope of the curve, and thus returns to education, *increases* with education level as experienced since the 1990s in India. Additional education has a much stronger proportionate impact on earnings at higher than at lower educational levels.

With this background on the key relationship between earnings and skill level, education, age cohorts and also the socio-religious groups in the Indian context, we proceed with the estimation of the Mincerian earning functions.

Results and Discussion

The estimated OLS results are reported in Table 3 at the annexure. Nine wage equations are estimated representing the rural, urban, all India besides six socio-religious categories of the population. The preliminary analysis such as correlation coefficient matrix indicates that there is no multicollinearity among the selected variables (Annexure Table A3). Also, the dependent variable logearn follows normal distribution as can be seen from the histogram (Annexure Figures A1). This is further examined by Kernel density (kdensity) plots, as it has the advantage of being smooth and independent of the choice of origin, unlike histograms. The kdensity plot also indicates that the dependent variable logearn appears normal (Annexure Figure A2). With these diagnostic tests, we proceed to estimate the log earnings function applying the OLS method. Post estimation checks have also been carried out by estimating the robust standard errors for addressing heteroscedasticity, multicollinearity test and Ramsey test to check whether there is any omitted variable bias. The variance inflation factor test statistic is reported in Table 3.

Table 3. Results of OLS Mincer Earnings Equations: Dependent Variable–log Earnings

Expla Var.	Category	RURAL	URBAN	ALL	H_SCST	H_OBC	H_UC	M_SDC	M_UC	OMINO
Skill_Level	Skill level 2	0.095***	0.090***	0.087***	0.065***	0.084***	0.070***	0.170***	0.192***	0.143***
Skill_Lev = 0		(0.011)	(0.014)	(0.009)	(0.015)	(0.014)	(0.020)	(0.030)	(0.042)	(0.038)
Ref. category	Skill level 3	0.291***	0.148***	0.214***	0.233***	0.212***	0.189***	0.222***	0.264***	0.251***
		(0.018)	(0.016)	(0.012)	(0.027)	(0.020)	(0.023)	(0.038)	(0.043)	(0.047)
	Skill level 4	0.534***	0.341***	0.440***	0.405***	0.503***	0.418***	0.488***	0.182*	0.519***
		(0.041)	(0.025)	(0.023)	(0.048)	(0.042)	(0.038)	(0.108)	(0.084)	(0.099)
Education	Elementary	0.129***	0.114***	0.128***	0.160***	0.082***	0.093**	0.131***	0.162***	0.205***
No Edun		(0.013)	(0.018)	(0.010)	(0.018)	(0.018)	(0.029)	(0.032)	(0.046)	(0.053)
Ref.	Secondary	0.284***	0.321***	0.299***	0.379***	0.241***	0.244***	0.202***	0.389***	0.361***
Category		(0.016)	(0.020)	(0.013)	(0.023)	(0.021)	(0.032)	(0.043)	(0.055)	(0.054)
	Higher	0.348***	0.477***	0.407***	0.463***	0.328***	0.373***	0.242*	0.621***	0.550***
		(0.027)	(0.024)	(0.018)	(0.038)	(0.029)	(0.038)	(0.099)	(0.069)	(0.074)
Age Cohort	36–45	0.126***	0.133***	0.130***	0.109***	0.154***	0.139***	0.098*	0.063	0.141**
15–35 ref.		(0.015)	(0.016)	(0.011)	(0.022)	(0.019)	(0.022)	(0.045)	(0.051)	(0.045)
Category	46–55	0.096***	0.147***	0.115***	0.062	0.134***	0.196***	0.043	0.129	0.070
		(0.026)	(0.029)	(0.020)	(0.041)	(0.032)	(0.038)	(0.081)	(0.082)	(0.081)
	56–65	0.026	0.126*	0.060	0.043	0.043	0.251***	–0.183	0.011	–0.118
		(0.043)	(0.049)	(0.033)	(0.066)	(0.056)	(0.060)	(0.126)	(0.143)	(0.133)
	Expsquare	–0.000*	–0.000*	–0.000***	–0.000	–0.000*	–0.000***	0.000	–0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Gender	0.193***	0.054***	0.153***	0.155***	0.134***	0.126***	0.159***	0.287***	0.214***
		(0.014)	(0.016)	(0.011)	(0.019)	(0.017)	(0.023)	(0.040)	(0.067)	(0.050)
	Int_Acc_D	0.355***	0.427***	0.378***	0.711***	0.334***	0.330***	0.044	–0.127	0.401***
		(0.047)	(0.038)	(0.034)	(0.107)	(0.034)	(0.050)	(0.093)	(0.103)	(0.078)
Freq. Intern	Regular	0.083	–0.019	0.046	–0.274*	0.092**	0.093	0.301**	0.515***	–0.031
Never		(0.048)	(0.037)	(0.034)	(0.107)	(0.036)	(0.051)	(0.097)	(0.108)	(0.081)
Ref	Occasional	–0.025	–0.156***	–0.071*	–0.329**	–0.066	–0.049	0.380***	0.363***	–0.073
Category		(0.046)	(0.039)	(0.033)	(0.105)	(0.035)	(0.053)	(0.100)	(0.107)	(0.080)
	Rare	0.003	–0.165	–0.046	–0.115	–0.181	–0.249	0.150	–0.035	0.615***
		(0.086)	(0.094)	(0.067)	(0.124)	(0.117)	(0.133)	(0.146)	(0.169)	(0.169)
Dwelling	Semi Pucca	0.152***	0.202***	0.167***	0.130***	0.198***	0.156***	0.122**	0.222***	0.249***
Kutcha		(0.012)	(0.023)	(0.011)	(0.017)	(0.018)	(0.032)	(0.040)	(0.050)	(0.065)
Ref	Pucca	0.286***	0.295***	0.285***	0.274***	0.302***	0.266***	0.256***	0.316***	0.350***

(Table 3 continued)

(Table 3 continued)

Expla Var.	Category	RURAL	URBAN	ALL	H_SCST	H_OBC	H_UC	M_SDC	M_UC	OMINO
Category		(0.014)	(0.021)	(0.011)	(0.020)	(0.019)	(0.031)	(0.039)	(0.055)	(0.065)
	Others	0.223***	0.134**	0.206***	0.056	0.292***	0.036	0.153	0.457**	0.437
		(0.041)	(0.042)	(0.034)	(0.052)	(0.051)	(0.113)	(0.086)	(0.153)	(0.396)
	No_Rooms	0.058***	0.039***	0.051***	0.054***	0.056***	0.028***	0.012	0.095***	0.083***
		(0.004)	(0.004)	(0.003)	(0.007)	(0.005)	(0.006)	(0.013)	(0.013)	(0.010)
	HH_Size	0.023***	0.027***	0.024***	0.025***	0.024***	0.031***	0.019***	0.009	0.031***
		(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.005)	(0.007)	(0.009)
Socio	Hindu (OBC)	0.031**	–0.019	0.017						
Religious		(0.012)	(0.015)	(0.009)						
Hin_SCST	Hindu (UC)	0.096***	0.050***	0.080***						
Ref		(0.015)	(0.014)	(0.011)						
Category	Muslim (SC/ ST/OBC)	0.071**	–0.089***	0.012						
		(0.022)	(0.020)	(0.016)						
	Muslim (UC)	0.022	–0.044*	0.003						
		(0.025)	(0.022)	(0.018)						
	Other Mino	0.095***	0.126***	0.112***						
		(0.024)	(0.022)	(0.018)						
	Sector			0.282***	0.311***	0.276***	0.273***	0.187***	0.218***	0.326***
				(0.008)	(0.016)	(0.014)	(0.015)	(0.027)	(0.030)	(0.031)
	Cons	10.766***	11.221***	10.542***	10.481***	10.590***	10.779***	10.794***	10.372***	10.21***
		(0.025)	(0.033)	(0.024)	(0.043)	(0.037)	(0.059)	(0.080)	(0.117)	(0.111)
	r2	0.310	0.364	0.401	0.373	0.370	0.412	0.293	0.485	0.473
	df_r	32,640.0	48,142.0	80,807.0	22,803.0	28,623.0	16,717.0	4,826.0	3,768.0	3,965.0
	N	32,666	48,168	80,834	22,825	28,645	16,739	4,848	3,790	3,987
	F (Xi, N)	F(25, 32,640)	F(25, 48,142)	F(26, 80,807)	F(21, 22,803)	F(21, 28,623)	F(21, 16,717)	F(21, 4,826)	F(21, 3,768)	F(21, 3,965)
		284.84***	290.14***	792.3***	278.10***	297.72***	218.01***	32.14***	60.11***	66.38***
	RMSE	0.57158	0.54166	0.56391	0.57292	0.56509	0.54517	0.51792	0.53504	0.5714
	VIF	2.64	3.22	2.78	3.14	2.95	4.02	2.90	3.14	3.60

Source: Estimates of OLS by authors.

Note: Robust Standard Errors within brackets; * p<0.05, ** p<0.01, *** p<0.001; H: Hindus, M: Muslims, UC: Upper caste, SDC:Socially–deprived caste, OBC: Other backward caste, SC/ST: scheduled caste and scheduled tribes.

Skill Levels

Skill levels ranging from 1–4 is ordered in a hierarchical scale of low to high. We can refer to $\beta 1$ as the return to skill. It does not correspond to a rate of return calculation, as we have no indication of the cost of achieving any given level of skill. Keeping skill level 1 as the reference category, marginal earnings of workers with skill level 2 are statistically significant across all groups (Table 3). The coefficient value of skill level 2 range from 6 per cent increase in earning premium among Hindu SC/ST to a maximum of 19 per cent increase among the Muslim upper-caste workforce (Table 3 and Figure 4).

With regards to skill level 3, which requires specialised training, the coefficient values are higher than skill level 2 and statistically significant across all groups. It ranges from a minimum of 15 per cent among the urban workforce to the highest level of 29 per cent among the rural workforce and 26 per cent among the Muslim upper-caste workforce. In the case of skill level 4, involving highly specialised and complex tasks, the coefficient values are higher than skill levels 2 and 3 and statistically significant except among the Muslim upper-caste groups. Also, the marginal effects improve over skill level 3 across all groups. The improvement in earnings is to the tune of 34 per cent among the urban groups and higher to the tune of 53 per cent across the rural groups (Figure 4). It is important to note that the higher order of skill levels reward the highest across rural areas than in urban areas. The earning premium at skill level 4 is quite substantial across the board. It is important to note that the skill premium variations across groups are marginal among workforce, especially at skill levels 3 and 4. This indicates that enhancing skill levels can help to address discrimination in the labour market.

Education

Three broad levels of education along with no education as a categorical variable is included in the earning function. Keeping no education as a base category, the workers who attained the basic education

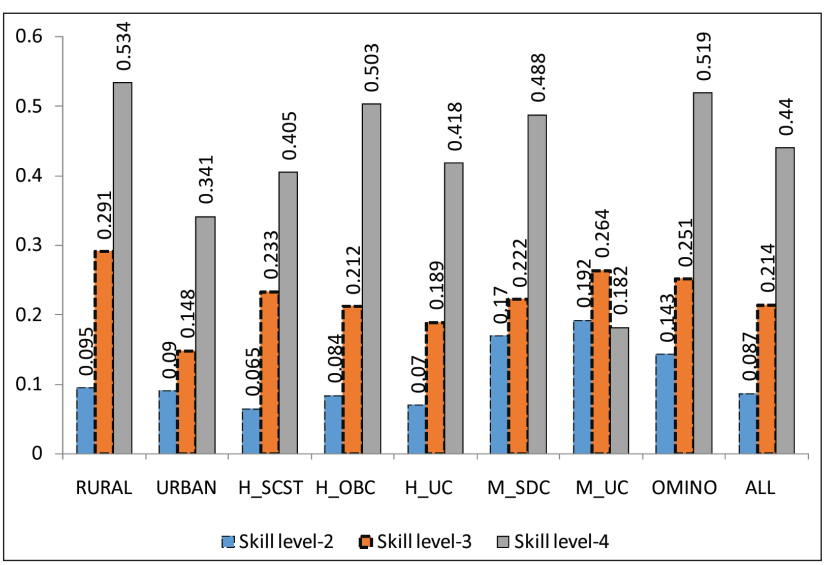

Figure 4. Marginal Returns of Various Skill Levels from Base Category of Skill Level 1

Source: India's Citizen Environment and Consumer Economy 360° Survey (2016).

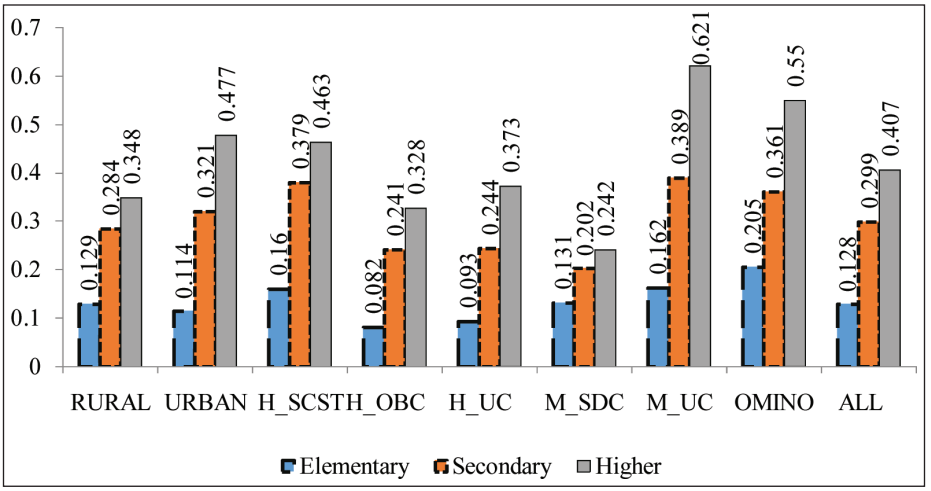

Figure 5. Marginal Returns of Various Educational Levels

Source: India's Citizen Environment and Consumer Economy 360° Survey (2016).

earn statistically significant across various groups. The marginal earning differential between elementary and no education ranges from 8 per cent among the Hindu upper caste to 20 per cent among the other minorities. With regards to secondary level of education, the coefficients are of higher value and also statistically significant across groups. It ranges from 20 per cent among the lower castes of Muslim to the highest level of 38 and 39 per cent among the Muslim upper caste and Hindu SC/ST caste groups. In the case of higher education, the substantial improvement is seen across the groups with the range of 24 per cent increase in the earning premium among the Muslim lower-caste groups to the maximum of 62 per cent among the Muslim upper-caste groups (Figure 5).

Further, with higher levels of education, the earnings premium is the highest. It can be also related to the skill content required for the changing job requirements in the labour market. The coefficient values across higher levels of education and the higher skill level 4 lead to the earning inequality. Like Ingram and Neumann (2006), this study shows that both cognitive and motor skills (pre-labour market skills) account for significant portion of variance in wages.

Age is another important determinant in the earnings equation, as age indicates experience or in other words, on-the-job training. As discussed earlier, we have grouped the age variable into four groups. Keeping the youngest age group of 15–35 years as the reference category, we tried to see changes in the earning premium of how the age cohort coefficient varies. In the caste of 36–45-years age group, the estimated coefficient values are statistically significant across all groups except among Muslim upper castes. The least coefficient value is among Muslim lower caste and Hindu SC/ST with 10 per cent to a maximum of around 15 percent among Hindu OBC, Hindu upper-case and other minorities. In the age group of 46–55 years, the experience does not make a value addition across the board. The coefficient values are statistically significant across rural, urban, Hindu OBC and upper caste groups. Here, the least coefficient value is among rural and with a minimum range of 9 per cent to a maximum range of 20 per cent among the Hindu upper-caste labour force. This Hindu upper-caste edge gets reconfirmed as we progress in the age group of seniors, that is, 56–65, with 25 per cent as the wage premium. It is the only group where the coefficient value is statistically significant. Age, rather than experience, is more than compensating for the Hindu upper-caste workforce. The experience square is brought in to the model to

take care of the non-linear relationship between earnings and experience, and it is found to be statistically significant across all groups except the Hindu SC/ST, Muslims and other minorities.

Role of ICT

Another important dimension that this article examines is the role and contribution of ICT skills in earnings of individuals. As economies continue to move towards 'knowledge-based societies', the access and use of ICT becomes pre-requisite. Internet access plays a significant role in increasing the earnings and is seen from the coefficient values, which are positive and statistically significant across the Hindu SC/ST, Hindu OBC and Muslims. The increase in earnings ranges from 33 per cent Hindu OBC and upper-caste groups to a maximum of 71 per cent among the Hindu SC/ST groups. Frequency of accessing the Internet is yet another important factor that influences earnings. Taking never accessing the Internet as the reference category, it is found that regular use of interest reports positive and statistically significant coefficient value among the Muslims and Hindu OBC. Rare use of Internet brings a wage premium only for other minorities.

To understand the role of ICT, an attempt is made here to construct the index of earnings of ICT users and non-users. For instance, if the overall income is indexed to 100, then ICT users earn 136 at skill level 1, while ICT non-users earn only 67 at the same level. This is quite apparent from Figure 6, which shows that the index of earnings of the ICT users is higher than that of the non-ICT users across skill levels. Similarly, the ICT users earn 276 at skill level 4, while the ICT non-users earn only 161 at same level. Also, the gap between the ICT users versus the non-users rises with the increase in skill levels, which highlights the impact of ICT usage in enhancing the earnings, which is the highest at skill level 4. Technological change, that is, the ICT, favours high-skilled workers because the Internet use complements their cognitive tasks. Medium-skilled workers are usually those that use routine tasks, being more substitutable.

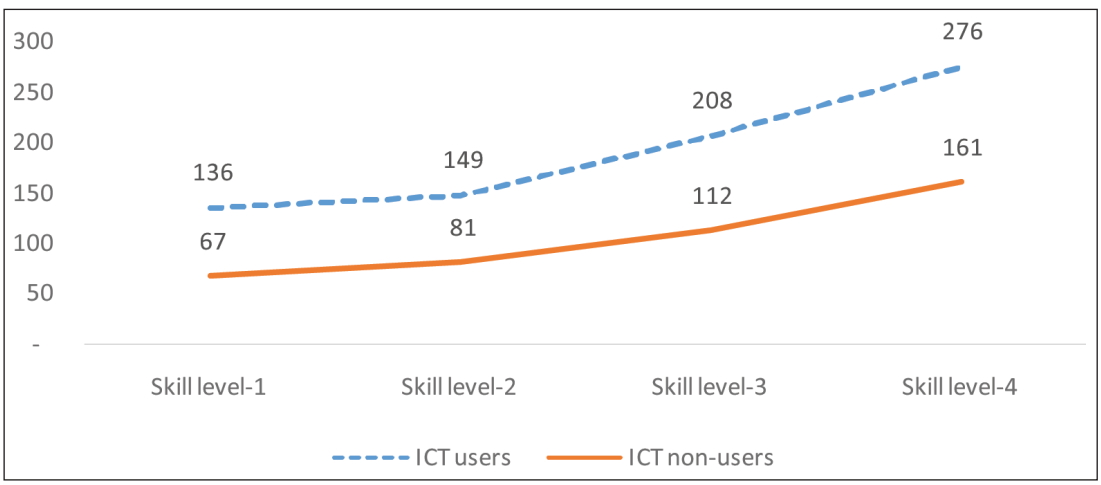

Figure 6. Index of Earnings Between ICT Enabled and Not Abled Individuals by Skill Levels

Source: India's Citizen Environment and Consumer Economy 360° Survey (2016).
Note: ** Where all-India average individual income is indexed to 100.

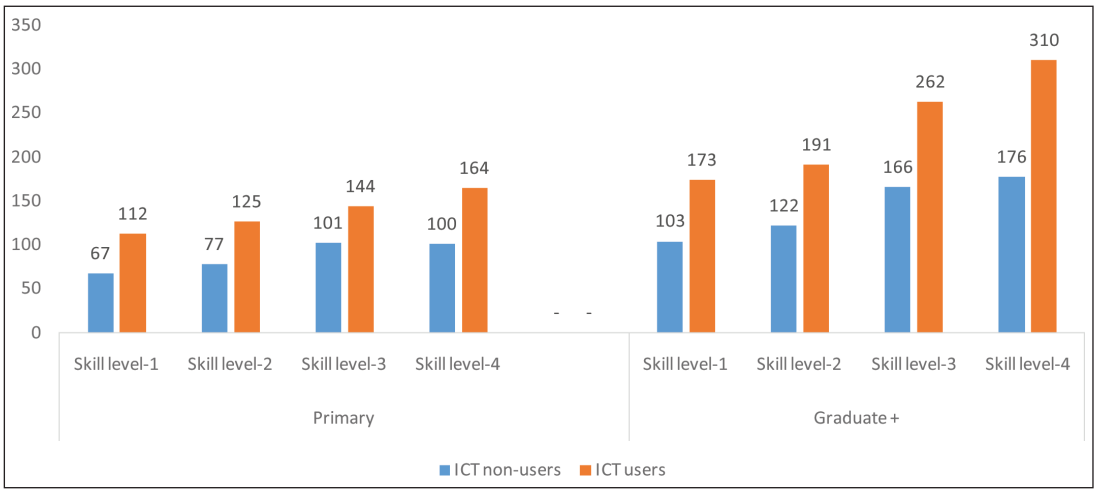

Figure 7. Index of Earnings by Skill Levels among ICT Users and Non-users across Primary Educated and Graduates

Source: India's Citizen Environment and Consumer Economy 360° Survey (2016).

Figure 7 highlights variations in earnings of the working population with primary levels of education and graduates. This comparison between ICT users and non-users by skill levels is attempted by making a baseline, where national average individual income is indexed to 100. At lower levels of education as well, individuals using Internet into their routine life earns more across skill levels than the non-ICT users. It is interesting to observe that among the ICT non-user of skill level 4 graduates, the index of earnings (176) is almost equivalent to the index of earning of the ICT user's skill level 1 graduates (173).

The index of earnings of the primary educated as well as graduate ICT users are more than average all-India earnings. Also, it is important to note that the difference in the index of earnings between the graduate and primary level educated is quite high among the ICT users in comparison to the ICT non-users. It is quite evident that higher education along with ICT usage augments the relationship between earning across skill levels.

The preceding analysis indicates that the Internet access can be a potential enabler for the high index on earning across skill levels. Most lines of business require specific skills, which cannot be provided by general-purpose education. Similarly, new technologies and organisations require continuous learning, best accomplished by workplace training. Higher the skill acquisition level, higher the adaptability to use ICT. Due to the progressive expansion of connectivity, digital divides are now more about the use than access to technology. Along with the usage, the frequency of its use does matter. Table 4 depicts that individuals who use Internet regularly gain more than others. If all-India Internet user's income is indexed to 100, then the index of earning of individuals who use the internet regularly is 108, while the index of earnings of individuals who rarely use the Internet is only 78. The impact is profound at skill level 4, where the index of earning of regular users is 183, while the index of earnings of rare users is only 83, which is almost similar to the regular users of skill level 1.

It is clear from the analyses that not everyone benefits equally from it and hence building resilience to this earning differential is crucial and also an important policy concern.

Table 4. Index of Earning of Skill Levels by Frequency of Internet Usage

Frequency	Skill Level 1	Skill Level 2	Skill Level 3	Skill Level 4	Total
Regular	84	93	130	183	108
Occasional	74	79	110	133	87
Rare	57	85	78	83	78
Total	80	88	123	163	100

Source: India's Citizen Environment and Consumer Economy 360° Survey (2016).
Note: **Where all-India average ICT skilled individual income is indexed to 100.

Economic Factors

Earnings are also directly related to assets that the workforce owes to. Hence, we try to control for the influence of the type of dwelling using the information on house types. Keeping the *kutcha*[8] type of house as a reference category, it is found that earnings of the workforce living in semi *pucca* houses increase across all categories and report statistically significant coefficient values. Living in a semi *pucca* house contributes to the increase of earnings from a minimum of 12 per cent among the Muslim lower caste to a maximum of 25 per cent among other minorities. When the house type is *pucca*, the coefficient value improves progressively across groups and is found to be statistically significant. This factor adds to the increase in earnings, which ranges from 26 per cent among Muslim lower caste to 35 per cent among other minorities. The other or miscellaneous category does show a positive relationship with earnings across groups, except among Hindu SC/ST, Hindu upper-caste and Muslim lower-caste workforce, which is statistically insignificant. Another dwelling related information available from the survey is the number of rooms available in a house. This indicates a positive and statistically significant relationship across the board, except among Muslim lower caste. However, it accounts for a marginal increase of 3–5 per cent among the Hindu upper caste, except for a 10 per cent increase among the Muslim upper caste and other minorities.

Gender as a dummy variable in the earning equation is statistically significant across all groups. The wage premium for a male member in the labour force range from a minimum of 5 per cent among the urban group to a maximum of around 28 per cent among Muslim upper caste and other minorities. The gender discrimination is quite evident in wage premium. One of the important characteristics of demography at the household level is the household size. The influence of the size of the household in to the wage equation is statistically significant across all groups, except Muslim upper caste. However, the effect of this is marginal at around 3 per cent across the board. The location of a worker, whether he lives in a rural or urban area, influence earnings to a larger extent. The variable sector, keeping rural as the reference category, is statistically significant across all categories. Earning premium of living in urban areas contribute to a range from 18 per cent among the Muslim lower caste to 33 per cent among other minorities.

The socio-religious group classification can indicate the labour market discrimination. Keeping Hindu SC/ST as the reference category, interesting patterns emerge: (a) the value of coefficients are statistically significant among the Hindu upper caste and other minorities across rural, urban and all the sample, though the earning premiums are higher for other minorities than the Hindu upper caste; (b) being a Muslim is a disadvantage, as there is negative relationship between earnings and this category more so in urban areas. Unlike the general perception, caste discrimination is more in rural areas; the results here indicate that there are significant positive coefficient values between the earnings of Hindu OBC and Muslim lower caste.

Conclusion and Policy Implications

The Indian labour market depicts a clear dichotomy between the higher skill levels being dominated largely by the high-skilled workers and the manual jobs with lower skill levels are for the relatively low skilled workers. Technology and digital usage have further accentuated this earnings differential. The approach adopted here provides an alternative perspective on the quality of the labour force, which depends on education, skill levels and technology. As well known, the growth rate of an economy depends on its investment rate and the productivity of capital or more precisely on its inverse incremental capital-output ratio. This incremental capital-output ratio, which is the key to economic growth, depends on a variety of factors. The most significant among them is the quality of labour. Further, this analysis provides important insights into the low skill levels of the vast Indian labour force, which would require re-qualification and re-specialisation of the labour force in order to compete in the fast-changing globalised India.

The decomposition for earnings across skill levels confirms that the sizeable earning gap exists, and it may have adverse effects on the economy. A substantial share (86% of the population) owe skill levels 1 and 2 and hence earn very less compared to higher skill levels of skill levels 3 and 4. This is a serious concern for "Young India", which is aspiring to become a "Skill India" in the near future. More educated individuals fall under the umbrella of high skill levels. Also, higher skill levels in India tend to have both higher average earning and education levels compared to their lower skill counterparts, consequently leading to widening the earning inequality. Thus, it becomes critical for the Indian policymakers to relook the education system, including TVET, to be able to swiftly and effectively respond to constantly evolving skills demand in the local, national and global market. Addressing to this high skill demands has important implications for education, training and skill formation.

The mismatch between education and training, skill, employment have widened to an extent where, on the one hand, employers are unable to discover suitably trained people, and on the other, the youth are unable to find employment that they aspire for. The latest India Skill Report shows that only about 45.6 per cent of the youth coming out of educational institutions are employable. Also, often employers in India lament that educated youth with graduate and post-graduate qualifications are not employable. The recent Talent Shortage Survey indicates that 48 per cent of employers in India face difficulties in filling job vacancies due to the skill and talent shortage (Manpower Group, 2016).

In order to address this tremendous task, Skill Development Initiative was launched under the Pradhan Mantri Kaushal Vikas Yojana to provide soft and other industry-relevant skills to 10 million youths. It aims at realising the potential of the workforce by enhancing their employability. It is notified by the National Apprenticeship Promotion Scheme to provide apprenticeship training to 5 million youth by 2019–2020. It has multiple objectives, which emphasises on strengthening the institutional training, infrastructure, convergence, training of trainers, overseas employment, sustainable livelihoods and leveraging public infrastructure. Yet, numerous challenges persist for skill development in India. A multi-pronged strategy need to be charted out addressing at both skill development initiatives with short-term skilling programme along with revamping the education system with a focus on entrepreneurship development and vocational training. With the school education focussing on developing cognitive and motor skills and with a higher education system collaborating with industry and society interaction can take a long way ahead.

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Notes

1. For more details, see Falck, Heimisch and Wiederhold (2016)
2. It is based on two main concepts, *job* and *skills*, in which job is defined as "set of tasks and duties performed or meant to be performed by one person, including for an employer or in self-employment". Further, the kind of work performed in a job is referred to occupation. In other words, the concept of occupation is defined as "set of jobs whose main tasks and duties are characterised by a degree of similarity" (ILO, 2012).
3. Under such cases, it is assumed that the skill prices are constant across occupations, though skill prices vary across occupations and sectors (Heckman, 2006).
4. The DOT is an American database that describes occupations based on the tasks performed, skill requirements and work context. It was replaced by the O-NET.
5. The experiential data is collected by submitting approximately 11,000 fictitious Curriculum Vitae (CVs) for real job vacancies published daily in the main job search engines in both cities. In their fictions, CVs, ICT skills are noted as Low and High ICT skills. It was defined that low ICT skills indicate basic knowledge of PC and high ICT skills denote advance knowledge of Office Tools.
6. ISCO intends that all jobs in the world can be assigned to the unit groups, whereas each unit group is made up of several "occupations" that have a high degree of similarity in terms of skill levels.
7. Skill education in India is formally provided via channels of formal vocation training institutions such as the government-run Industrial Training Institutes, privately operated Industrial Training Centres, vocational schools, specialised institutes for technical training and apprenticeship training by the industry. Besides the general and vocational skills acquired through formal education, the informal training, aptly the on-the-job training, form an important component of skill acquisition while working in the labour market.
8. Houses made with high-quality materials throughout, including the floor, roof and exterior walls, are called *pucca* houses. Houses made from mud, thatch or other low-quality materials are called *kutcha* houses.

Appendix

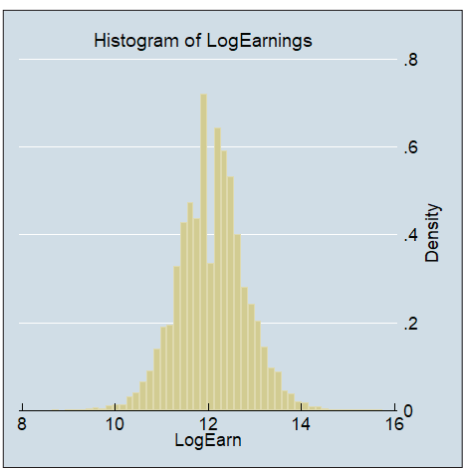

Figure A1. Histogram of Logearn

Source: Based on ICE unit data (2016).

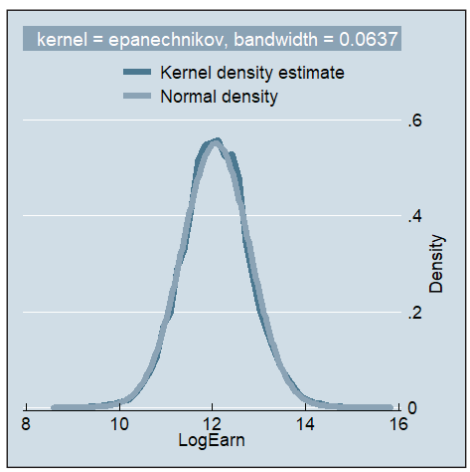

Figure A2. Kernel and Normal Density of Logearn

Source: Based on ICE unit data (2016).

Table A3. Correlation Coefficient Matrix of Selected Variables

Variables	LogEarn	Skill	EdnLev	Age_ Cohot	Expsquar	Gender	Int_Acc	Inter_Uq	House_ typ	No_ Room	HH_ Size	Socio_ ret	Sector
LogEarn	1												
Skill	0.3278*	1											
EdnLevel	0.4315*	0.3180*	1										
Age_Cohort	–0.0107*	0.0608*	–0.0692*	1									
Expsquare	–0.1585*	–0.045*	–0.3161*	0.897*	1								
Gender	0.1421*	0.0167*	0.0842*	–0.0166*	–0.0923*	1							
Int_Acc_D	0.4335*	0.2721*	0.3481*	0.0096*	–0.1171*	0.0410*	1						
Internet_U~q	0.3559*	0.2246*	0.2979*	0.0114*	–0.0966*	0.0305*	0.8645*	1					
House_type	0.3502*	0.2029*	0.2644*	0.0064	–0.0860*	0.0863*	0.2108*	0.1784*	1				
No_Rooms	0.2714*	0.1803*	0.1914*	0.0511*	–0.0346*	0.0624*	0.2010*	0.1779*	0.2315*	1			
HH_Size	0.1031*	–0.0071*	–0.0372*	–0.1093*	–0.1066*	0.1345*	0.0130*	0.0163*	0.0349*	0.2744*	1		
Socio_reli~t	0.1256*	0.0930*	0.0898*	0.0159*	–0.0257*	0.0485*	0.1091*	0.0983*	0.1344*	0.0897*	0.0218*	1	
Sector	0.3417*	0.1361*	0.2186*	–0.0392*	–0.1100*	0.0613*	0.2236*	0.1744*	0.2520*	0.0272*	–0.0597*	0.0585*	1

Note: * Statistically significant at 95 % level.

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